Task 1

Implement the OR Boolean logic gate using perceptron Neural Network. Inputs = x1, x2 and bias, weights should be fed into the perceptron with single Output = y. Display final weights and bias of each perceptron.

In [80]:
```
import numpy as np
import tensorflow as tf
```

In [51]:
```
X = np.array([
    [0, 0],
    [0, 1],
    [1, 0],
    [1, 1]
])
y = np.array([0, 1, 1, 1])
w1 = 1
w2 = 1
b = 0
```

In [52]:
```
def step(z):
    return 1 if z>=1 else 0
```

In [53]:
```
for i in range(X.shape[0]):
    z = w1*X[i][0] + w2*X[i][1] + b
    print(f"Input: {X[i]} → Output:", step(z))
```

```
Input: [0 0] → Output: 0
Input: [0 1] → Output: 1
Input: [1 0] → Output: 1
Input: [1 1] → Output: 1
```

Using the updating weights and bias approach:

In [54]:
```
w = np.random.rand(2)
b = np.random.rand(1)

epochs = 5
learning_rate = 0.1

for epoch in range(epochs):
    for i in range(X.shape[0]):
        z = np.dot(w, X[i]) + b
        y_pred = step(z)
        error = y[i] - y_pred
        w += learning_rate * error * X[i]
        b += learning_rate * error

print("Trained weights:", w)
print("Trained bias:", b)
```

```
Trained weights: [0.46398638 0.64831232]
Trained bias: [0.56438044]
```

In [55]:
```
print("\nPredictions:")
for i in range(len(X)):
    z = np.dot(w, X[i]) + b
    print(f"Input: {X[i]} → Output:", step(z))
```

```
Predictions:
Input: [0 0] → Output: 0
Input: [0 1] → Output: 1
Input: [1 0] → Output: 1
Input: [1 1] → Output: 1
```

Task 2

- Use the iris dataset Encode the input and show the new representation
- Decode the lossy representation for the output
- Map the input to reconstruction and visualize

In [56]:
```
from sklearn.datasets import load_iris
```

In [57]:
```
iris =load_iris()
```

In [58]:
```
data = iris.data
```

In [59]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
data = scaler.fit_transform(data)
```

In [60]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Input
```

In [61]:
```
autoencoder = Sequential([
    Input(shape = (4,)),
    Dense(2, activation='relu'),
    Dense(4, activation='sigmoid')
])
```

In [62]:
```
autoencoder.compile(optimizer='adam', loss='mse')
```

In [63]:
```
autoencoder.summary()
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
dense_4 (Dense)	(None, 2)	10
dense_5 (Dense)	(None, 4)	12

Total params: 22 (88.00 B)

Trainable params: 22 (88.00 B)

Non-trainable params: 0 (0.00 B)

In [64]:
```
autoencoder.fit(data, data, epochs=50, batch_size=8, shuffle=True)
```

```
Epoch 1/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9844
Epoch 2/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9777
Epoch 3/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9709
Epoch 4/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9649
Epoch 5/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9589
Epoch 6/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9533
Epoch 7/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9480
Epoch 8/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9428
Epoch 9/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9379
Epoch 10/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9328
Epoch 11/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9281
Epoch 12/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9233
Epoch 13/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9185
Epoch 14/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9135
Epoch 15/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9086
Epoch 16/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9035
Epoch 17/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8981
Epoch 18/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8929
Epoch 19/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8872
Epoch 20/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8816
Epoch 21/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8758
Epoch 22/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8701
Epoch 23/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8641
Epoch 24/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8582
Epoch 25/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 975us/step - loss:
0.8522
Epoch 26/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8460
Epoch 27/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8399
Epoch 28/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8338
Epoch 29/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8275
Epoch 30/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8213
Epoch 31/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8150
Epoch 32/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8089
Epoch 33/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8027
```

```
Epoch 34/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7966
Epoch 35/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7907
Epoch 36/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7853
Epoch 37/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7797
Epoch 38/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7746
Epoch 39/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7699
Epoch 40/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7654
Epoch 41/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7614
Epoch 42/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7574
Epoch 43/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7537
Epoch 44/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7503
Epoch 45/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7470
Epoch 46/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7441
Epoch 47/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 992us/step - loss:
0.7414
Epoch 48/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7385
Epoch 49/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7361
Epoch 50/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7337
```

Out[64]:
```
<keras.src.callbacks.history.History at 0x2f4c7be51f0>
```

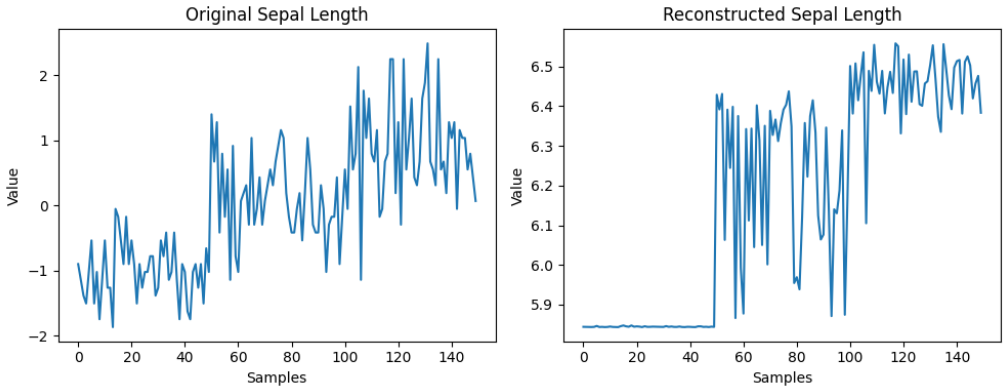
In [66]:
```
encoder = Sequential([
    autoencoder.layers[0]
])

encoded_data = encoder.predict(data)

print("Encoded (Lossy) Representation - First 5 Samples:\n")
print(encoded_data[:5])
```

```
[1m5/5[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 5ms/step
Encoded (Lossy) Representation - First 5 Samples:

[[5.126318  0.       ]
 [5.3782887 0.       ]
 [5.74848   0.       ]
 [5.7439027 0.       ]
 [5.2762113 0.       ]]
```

In [67]:
```
decoded_data = autoencoder.predict(data)

# Convert back to original scale
decoded_original = scaler.inverse_transform(decoded_data)
```

```
[1m5/5[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step
```

In [69]:
```
import matplotlib.pyplot as plt
plt.figure(figsize=(10,4))

# Original Sepal Length
plt.subplot(1,2,1)
plt.title("Original Sepal Length")
plt.plot(data[:, 0])
plt.xlabel("Samples")
plt.ylabel("Value")

# Reconstructed Sepal Length
plt.subplot(1,2,2)
plt.title("Reconstructed Sepal Length")
plt.plot(decoded_original[:, 0])
plt.xlabel("Samples")
plt.ylabel("Value")

plt.tight_layout()
plt.show()
```



In [76]:
```
import numpy as np

def mean_squared_error(original, reconstructed):
    return np.mean((original - reconstructed) ** 2)
```

In [77]:
```
for i in range(data.shape[1]):
    mse = mean_squared_error(data[:, i], decoded_data[:, i])
    print(f"MSE for feature {i+1}: {mse}")
```

```
MSE for feature 1: 0.6729832965435186
MSE for feature 2: 0.9959780458365102
MSE for feature 3: 0.6365716894583316
MSE for feature 4: 0.6239168277227577
```

Task 1

Implement the OR Boolean logic gate using perceptron Neural Network. Inputs = x1, x2 and bias, weights should be fed into the perceptron with single Output = y. Display final weights and bias of each perceptron.

In [42]:
```
import numpy as np
```

In [43]:
```
def step(z):
    return 1 if z >= 1 else 0
```

In [44]:
```
w1 = 1
w2 = 1
b = 0

X =np.array([[0,0],
             [0,1],
             [1,0],
             [1,1]])
Y = np.array([0,1,1,1])
```

In [45]:
```
z = np.dot(X, np.array([w1, w2])) + b
predictions = np.array([step(i) for i in z])
```

In [46]:
```
predictions
```

Out[46]:
```
array([0, 1, 1, 1])
```

Task 2

- Use the heart disease Dataset
- Create an Auto Encoder and fit it with our data using 3 neurons in the dense layer
- Display new reduced dimension values
- Plot loss for different Auto encoders

In [47]:
```
import pandas as pd
```

In [48]:
```
X = pd.read_csv('Data/heart.csv')
```

In [49]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [50]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Input
```

In [51]:
```
autoencoder = Sequential([
    Input(shape = (X.shape[1], )),
    Dense(3, activation='relu'),
    Dense(X.shape[1], activation='sigmoid')
])
```

In [52]:
```
autoencoder.compile(optimizer='adam', loss='mse')
```

In [53]:
```
autoencoder.fit(X_scaled, X_scaled, epochs=50, batch_size=16, shuffle=True,
validation_split=0.2)
```

```
Epoch 1/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2ms/step - loss: 1.2515
- val_loss: 1.1724
Epoch 2/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2214
- val_loss: 1.1460
Epoch 3/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1920
- val_loss: 1.1183
Epoch 4/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1609
- val_loss: 1.0897
Epoch 5/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1281
- val_loss: 1.0596
Epoch 6/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0948
- val_loss: 1.0293
Epoch 7/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0616
- val_loss: 0.9989
Epoch 8/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0309
- val_loss: 0.9719
Epoch 9/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0033
- val_loss: 0.9475
Epoch 10/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9790
- val_loss: 0.9265
Epoch 11/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9586
- val_loss: 0.9087
Epoch 12/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9414
- val_loss: 0.8940
Epoch 13/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2ms/step - loss: 0.9272
- val_loss: 0.8813
Epoch 14/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9152
- val_loss: 0.8706
Epoch 15/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9053
- val_loss: 0.8615
Epoch 16/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8969
- val_loss: 0.8537
Epoch 17/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8897
- val_loss: 0.8470
Epoch 18/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8835
- val_loss: 0.8409
Epoch 19/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8780
- val_loss: 0.8354
Epoch 20/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8732
- val_loss: 0.8305
Epoch 21/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8689
- val_loss: 0.8262
Epoch 22/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8651
- val_loss: 0.8223
```

```
Epoch 23/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8616
- val_loss: 0.8187
Epoch 24/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8584
- val_loss: 0.8152
Epoch 25/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8556
- val_loss: 0.8124
Epoch 26/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8530
- val_loss: 0.8096
Epoch 27/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8506
- val_loss: 0.8071
Epoch 28/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8484
- val_loss: 0.8047
Epoch 29/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8463
- val_loss: 0.8027
Epoch 30/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8445
- val_loss: 0.8006
Epoch 31/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8427
- val_loss: 0.7985
Epoch 32/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8409
- val_loss: 0.7967
Epoch 33/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8393
- val_loss: 0.7944
Epoch 34/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8376
- val_loss: 0.7929
Epoch 35/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8362
- val_loss: 0.7914
Epoch 36/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8348
- val_loss: 0.7898
Epoch 37/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8335
- val_loss: 0.7883
Epoch 38/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8323
- val_loss: 0.7871
Epoch 39/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8312
- val_loss: 0.7858
Epoch 40/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8301
- val_loss: 0.7847
Epoch 41/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8290
- val_loss: 0.7837
Epoch 42/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8281
- val_loss: 0.7828
Epoch 43/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8272
- val_loss: 0.7816
Epoch 44/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8262
- val_loss: 0.7809
Epoch 45/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8253
- val_loss: 0.7800
Epoch 46/50
```

```
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8244
- val_loss: 0.7792
Epoch 47/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8236
- val_loss: 0.7784
Epoch 48/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8227
- val_loss: 0.7777
Epoch 49/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8220
- val_loss: 0.7771
Epoch 50/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8213
- val_loss: 0.7765
```

Out[53]:
```
<keras.src.callbacks.history.History at 0x1e91b9de390>
```

In [54]:
```
encoder  =Sequential([autoencoder.layers[0]])
encoded_data = encoder.predict(X_scaled)
```

```
[1m33/33[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 963us/step
```

The reduced dimention values are as follows:

In [55]:
```
encoded_data
```

Out[55]:
```
array([[2.6006954 , 0.        , 2.8786101 ],
       [4.6247406 , 4.141082  , 0.        ],
       [5.9165525 , 1.2400119 , 0.        ],
       ...,
       [6.4260826 , 0.27540517, 2.3368797 ],
       [0.2857455 , 2.299008  , 8.678795  ],
       [5.1289797 , 0.        , 1.1936338 ]],
      shape=(1025, 3), dtype=float32)
```

In [56]:
```
preds = []
loss = []
for i in range(1,5):
    autoencoder = Sequential([
        Input(shape = (X.shape[1], )),
        Dense(i, activation='relu'),
        Dense(X.shape[1], activation='sigmoid')
    ])
    autoencoder.compile(optimizer='adam', loss='mse')
    history = autoencoder.fit(X_scaled, X_scaled, epochs=20, batch_size=16,
shuffle=True, validation_split=0.2)
    preds.append(autoencoder.predict(X_scaled))
    loss.append(history.history['loss'])
    print(f'Encoding Dimension: {i}, Loss: {loss[-1]}')
```

```
Epoch 1/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2ms/step - loss: 1.2385
- val_loss: 1.1537
Epoch 2/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2215
- val_loss: 1.1352
Epoch 3/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2050
- val_loss: 1.1178
Epoch 4/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1894
- val_loss: 1.1010
Epoch 5/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1743
- val_loss: 1.0853
Epoch 6/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1600
- val_loss: 1.0701
Epoch 7/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1465
- val_loss: 1.0565
Epoch 8/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1338
- val_loss: 1.0435
Epoch 9/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1218
- val_loss: 1.0313
Epoch 10/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1108
- val_loss: 1.0201
Epoch 11/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2ms/step - loss: 1.1005
- val_loss: 1.0100
Epoch 12/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0909
- val_loss: 1.0009
Epoch 13/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0822
- val_loss: 0.9922
Epoch 14/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0742
- val_loss: 0.9845
Epoch 15/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0668
- val_loss: 0.9774
Epoch 16/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0602
- val_loss: 0.9715
Epoch 17/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0544
- val_loss: 0.9658
Epoch 18/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0488
- val_loss: 0.9607
```

```
Epoch 19/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0435
- val_loss: 0.9556
Epoch 20/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0385
- val_loss: 0.9513
[1m33/33[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 969us/step
Encoding Dimension: 1, Loss: [1.2384586334228516, 1.2215328216552734,
1.205014705657959, 1.1893672943115234, 1.1742677688598633, 1.1600158214569092,
1.1465078592300415, 1.133806586265564, 1.1218146085739136, 1.110803246498108,
1.1005158424377441, 1.0908856391906738, 1.0821701288223267, 1.0741585493087769,
1.0668381452560425, 1.0602295398712158, 1.0543524026870728, 1.048801302909851,
1.0435290336608887, 1.0384565591812134]
Epoch 1/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2ms/step - loss: 1.2879
- val_loss: 1.2122
Epoch 2/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2598
- val_loss: 1.1866
Epoch 3/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2351
- val_loss: 1.1646
Epoch 4/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2125
- val_loss: 1.1445
Epoch 5/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1902
- val_loss: 1.1249
Epoch 6/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1679
- val_loss: 1.1048
Epoch 7/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1450
- val_loss: 1.0844
Epoch 8/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1219
- val_loss: 1.0637
Epoch 9/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0983
- val_loss: 1.0431
Epoch 10/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0747
- val_loss: 1.0222
Epoch 11/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0514
- val_loss: 1.0015
Epoch 12/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0292
- val_loss: 0.9820
Epoch 13/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0091
- val_loss: 0.9646
Epoch 14/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9918
- val_loss: 0.9499
Epoch 15/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9772
- val_loss: 0.9369
Epoch 16/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9650
- val_loss: 0.9264
Epoch 17/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9550
- val_loss: 0.9177
Epoch 18/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9469
- val_loss: 0.9100
Epoch 19/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9402
- val_loss: 0.9039
```

```
Epoch 20/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9348
- val_loss: 0.8985
[1m33/33[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 988us/step
Encoding Dimension: 2, Loss: [1.2878590822219849, 1.2598187923431396,
1.2351021766662598, 1.2124847173690796, 1.1901849508285522, 1.1678563356399536,
1.145045280456543, 1.121875524520874, 1.0983086824417114, 1.0746984481811523,
1.0514470338821411, 1.0292381048202515, 1.0090503692626953, 0.9917647838592529,
0.9772189259529114, 0.9649945497512817, 0.9550153017044067, 0.9468544721603394,
0.9402382969856262, 0.9347590208053589]
Epoch 1/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2ms/step - loss: 1.3135
- val_loss: 1.2240
Epoch 2/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2749
- val_loss: 1.1902
Epoch 3/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2437
- val_loss: 1.1626
Epoch 4/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2171
- val_loss: 1.1377
Epoch 5/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1925
- val_loss: 1.1143
Epoch 6/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1682
- val_loss: 1.0899
Epoch 7/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1434
- val_loss: 1.0649
Epoch 8/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1180
- val_loss: 1.0392
Epoch 9/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0921
- val_loss: 1.0141
Epoch 10/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0669
- val_loss: 0.9899
Epoch 11/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0426
- val_loss: 0.9669
Epoch 12/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0191
- val_loss: 0.9453
Epoch 13/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9969
- val_loss: 0.9253
Epoch 14/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9764
- val_loss: 0.9074
Epoch 15/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9584
- val_loss: 0.8920
Epoch 16/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9429
- val_loss: 0.8790
Epoch 17/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9300
- val_loss: 0.8684
Epoch 18/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9193
- val_loss: 0.8597
Epoch 19/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9105
- val_loss: 0.8524
Epoch 20/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9033
- val_loss: 0.8465
```

```
[1m33/33[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 953us/step
Encoding Dimension: 3, Loss: [1.3135099411010742, 1.2749431133270264,
1.2437139749526978, 1.2170566320419312, 1.1925243139266968, 1.1682037115097046,
1.143405795097351, 1.1179910898208618, 1.092088222503662, 1.066867709159851,
1.0425903797149658, 1.01913583278656, 0.9968659281730652, 0.9763920307159424,
0.9583531022071838, 0.9428660869598389, 0.9299794435501099, 0.919308602809906,
0.9105072617530823, 0.9033305048942566]
Epoch 1/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2ms/step - loss: 1.2920
- val_loss: 1.1891
Epoch 2/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2444
- val_loss: 1.1501
Epoch 3/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2020
- val_loss: 1.1124
Epoch 4/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1620
- val_loss: 1.0776
Epoch 5/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1245
- val_loss: 1.0448
Epoch 6/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0904
- val_loss: 1.0140
Epoch 7/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0595
- val_loss: 0.9858
Epoch 8/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0313
- val_loss: 0.9595
Epoch 9/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0050
- val_loss: 0.9340
Epoch 10/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9805
- val_loss: 0.9111
Epoch 11/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9587
- val_loss: 0.8906
Epoch 12/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9398
- val_loss: 0.8732
Epoch 13/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9238
- val_loss: 0.8591
Epoch 14/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9104
- val_loss: 0.8467
Epoch 15/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8991
- val_loss: 0.8363
Epoch 16/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8895
- val_loss: 0.8279
Epoch 17/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8814
- val_loss: 0.8209
Epoch 18/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8747
- val_loss: 0.8149
Epoch 19/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8689
- val_loss: 0.8099
Epoch 20/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8638
- val_loss: 0.8055
[1m33/33[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 953us/step
Encoding Dimension: 4, Loss: [1.2919960021972656, 1.2444182634353638,
1.20195472240448, 1.1620312929153442, 1.1245213747024536, 1.0904380083084106,
```

```
1.0595048666000366, 1.0313063859939575, 1.004961609840393, 0.9805213212966919,
0.9586631059646606, 0.9397965669631958, 0.9238115549087524, 0.9103679656982422,
0.8990597128868103, 0.8894584774971008, 0.8814430236816406, 0.8746541738510132,
0.86887526512146, 0.8638182878494263]
```

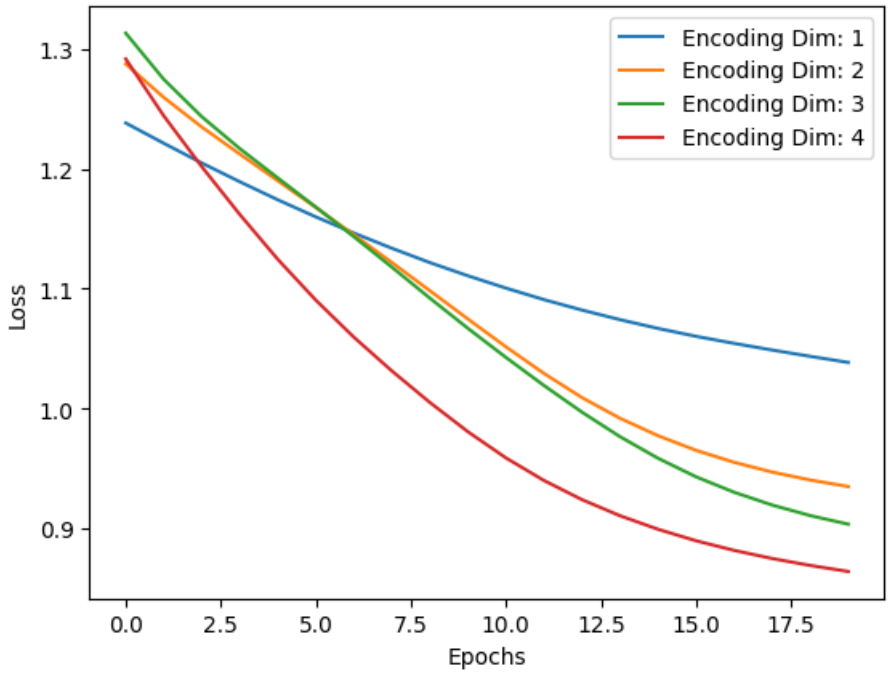
In [57]:
```
loss
```

Out[57]:
```
[[1.2384586334228516,
  1.2215328216552734,
  1.205014705657959,
  1.1893672943115234,
  1.1742677688598633,
  1.1600158214569092,
  1.1465078592300415,
  1.133806586265564,
  1.1218146085739136,
  1.110803246498108,
  1.1005158424377441,
  1.0908856391906738,
  1.0821701288223267,
  1.0741585493087769,
  1.0668381452560425,
  1.0602295398712158,
  1.0543524026870728,
  1.048801302909851,
  1.0435290336608887,
  1.0384565591812134],
 [1.2878590822219849,
  1.2598187923431396,
  1.2351021766662598,
  1.2124847173690796,
  1.1901849508285522,
  1.1678563356399536,
  1.145045280456543,
  1.121875524520874,
  1.0983086824417114,
  1.0746984481811523,
  1.0514470338821411,
  1.0292381048202515,
  1.0090503692626953,
  0.9917647838592529,
  0.9772189259529114,
  0.9649945497512817,
  0.9550153017044067,
  0.9468544721603394,
  0.9402382969856262,
  0.9347590208053589],
 [1.3135099411010742,
  1.2749431133270264,
  1.2437139749526978,
  1.2170566320419312,
  1.1925243139266968,
  1.1682037115097046,
  1.143405795097351,
  1.1179910898208618,
  1.092088222503662,
  1.066867709159851,
  1.0425903797149658,
  1.01913583278656,
  0.9968659281730652,
  0.9763920307159424,
  0.9583531022071838,
  0.9428660869598389,
  0.9299794435501099,
  0.919308602809906,
  0.9105072617530823,
  0.9033305048942566],
 [1.2919960021972656,
  1.2444182634353638,
  1.20195472240448,
  1.1620312929153442,
  1.1245213747024536,
  1.0904380083084106,
  1.0595048666000366,
```

```
1.0313063859939575,
1.004961609840393,
0.9805213212966919,
0.9586631059646606,
0.9397965669631958,
0.9238115549087524,
0.9103679656982422,
0.8990597128868103,
0.8894584774971008,
0.8814430236816406,
0.8746541738510132,
0.86887526512146,
0.8638182878494263]]
```

In [59]:
```
import matplotlib.pyplot as plt

for i in range(4):
    plt.plot(loss[i], label=f'Encoding Dim: {i+1}')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
```

Out[59]: <matplotlib.legend.Legend at 0x1e9253b64e0>



Task 2

- Load the Intel Image dataset
- Train and test the dataset
- Create a model using CNN
- Evaluate the model using confusion matrix.

In [1]:
```
from tensorflow.keras.preprocessing import image_dataset_from_directory
```

```
2026-01-06 15:44:10.584353: I tensorflow/core/util/port.cc:153] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn
them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2026-01-06 15:44:10.592822: E external/local_xla/xla/stream_executor/cuda/
cuda_fft.cc:467] Unable to register cuFFT factory: Attempting to register
factory for plugin cuFFT when one has already been registered
WARNING: All log messages before absl::InitializeLog() is called are written
to STDERR
E0000 00:00:1767694450.606663  192584 cuda_dnn.cc:8579] Unable to register
cuDNN factory: Attempting to register factory for plugin cuDNN when one has
already been registered
E0000 00:00:1767694450.610799  192584 cuda_blas.cc:1407] Unable to register
cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has
already been registered
W0000 00:00:1767694450.620009  192584 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767694450.620023  192584 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767694450.620025  192584 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767694450.620026  192584 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
2026-01-06 15:44:10.622325: I tensorflow/core/platform/
cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use
available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operations,
rebuild TensorFlow with the appropriate compiler flags.
```

In [2]:
```
dir = 'Data/Intel Image Data/seg_train/seg_train'
train = image_dataset_from_directory(
        dir,
        image_size=(150, 150),
        batch_size=32,
        subset = "training",
        validation_split=0.2,
        seed=42,
)
```

```
Found 14034 files belonging to 6 classes.
Using 11228 files for training.
```

```
I0000 00:00:1767694452.375605  192584 gpu_device.cc:2019] Created device /
job:localhost/replica:0/task:0/device:GPU:0 with 9791 MB memory:  -> device:
0, name: NVIDIA GeForce RTX 4070 SUPER, pci bus id: 0000:01:00.0, compute
capability: 8.9
```

In [3]:
```
train.as_numpy_iterator().next()[0].shape
```

Out[3]:
```
(32, 150, 150, 3)
```

In [4]:
```
train.as_numpy_iterator().next()[0].shape[0]
```

Out[4]:
```
32
```

In [5]:
```
val = image_dataset_from_directory(
        'Data/Intel Image Data/seg_test/seg_test',
        image_size=(150, 150),
        batch_size=32,
        subset = "validation",
        validation_split=0.2,
        seed=42
)
```

```
Found 3000 files belonging to 6 classes.
Using 600 files for validation.
```

In [6]:
```
class_names = train.class_names
print(class_names)
```

```
['buildings', 'forest', 'glacier', 'mountain', 'sea', 'street']
```

In [7]:
```
import tensorflow as tf
AUTOTUNE = tf.data.AUTOTUNE
data_augmentation = tf.keras.Sequential([
    tf.keras.layers.RandomFlip("horizontal"),
    tf.keras.layers.RandomRotation(0.1),
    tf.keras.layers.RandomZoom(0.1),
])
train = train.map(lambda x, y: (data_augmentation(x, training=True),
y)).prefetch(AUTOTUNE)
val = val.prefetch(AUTOTUNE)
```

In [8]:
```
for image_batch, labels_batch in train:
  print(image_batch.shape)
  print(labels_batch.shape)
  break
```

```
(32, 150, 150, 3)
(32,)
```

```
2026-01-06 15:44:13.183111: I tensorflow/core/framework/
local_rendezvous.cc:407] Local rendezvous is aborting with status: CANCELLED:
RecvAsync is cancelled.
         [[{{node GroupCrossDeviceControlEdges_0/NoOp/_21}}]]
[type.googleapis.com/tensorflow.DerivedStatus='']
2026-01-06 15:44:13.183169: I tensorflow/core/framework/
local_rendezvous.cc:407] Local rendezvous is aborting with status: CANCELLED:
RecvAsync is cancelled.
         [[{{node GroupCrossDeviceControlEdges_0/NoOp/_21}}]]
         [[GroupCrossDeviceControlEdges_0/NoOp/_20]] [type.googleapis.com/
tensorflow.DerivedStatus='']
```

In [9]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout,
Rescaling
```

In [10]:
```
model = Sequential([
    Rescaling(1./255, input_shape=(150, 150, 3)),
    Conv2D(32, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Dense(128, activation='relu'),
    Flatten(),
    Dropout(0.5),
    Dense(6, activation='softmax')
])
```

```
/home/smayan/Desktop/AI-ML-DS/AI-and-ML-Course/.conda/lib/python3.11/site-
packages/keras/src/layers/preprocessing/tf_data_layer.py:19: UserWarning: Do
not pass an `input_shape`/`input_dim` argument to a layer. When using
Sequential models, prefer using an `Input(shape)` object as the first layer
in the model instead.
  super().__init__(**kwargs)
```

In [11]:
```
model.compile(optimizer='adam', loss='categorical_crossentropy',
metrics=['accuracy'])
```

In [12]:
```
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',
metrics=['accuracy'])
model.fit(train, validation_data=val, epochs=10,)
```

```
Epoch 1/10


 WARNING: All log messages before absl::InitializeLog() is called are written
 to STDERR
 I0000 00:00:1767694454.011222  192925 service.cc:152] XLA service
 0x73f358009660 initialized for platform CUDA (this does not guarantee that
 XLA will be used). Devices:
 I0000 00:00:1767694454.011254  192925 service.cc:160]   StreamExecutor device
 (0): NVIDIA GeForce RTX 4070 SUPER, Compute Capability 8.9
 2026-01-06 15:44:14.024145: I tensorflow/compiler/mlir/tensorflow/utils/
 dump_mlir_util.cc:269] disabling MLIR crash reproducer, set env var
 `MLIR_CRASH_REPRODUCER_DIRECTORY` to enable.
 I0000 00:00:1767694454.099434  192925 cuda_dnn.cc:529] Loaded cuDNN version
 91701
 2026-01-06 15:44:14.838585: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot', 256 bytes spill stores, 256 bytes spill
 loads

 2026-01-06 15:44:14.957308: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot', 256 bytes spill stores, 256 bytes spill
 loads

 2026-01-06 15:44:14.957330: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot', 568 bytes spill stores, 476 bytes spill
 loads

 2026-01-06 15:44:14.973590: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot', 668 bytes spill stores, 544 bytes spill
 loads

 2026-01-06 15:44:15.259703: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot', 244 bytes spill stores, 244 bytes spill
 loads


[1m  5/351[0m [37m━━━━━━━━━━━━━━━━━━━━[0m [1m13s[0m 40ms/step - accuracy: 0.2624
- loss: 1.8556

 I0000 00:00:1767694457.014611  192925 device_compiler.h:188] Compiled cluster
 using XLA!  This line is logged at most once for the lifetime of the process.

[1m350/351[0m [32m━━━━━━━━━━━━━━━━━━━[0m[37m━[0m [1m0s[0m 47ms/step - accuracy:
0.5411 - loss: 1.1942

 2026-01-06 15:44:34.178632: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot', 568 bytes spill stores, 476 bytes spill
 loads

 2026-01-06 15:44:34.218802: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot', 244 bytes spill stores, 244 bytes spill
 loads

 2026-01-06 15:44:34.229612: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot', 256 bytes spill stores, 256 bytes spill
 loads
```

```
2026-01-06 15:44:34.555812: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot', 256 bytes spill stores, 256 bytes spill
loads

2026-01-06 15:44:34.635761: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot', 668 bytes spill stores, 544 bytes spill
loads
```

```
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 55ms/step - accuracy:
0.5413 - loss: 1.1937
```

```
2026-01-06 15:44:36.517198: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_72', 4 bytes spill stores, 4 bytes spill
loads

2026-01-06 15:44:36.630863: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_72', 68 bytes spill stores, 68 bytes
spill loads

2026-01-06 15:44:36.768215: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_72', 3884 bytes spill stores, 3836 bytes
spill loads

2026-01-06 15:44:36.780207: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_72', 3628 bytes spill stores, 3604 bytes
spill loads

2026-01-06 15:44:37.956331: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_72', 72 bytes spill stores, 72 bytes
spill loads

2026-01-06 15:44:38.031763: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_72', 1012 bytes spill stores, 1012 bytes
spill loads

2026-01-06 15:44:38.186527: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot', 568 bytes spill stores, 476 bytes spill
loads

2026-01-06 15:44:38.217096: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot', 256 bytes spill stores, 256 bytes spill
loads

2026-01-06 15:44:38.247614: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot', 668 bytes spill stores, 544 bytes spill
loads

2026-01-06 15:44:38.250381: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot', 244 bytes spill stores, 244 bytes spill
loads

2026-01-06 15:44:38.262545: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot', 256 bytes spill stores, 256 bytes spill
loads
```

```
2026-01-06 15:44:38.330646: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_72', 3880 bytes spill stores, 3536 bytes
spill loads
```

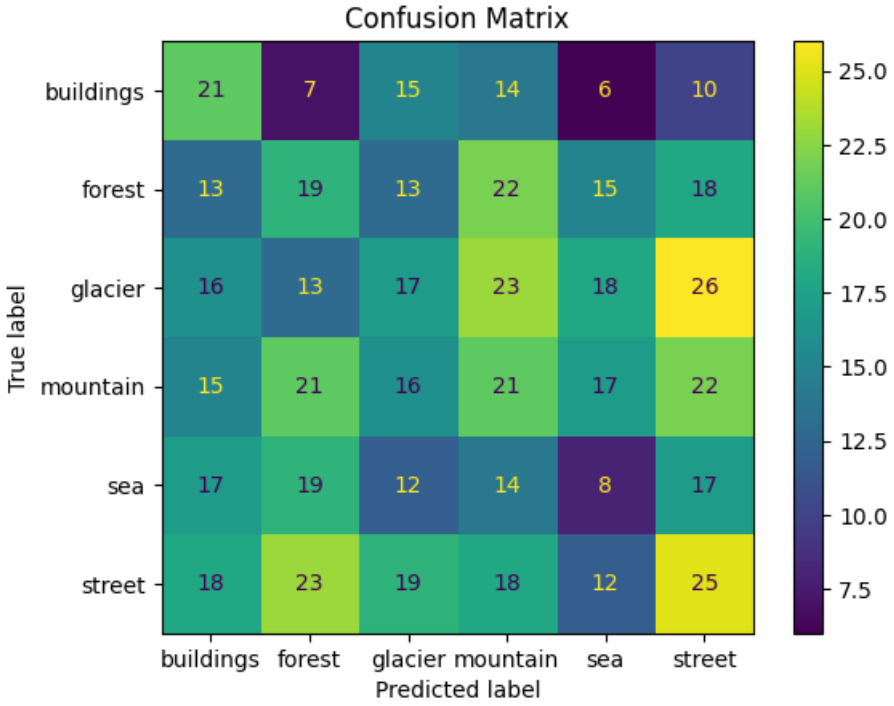
```
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m25s[0m 62ms/step - accuracy:
0.5415 - loss: 1.1933 - val_accuracy: 0.6100 - val_loss: 1.1427
Epoch 2/10
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m17s[0m 47ms/step - accuracy:
0.6818 - loss: 0.8630 - val_accuracy: 0.7117 - val_loss: 0.8516
Epoch 3/10
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m17s[0m 47ms/step - accuracy:
0.7000 - loss: 0.7886 - val_accuracy: 0.7400 - val_loss: 0.7684
Epoch 4/10
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m17s[0m 47ms/step - accuracy:
0.7390 - loss: 0.7052 - val_accuracy: 0.7567 - val_loss: 0.6923
Epoch 5/10
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m17s[0m 47ms/step - accuracy:
0.7547 - loss: 0.6715 - val_accuracy: 0.7350 - val_loss: 0.8189
Epoch 6/10
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m17s[0m 47ms/step - accuracy:
0.7645 - loss: 0.6507 - val_accuracy: 0.7783 - val_loss: 0.6588
Epoch 7/10
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m17s[0m 47ms/step - accuracy:
0.7801 - loss: 0.6226 - val_accuracy: 0.7867 - val_loss: 0.6245
Epoch 8/10
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m17s[0m 49ms/step - accuracy:
0.7881 - loss: 0.5983 - val_accuracy: 0.7650 - val_loss: 0.7221
Epoch 9/10
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m17s[0m 48ms/step - accuracy:
0.7830 - loss: 0.6017 - val_accuracy: 0.7733 - val_loss: 0.6432
Epoch 10/10
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m17s[0m 48ms/step - accuracy:
0.7935 - loss: 0.5732 - val_accuracy: 0.7817 - val_loss: 0.6309
```

Out[12]:
```
<keras.src.callbacks.history.History at 0x73f4f3026d50>
```

In [13]:
```
preds = model.predict(val)
```

```
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 15ms/step
```

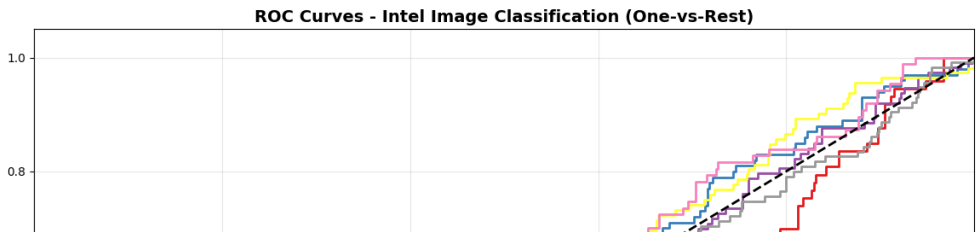
In [14]:
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import numpy as np
import matplotlib.pyplot as plt

true_labels = np.concatenate([y for x, y in val], axis=0)

predicted_labels = np.argmax(preds, axis=1)

cm = confusion_matrix(true_labels, predicted_labels)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_names)
disp.plot(
)
plt.title('Confusion Matrix')
plt.show()
```

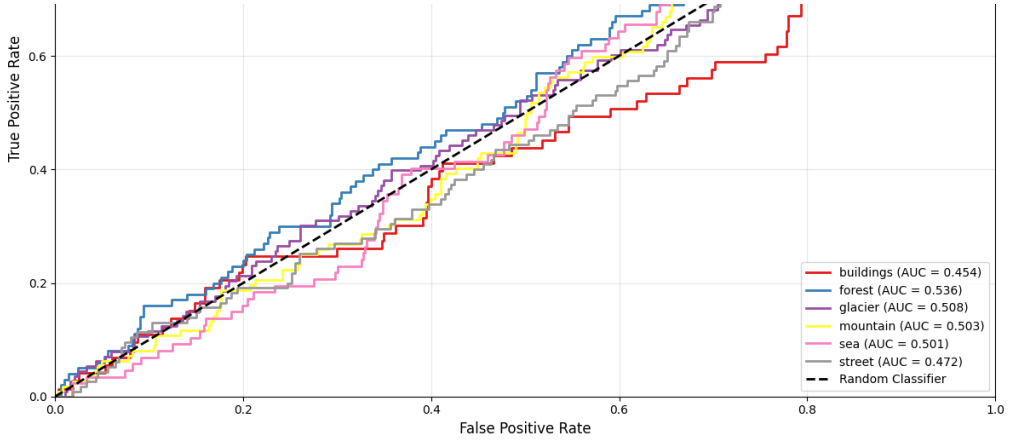


In [15]:

```
# Plot ROC AUC Curves for Multi-class Classification (One-vs-Rest)
from sklearn.metrics import roc_curve, auc, roc_auc_score
from sklearn.preprocessing import label_binarize
import numpy as np
import matplotlib.pyplot as plt

# Get probability predictions
y_true = np.concatenate([y for x, y in val], axis=0)
y_pred_proba = preds

# Number of classes
n_classes = len(class_names)

# Binarize the output for multi-class ROC AUC
y_bin = label_binarize(y_true, classes=list(range(n_classes)))

# Compute ROC curve and AUC for each class (One-vs-Rest)
fpr = dict()
tpr = dict()
roc_auc_dict = dict()
colors = plt.cm.Set1(np.linspace(0, 1, n_classes))

plt.figure(figsize=(12, 8))

for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_bin[:, i], y_pred_proba[:, i])
    roc_auc_dict[i] = auc(fpr[i], tpr[i])
    plt.plot(fpr[i], tpr[i], color=colors[i], lw=2,
             label=f'{class_names[i]} (AUC = {roc_auc_dict[i]:.3f})')

# Plot random classifier baseline
plt.plot([0, 1], [0, 1], 'k--', lw=2, label='Random Classifier')

plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate', fontsize=12)
plt.ylabel('True Positive Rate', fontsize=12)
plt.title('ROC Curves - Intel Image Classification (One-vs-Rest)', fontsize=14,
fontweight='bold')
plt.legend(loc="lower right", fontsize=10)
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

# Calculate and display macro-average AUC
macro_auc = np.mean(list(roc_auc_dict.values()))
print(f"\nROC AUC Scores per Class:")
for i in range(n_classes):
    print(f"  {class_names[i]}: {roc_auc_dict[i]:.4f}")
print(f"\nMacro-average AUC: {macro_auc:.4f}")

# Calculate weighted average AUC
weights = np.bincount(y_true) / len(y_true)
weighted_auc = np.average([roc_auc_dict[i] for i in range(n_classes)],
weights=weights)
print(f"Weighted-average AUC: {weighted_auc:.4f}")
```

```
2026-01-06 15:47:10.260931: I tensorflow/core/framework/
local_rendezvous.cc:407] Local rendezvous is aborting with status:
OUT_OF_RANGE: End of sequence
```






```
ROC AUC Scores per Class:
  buildings: 0.4542
  forest: 0.5362
  glacier: 0.5084
  mountain: 0.5026
  sea: 0.5011
  street: 0.4716

Macro-average AUC: 0.4957
Weighted-average AUC: 0.4973
```

In [ ]:

Task 1

Implement the NOT Boolean logic gate using perceptron Neural Network. Inputs = x1, x2 and bias, weights should be fed into the perceptron with single Output = y. Display final weights and bias of each perceptron

In [112]:
```
import numpy as np
import tensorflow as tf
```

In [113]:
```
X,y = np.array([
    [0, 1],
    [1, 0]
])
w1 = 1
w2 = -2
b = 1
X,y
```

Out[113]:
```
(array([0, 1]), array([1, 0]))
```

In [114]:
```
def step(z):
    return 1 if z>=1 else 0
```

In [115]:
```
for i in range(X.shape[0]):
    z = w1*X[i] + w2*X[i] + b
    print(f"Input: {X[i]} → Output:", step(z))
```

```
Input: 0 → Output: 1
Input: 1 → Output: 0
```

Using the updating weights and bias approach:

In [116]:
```
w = np.random.rand(1)
b = np.random.rand(1)

epochs = 100
learning_rate = 0.1

for epoch in range(epochs):
    for i in range(X.shape[0]):
        z = np.dot(w, X[i]) + b
        y_pred = step(z)
        error = y[i] - y_pred
        w += learning_rate * error * X[i]
        b += learning_rate * error

print("Trained weights:", w)
print("Trained bias:", b)
```

```
Trained weights: [-0.10659023]
Trained bias: [1.04670623]
```

In [117]:
```
print("\nPredictions:")
for i in range(len(X)):
    z = np.dot(w, X[i]) + b
    print(f"Input: {X[i]} → Output:", step(z))
```

```
Predictions:
Input: 0 → Output: 1
Input: 1 → Output: 0
```

Task 2

1. Use the Iris Dataset
2. Create an Auto Encoder and fit it with our data using 3 neurons in the dense layer
3. Display new reduced dimension values
4. Plot loss for different encoders

In [118]:
```
import pandas as pd
```

In [119]:
```
from sklearn.datasets import load_iris
X = load_iris().data
```

In [120]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [121]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [122]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Input
```

In [123]:
```
autoencoder = Sequential([
    Input(shape = (X.shape[1], )),
    Dense(3, activation='relu'),
    Dense(X.shape[1], activation='sigmoid')
])
```

In [124]:
```
autoencoder.compile(optimizer='adam', loss='mse')
```

In [125]:
```
autoencoder.fit(X_scaled, X_scaled, epochs=50, batch_size=16, shuffle=True,
validation_split=0.2)
```

```
Epoch 1/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 13ms/step - loss: 1.5463 -
val_loss: 0.6187
Epoch 2/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.5356 -
val_loss: 0.6109
Epoch 3/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.5247 -
val_loss: 0.6034
Epoch 4/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.5138 -
val_loss: 0.5959
Epoch 5/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.5032 -
val_loss: 0.5887
Epoch 6/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.4928 -
val_loss: 0.5814
Epoch 7/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.4824 -
val_loss: 0.5745
Epoch 8/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.4719 -
val_loss: 0.5671
Epoch 9/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.4618 -
val_loss: 0.5606
Epoch 10/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.4518 -
val_loss: 0.5546
Epoch 11/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.4422 -
val_loss: 0.5479
Epoch 12/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.4325 -
val_loss: 0.5416
Epoch 13/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.4233 -
val_loss: 0.5358
Epoch 14/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 7ms/step - loss: 1.4141 -
val_loss: 0.5291
Epoch 15/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.4054 -
val_loss: 0.5232
Epoch 16/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.3969 -
val_loss: 0.5171
Epoch 17/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.3887 -
val_loss: 0.5118
Epoch 18/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.3808 -
val_loss: 0.5073
Epoch 19/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.3729 -
val_loss: 0.5028
Epoch 20/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.3656 -
val_loss: 0.4982
Epoch 21/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.3581 -
val_loss: 0.4940
Epoch 22/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.3511 -
val_loss: 0.4896
```

```
Epoch 23/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.3446 -
val_loss: 0.4861
Epoch 24/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 7ms/step - loss: 1.3380 -
val_loss: 0.4817
Epoch 25/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.3316 -
val_loss: 0.4780
Epoch 26/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.3255 -
val_loss: 0.4748
Epoch 27/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.3195 -
val_loss: 0.4718
Epoch 28/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.3138 -
val_loss: 0.4693
Epoch 29/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.3080 -
val_loss: 0.4662
Epoch 30/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.3026 -
val_loss: 0.4634
Epoch 31/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.2973 -
val_loss: 0.4608
Epoch 32/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.2922 -
val_loss: 0.4581
Epoch 33/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.2870 -
val_loss: 0.4555
Epoch 34/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.2820 -
val_loss: 0.4532
Epoch 35/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.2771 -
val_loss: 0.4510
Epoch 36/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.2721 -
val_loss: 0.4489
Epoch 37/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 7ms/step - loss: 1.2675 -
val_loss: 0.4470
Epoch 38/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 7ms/step - loss: 1.2627 -
val_loss: 0.4455
Epoch 39/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 7ms/step - loss: 1.2581 -
val_loss: 0.4433
Epoch 40/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.2533 -
val_loss: 0.4414
Epoch 41/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 7ms/step - loss: 1.2489 -
val_loss: 0.4401
Epoch 42/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 7ms/step - loss: 1.2443 -
val_loss: 0.4388
Epoch 43/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.2397 -
val_loss: 0.4374
Epoch 44/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.2351 -
val_loss: 0.4358
Epoch 45/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 6ms/step - loss: 1.2305 -
val_loss: 0.4344
Epoch 46/50
```

```
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1m0s[0m 6ms/step - loss: 1.2261 -
val_loss: 0.4332
Epoch 47/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1m0s[0m 6ms/step - loss: 1.2215 -
val_loss: 0.4323
Epoch 48/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1m0s[0m 6ms/step - loss: 1.2170 -
val_loss: 0.4314
Epoch 49/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1m0s[0m 6ms/step - loss: 1.2125 -
val_loss: 0.4302
Epoch 50/50
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1m0s[0m 6ms/step - loss: 1.2079 -
val_loss: 0.4295
```

Out[125]:
```
<keras.src.callbacks.history.History at 0x2667f0428a0>
```

In [126]:
```
encoder  =Sequential([autoencoder.layers[0]])
encoded_data = encoder.predict(X_scaled)
```

```
[1m5/5[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1m0s[0m 5ms/step
```

The reduced dimention values are as follows:

In [127]:
```
encoded_data
```

Out[127]:
```
array([[0.9406513 , 0.        , 0.        ],
       [0.32772845, 0.        , 0.        ],
       [0.5817579 , 0.        , 0.        ],
       [0.40021795, 0.        , 0.        ],
       [1.0539247 , 0.        , 0.        ],
       [1.3686391 , 0.        , 0.        ],
       [0.7928662 , 0.        , 0.        ],
       [0.78659374, 0.        , 0.        ],
       [0.1745504 , 0.        , 0.        ],
       [0.41477722, 0.        , 0.        ],
       [1.1729696 , 0.        , 0.        ],
       [0.74580973, 0.        , 0.        ],
       [0.31568468, 0.        , 0.        ],
       [0.36487836, 0.        , 0.        ],
       [1.6417928 , 0.        , 0.        ],
       [2.0431776 , 0.        , 0.        ],
       [1.478569  , 0.        , 0.        ],
       [0.9460442 , 0.        , 0.        ],
       [1.2632741 , 0.        , 0.        ],
       [1.2783345 , 0.        , 0.        ],
       [0.7582318 , 0.        , 0.        ],
       [1.1638032 , 0.        , 0.        ],
       [1.1372516 , 0.        , 0.        ],
       [0.63453424, 0.        , 0.        ],
       [0.6633623 , 0.        , 0.        ],
       [0.27941424, 0.        , 0.        ],
       [0.7698972 , 0.        , 0.        ],
       [0.9198195 , 0.        , 0.        ],
       [0.82737774, 0.        , 0.        ],
       [0.4993105 , 0.        , 0.        ],
       [0.38603693, 0.        , 0.        ],
       [0.8239827 , 0.        , 0.        ],
       [1.633972  , 0.        , 0.        ],
       [1.8067242 , 0.        , 0.        ],
       [0.4201702 , 0.        , 0.        ],
       [0.6291927 , 0.        , 0.        ],
       [0.9947368 , 0.        , 0.        ],
       [1.041881  , 0.        , 0.        ],
       [0.3219571 , 0.        , 0.        ],
       [0.79324454, 0.        , 0.        ],
       [0.9668759 , 0.        , 0.        ],
       [0.        , 0.        , 0.48330545],
       [0.5618056 , 0.        , 0.        ],
       [0.90060747, 0.        , 0.        ],
       [1.1737976 , 0.        , 0.        ],
       [0.3264706 , 0.        , 0.        ],
       [1.2454591 , 0.        , 0.        ],
       [0.5476247 , 0.        , 0.        ],
       [1.1663188 , 0.        , 0.        ],
       [0.694152  , 0.        , 0.        ],
       [0.        , 1.006562  , 0.        ],
       [0.        , 0.76434267, 0.        ],
       [0.        , 1.4012833 , 0.        ],
       [0.        , 2.393271  , 1.0389706 ],
       [0.        , 1.9140996 , 0.16736107],
       [0.        , 1.334302  , 0.2978707 ],
       [0.        , 0.6249491 , 0.        ],
       [0.        , 1.3115089 , 0.84407806],
       [0.        , 1.4989582 , 0.        ],
       [0.        , 1.2518963 , 0.64380115],
       [0.        , 2.49902   , 1.38809   ],
       [0.        , 0.9663284 , 0.06718512],
       [0.        , 2.5914092 , 0.7899711 ],
       [0.        , 1.4137746 , 0.10196503],
       [0.        , 0.6836834 , 0.12815385],
       [0.        , 1.029037  , 0.        ],
       [0.        , 0.94827116, 0.19365673],
```

```
[0.        , 1.2063298 , 0.16099681],
[0.        , 3.3473697 , 1.1130521 ],
[0.        , 1.6733181 , 0.571141  ],
[0.        , 0.94652474, 0.04184525],
[0.        , 1.3206239 , 0.12217896],
[0.        , 2.7409878 , 0.68247384],
[0.        , 1.4889748 , 0.10002814],
[0.        , 1.298149  , 0.        ],
[0.        , 1.252321  , 0.        ],
[0.        , 2.0249991 , 0.00461288],
[0.        , 1.8104054 , 0.        ],
[0.        , 1.3904216 , 0.19452463],
[0.        , 1.2030888 , 0.29495907],
[0.        , 1.8588481 , 0.7404176 ],
[0.        , 1.7251654 , 0.6617637 ],
[0.        , 1.3226787 , 0.29005313],
[0.        , 2.2469902 , 0.5909833 ],
[0.        , 0.8607246 , 0.26384538],
[0.10412884, 0.15106341, 0.        ],
[0.        , 1.2382282 , 0.        ],
[0.        , 2.894474  , 0.78646755],
[0.        , 0.6053971 , 0.02222313],
[0.        , 1.8591564 , 0.75648034],
[0.        , 1.6471874 , 0.5718957 ],
[0.        , 1.1089631 , 0.        ],
[0.        , 1.6274903 , 0.43836117],
[0.        , 1.6223395 , 0.9502289 ],
[0.        , 1.4443234 , 0.45302153],
[0.        , 0.59099597, 0.        ],
[0.        , 0.95398194, 0.13543685],
[0.        , 1.2106025 , 0.        ],
[0.        , 1.1146638 , 0.6830466 ],
[0.        , 1.183285  , 0.2696191 ],
[0.        , 1.9791113 , 0.3461148 ],
[0.        , 2.4472294 , 0.875945  ],
[0.        , 2.709001  , 0.1956686 ],
[0.        , 2.2248235 , 0.38170654],
[0.        , 2.5045357 , 0.4707626 ],
[0.        , 3.1921468 , 0.06963722],
[0.        , 2.169002  , 1.2887248 ],
[0.        , 2.926836  , 0.08020346],
[0.        , 3.5436544 , 0.8204355 ],
[0.03260367, 1.609653  , 0.        ],
[0.        , 1.5142841 , 0.        ],
[0.        , 2.7853775 , 0.6795049 ],
[0.        , 2.4266644 , 0.2727    ],
[0.        , 2.9957452 , 1.2580577 ],
[0.        , 2.6598153 , 1.0926551 ],
[0.        , 1.8338052 , 0.25964332],
[0.        , 2.0075583 , 0.16320984],
[0.12463228, 1.2331438 , 0.        ],
[0.        , 4.609269  , 0.7638942 ],
[0.        , 3.448594  , 1.2185552 ],
[0.        , 2.2036884 , 0.11242323],
[0.        , 2.1130457 , 0.8623538 ],
[0.        , 3.7118602 , 0.25250506],
[0.        , 2.494659  , 0.61475664],
[0.        , 1.6572274 , 0.        ],
[0.        , 1.9686278 , 0.        ],
[0.        , 2.1460738 , 0.5015429 ],
[0.        , 1.6059402 , 0.26120985],
[0.        , 2.82344   , 0.7026306 ],
[0.        , 2.2353768 , 0.        ],
[0.        , 3.2580867 , 0.24381964],
[0.20959525, 1.0155708 , 0.        ],
[0.        , 2.9193687 , 0.7742214 ],
[0.        , 2.015324  , 0.27286416],
[0.        , 2.5547347 , 0.58926654],
[0.        , 3.239006  , 0.1424105 ],
[0.        , 1.4651085 , 0.10502701],
```

```
[0.        , 1.6967279 , 0.057059  ],
[0.        , 1.5244128 , 0.28924125],
[0.        , 2.165626  , 0.08929764],
[0.        , 2.4413738 , 0.38838518],
[0.        , 2.2442203 , 0.21129103],
[0.        , 2.4472294 , 0.875945  ],
[0.        , 2.2354236 , 0.16164334],
[0.        , 2.0409417 , 0.18454884],
[0.        , 2.4614854 , 0.42978776],
[0.        , 3.1624565 , 0.97590077],
[0.        , 2.086153  , 0.28520328],
[0.        , 1.2498982 , 0.05440451],
[0.        , 1.593902  , 0.34552425]], dtype=float32)
```

In [128]:
```
preds = []
loss = []
for i in range(1,5):
    autoencoder = Sequential([
        Input(shape = (X.shape[1], )),
        Dense(i, activation='relu'),
        Dense(X.shape[1], activation='sigmoid')
    ])
    autoencoder.compile(optimizer='adam', loss='mse')
    history = autoencoder.fit(X_scaled, X_scaled, epochs=20, batch_size=16,
shuffle=True, validation_split=0.2)
    preds.append(autoencoder.predict(X_scaled))
    loss.append(history.history['loss'])
    print(f'Encoding Dimension: {i}, Loss: {loss[-1]}')
```

```
Epoch 1/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 13ms/step - loss: 1.3208 -
val_loss: 0.5423
Epoch 2/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3146 -
val_loss: 0.5431
Epoch 3/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3084 -
val_loss: 0.5439
Epoch 4/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3022 -
val_loss: 0.5448
Epoch 5/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.2958 -
val_loss: 0.5456
Epoch 6/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 7ms/step - loss: 1.2899 -
val_loss: 0.5465
Epoch 7/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.2835 -
val_loss: 0.5474
Epoch 8/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.2773 -
val_loss: 0.5482
Epoch 9/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.2712 -
val_loss: 0.5490
Epoch 10/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.2652 -
val_loss: 0.5497
Epoch 11/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.2593 -
val_loss: 0.5505
Epoch 12/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.2534 -
val_loss: 0.5513
Epoch 13/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.2475 -
val_loss: 0.5520
Epoch 14/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.2418 -
val_loss: 0.5528
Epoch 15/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 7ms/step - loss: 1.2359 -
val_loss: 0.5536
Epoch 16/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 7ms/step - loss: 1.2303 -
val_loss: 0.5543
Epoch 17/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.2245 -
val_loss: 0.5550
Epoch 18/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.2188 -
val_loss: 0.5557
```

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Epoch 19/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.2132 -
val_loss: 0.5563
Epoch 20/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.2077 -
val_loss: 0.5570
[1m5/5[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step
Encoding Dimension: 1, Loss: [1.3208034038543701, 1.3146188259124756,
1.3084051609039307, 1.3022257089614868, 1.2958046197891235, 1.289927363395691,
1.2834537029266357, 1.2772845029830933, 1.271241307258606, 1.2652369737625122,
1.2592722177505493, 1.2534306049346924, 1.2475420236587524, 1.2417625188827515,
1.235927700996399, 1.230284333229065, 1.2244750261306763, 1.2187851667404175,
1.213154673576355, 1.2076836824417114]
Epoch 1/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 13ms/step - loss: 1.5125 -
val_loss: 0.5473
Epoch 2/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.5033 -
val_loss: 0.5483
Epoch 3/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4939 -
val_loss: 0.5493
Epoch 4/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4848 -
val_loss: 0.5503
Epoch 5/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4755 -
val_loss: 0.5514
Epoch 6/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4662 -
val_loss: 0.5524
Epoch 7/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4569 -
val_loss: 0.5534
Epoch 8/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4480 -
val_loss: 0.5544
Epoch 9/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4391 -
val_loss: 0.5553
Epoch 10/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4295 -
val_loss: 0.5563
Epoch 11/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4205 -
val_loss: 0.5574
Epoch 12/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4113 -
val_loss: 0.5585
Epoch 13/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4018 -
val_loss: 0.5594
Epoch 14/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3923 -
val_loss: 0.5605
Epoch 15/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3831 -
val_loss: 0.5614
Epoch 16/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3737 -
val_loss: 0.5624
Epoch 17/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3642 -
val_loss: 0.5633
Epoch 18/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3553 -
val_loss: 0.5643
Epoch 19/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3459 -
val_loss: 0.5653
```

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Epoch 20/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3370 -
val_loss: 0.5663
[1m5/5[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step
Encoding Dimension: 2, Loss: [1.5125142335891724, 1.5032681226730347,
1.4939273595809937, 1.4848178625106812, 1.475497841835022, 1.4661580324172974,
1.4569032192230225, 1.447950005531311, 1.439149022102356, 1.4295470714569092,
1.4205071926116943, 1.4112592935562134, 1.4017635583877563, 1.3923107385635376,
1.3830643892288208, 1.3737413883209229, 1.3641504049301147, 1.3552883863449097,
1.3459017276763916, 1.3369556665420532]
Epoch 1/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 13ms/step - loss: 1.4679 -
val_loss: 0.5715
Epoch 2/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4599 -
val_loss: 0.5693
Epoch 3/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4525 -
val_loss: 0.5674
Epoch 4/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4456 -
val_loss: 0.5654
Epoch 5/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4390 -
val_loss: 0.5630
Epoch 6/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4324 -
val_loss: 0.5609
Epoch 7/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4260 -
val_loss: 0.5585
Epoch 8/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4199 -
val_loss: 0.5563
Epoch 9/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4139 -
val_loss: 0.5543
Epoch 10/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4081 -
val_loss: 0.5519
Epoch 11/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4024 -
val_loss: 0.5494
Epoch 12/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3969 -
val_loss: 0.5473
Epoch 13/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3916 -
val_loss: 0.5452
Epoch 14/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3867 -
val_loss: 0.5436
Epoch 15/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3819 -
val_loss: 0.5419
Epoch 16/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3771 -
val_loss: 0.5399
Epoch 17/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3724 -
val_loss: 0.5381
Epoch 18/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3677 -
val_loss: 0.5362
Epoch 19/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3632 -
val_loss: 0.5348
Epoch 20/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 8ms/step - loss: 1.3585 -
val_loss: 0.5328
```

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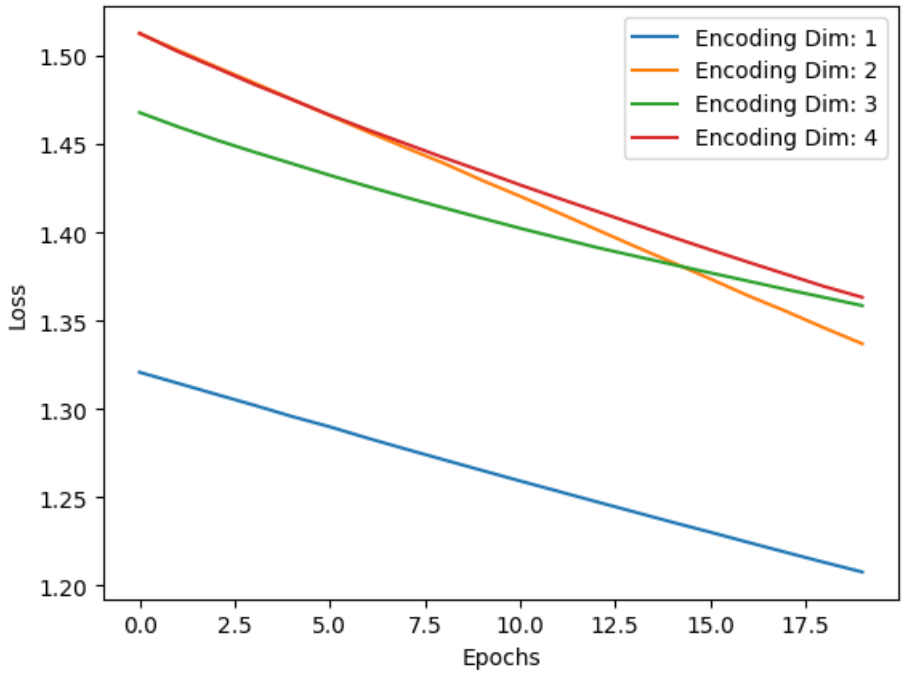
[1m5/5[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 5ms/step
Encoding Dimension: 3, Loss: [1.4678815603256226, 1.4599121809005737,
1.4524868726730347, 1.445599913597107, 1.4390289783477783, 1.4323586225509644,
1.4260315895080566, 1.4198707342147827, 1.4139213562011719, 1.408059000968933,
1.4023598432540894, 1.3969483375549316, 1.3915820121765137, 1.38671875,
1.3818602561950684, 1.377134084701538, 1.3724324703216553, 1.3677042722702026,
1.3631787300109863, 1.3585273027420044]
Epoch 1/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 13ms/step - loss: 1.5128 -
val_loss: 0.7940
Epoch 2/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.5025 -
val_loss: 0.7851
Epoch 3/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4933 -
val_loss: 0.7760
Epoch 4/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4839 -
val_loss: 0.7669
Epoch 5/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4753 -
val_loss: 0.7590
Epoch 6/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4665 -
val_loss: 0.7500
Epoch 7/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4581 -
val_loss: 0.7414
Epoch 8/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 7ms/step - loss: 1.4502 -
val_loss: 0.7334
Epoch 9/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4423 -
val_loss: 0.7244
Epoch 10/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 7ms/step - loss: 1.4347 -
val_loss: 0.7158
Epoch 11/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4269 -
val_loss: 0.7079
Epoch 12/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4194 -
val_loss: 0.7001
Epoch 13/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4121 -
val_loss: 0.6923
Epoch 14/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.4047 -
val_loss: 0.6849
Epoch 15/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3974 -
val_loss: 0.6771
Epoch 16/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3902 -
val_loss: 0.6696
Epoch 17/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3832 -
val_loss: 0.6627
Epoch 18/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3763 -
val_loss: 0.6550
Epoch 19/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3694 -
val_loss: 0.6480
Epoch 20/20
[1m8/8[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - loss: 1.3632 -
val_loss: 0.6415
[1m5/5[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 5ms/step
Encoding Dimension: 4, Loss: [1.512825846672058, 1.5024619102478027,
1.4933172464370728, 1.48392653465271, 1.4753153324127197, 1.4664556980133057,
```

```
1.4581149816513062, 1.450237512588501, 1.4423035383224487, 1.4347180128097534,
1.4269241094589233, 1.419448733329773, 1.4121322631835938, 1.404748797416687,
1.3973814249038696, 1.3902099132537842, 1.3831521272659302, 1.3762688636779785,
1.3693735599517822, 1.3632349967956543]
```

In [130]:
```
import matplotlib.pyplot as plt

for i in range(4):
    plt.plot(loss[i], label=f'Encoding Dim: {i+1}')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
```

Out[130]: <matplotlib.legend.Legend at 0x2667f1313d0>



Task 1

Implement the OR Boolean logic gate using perceptron Neural Network. Inputs = x1, x2 and bias, weights should be fed into the perceptron with single Output = y. Display final weights and bias of each perceptron

In [21]:
```
import numpy as np
import tensorflow as tf
```

In [22]:
```
X = np.array([
    [0, 0],
    [0, 1],
    [1, 0],
    [1, 1]
])
y = np.array([0, 1, 1, 1])
w1 = 1
w2 = 1
b = 0
```

In [23]:
```
def step(z):
    return 1 if z>=1 else 0
```

In [24]:
```
for i in range(X.shape[0]):
    z = w1*X[i][0] + w2*X[i][1] + b
    print(f"Input: {X[i]} → Output:", step(z))
```

```
Input: [0 0] → Output: 0
Input: [0 1] → Output: 1
Input: [1 0] → Output: 1
Input: [1 1] → Output: 1
```

Using the updating weights and bias approach:

In [25]:
```
w = np.random.rand(2)
b = np.random.rand(1)

epochs = 5
learning_rate = 0.1

for epoch in range(epochs):
    for i in range(X.shape[0]):
        z = np.dot(w, X[i]) + b
        y_pred = step(z)
        error = y[i] - y_pred
        w += learning_rate * error * X[i]
        b += learning_rate * error

print("Trained weights:", w)
print("Trained bias:", b)
```

```
Trained weights: [0.67763061 0.98066931]
Trained bias: [0.96288341]
```

In [26]:
```
print("\nPredictions:")
for i in range(len(X)):
    z = np.dot(w, X[i]) + b
    print(f"Input: {X[i]} → Output:", step(z))
```

```
Predictions:
Input: [0 0] → Output: 0
Input: [0 1] → Output: 1
Input: [1 0] → Output: 1
Input: [1 1] → Output: 1
```

Task 2

Use the heart disease dataset and do the following
- Use the Dataset
- Create an autoencoder and fit it with our data using 2 neurons in the dense layer
- Plot loss w.r.t. epochs
- Calculate reconstruction error using Mean Squared Error (MSE).

In [27]:
```
import pandas as pd
```

In [28]:
```
X = pd.read_csv('Data/heart.csv')
```

In [29]:
```
X
```

Out[29]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope
0	52	1	0	125	212	0	1	168	0	1.0	2
1	53	1	0	140	203	1	0	155	1	3.1	0
2	70	1	0	145	174	0	1	125	1	2.6	0
3	61	1	0	148	203	0	1	161	0	0.0	2
4	62	0	0	138	294	1	1	106	0	1.9	1
...	...	...	...	...	...	...	...	...	...	...	...
1020	59	1	1	140	221	0	1	164	1	0.0	2
1021	60	1	0	125	258	0	0	141	1	2.8	1
1022	47	1	0	110	275	0	0	118	1	1.0	1
1023	50	0	0	110	254	0	0	159	0	0.0	2
1024	54	1	0	120	188	0	1	113	0	1.4	1

1025 rows × 14 columns

In [30]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [31]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Input
```

In [32]:
```
autoencoder = Sequential([
    Input(shape = (X.shape[1], )),
    Dense(2, activation='relu'),
    Dense(X.shape[1], activation='sigmoid')
])
```

In [33]:
```
autoencoder.compile(optimizer='adam', loss='mse')
```

In [34]:
```
autoencoder.fit(X_scaled, X_scaled, epochs=50, batch_size=16, shuffle=True,
validation_split=0.2)
```

```
Epoch 1/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2ms/step - loss: 1.3091
- val_loss: 1.2259
Epoch 2/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2780
- val_loss: 1.1955
Epoch 3/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2502
- val_loss: 1.1680
Epoch 4/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2253
- val_loss: 1.1423
Epoch 5/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2028
- val_loss: 1.1191
Epoch 6/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1821
- val_loss: 1.0968
Epoch 7/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1622
- val_loss: 1.0754
Epoch 8/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1433
- val_loss: 1.0551
Epoch 9/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1254
- val_loss: 1.0362
Epoch 10/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1087
- val_loss: 1.0190
Epoch 11/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0934
- val_loss: 1.0038
Epoch 12/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0796
- val_loss: 0.9901
Epoch 13/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0669
- val_loss: 0.9782
Epoch 14/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0558
- val_loss: 0.9678
Epoch 15/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0456
- val_loss: 0.9587
Epoch 16/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0364
- val_loss: 0.9506
Epoch 17/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0280
- val_loss: 0.9433
Epoch 18/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0204
- val_loss: 0.9367
Epoch 19/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0132
- val_loss: 0.9300
Epoch 20/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0060
- val_loss: 0.9238
Epoch 21/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9989
- val_loss: 0.9171
Epoch 22/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9917
- val_loss: 0.9107
```

```
Epoch 23/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9845
- val_loss: 0.9043
Epoch 24/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9773
- val_loss: 0.8981
Epoch 25/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9701
- val_loss: 0.8918
Epoch 26/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9631
- val_loss: 0.8860
Epoch 27/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9567
- val_loss: 0.8807
Epoch 28/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9509
- val_loss: 0.8760
Epoch 29/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9459
- val_loss: 0.8720
Epoch 30/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9416
- val_loss: 0.8684
Epoch 31/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9377
- val_loss: 0.8653
Epoch 32/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9341
- val_loss: 0.8624
Epoch 33/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9308
- val_loss: 0.8598
Epoch 34/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9277
- val_loss: 0.8575
Epoch 35/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9248
- val_loss: 0.8552
Epoch 36/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9221
- val_loss: 0.8532
Epoch 37/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9195
- val_loss: 0.8514
Epoch 38/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9171
- val_loss: 0.8496
Epoch 39/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9148
- val_loss: 0.8481
Epoch 40/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9127
- val_loss: 0.8465
Epoch 41/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9107
- val_loss: 0.8452
Epoch 42/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9088
- val_loss: 0.8439
Epoch 43/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9071
- val_loss: 0.8428
Epoch 44/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9054
- val_loss: 0.8417
Epoch 45/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9039
- val_loss: 0.8406
Epoch 46/50
```

```
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9024
- val_loss: 0.8396
Epoch 47/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9009
- val_loss: 0.8386
Epoch 48/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8994
- val_loss: 0.8375
Epoch 49/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8980
- val_loss: 0.8365
Epoch 50/50
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8965
- val_loss: 0.8355
```

Out[34]:
```
<keras.src.callbacks.history.History at 0x1e201a69250>
```

In [35]:
```
encoder  =Sequential([autoencoder.layers[0]])
encoded_data = encoder.predict(X_scaled)
```

```
[1m33/33[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 790us/step
```

The reduced dimention values are as follows:

In [36]:
```
encoded_data
```

Out[36]:
```
array([[0.4363609, 0.6735984],
       [0.       , 4.5518847],
       [0.       , 6.68523  ],
       ...,
       [0.       , 7.929942 ],
       [6.1295547, 2.3963432],
       [0.       , 4.846034 ]], shape=(1025, 2), dtype=float32)
```

In [37]:
```
preds = []
loss = []
for i in range(1,8):
    autoencoder = Sequential([
        Input(shape = (X.shape[1], )),
        Dense(i, activation='relu'),
        Dense(X.shape[1], activation='sigmoid')
    ])
    autoencoder.compile(optimizer='adam', loss='mse')
    history = autoencoder.fit(X_scaled, X_scaled, epochs=20, batch_size=16,
shuffle=True, validation_split=0.2)
    preds.append(autoencoder.predict(X_scaled))
    loss.append(history.history['loss'])
    print(f'Encoding Dimension: {i}, Loss: {loss[-1]}')
```

```
  Epoch 1/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2ms/step - loss: 1.2832
  - val_loss: 1.2033
  Epoch 2/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2611
  - val_loss: 1.1835
  Epoch 3/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2422
  - val_loss: 1.1661
  Epoch 4/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2255
  - val_loss: 1.1510
  Epoch 5/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2104
  - val_loss: 1.1373
  Epoch 6/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1962
  - val_loss: 1.1240
  Epoch 7/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1820
  - val_loss: 1.1110
  Epoch 8/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1676
  - val_loss: 1.0974
  Epoch 9/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1522
  - val_loss: 1.0834
  Epoch 10/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1363
  - val_loss: 1.0688
  Epoch 11/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1201
  - val_loss: 1.0545
  Epoch 12/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1037
  - val_loss: 1.0401
  Epoch 13/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0878
  - val_loss: 1.0263
  Epoch 14/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0732
  - val_loss: 1.0142
  Epoch 15/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0602
  - val_loss: 1.0028
  Epoch 16/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0486
  - val_loss: 0.9930
  Epoch 17/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0384
  - val_loss: 0.9842
  Epoch 18/20
  [1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0296
  - val_loss: 0.9767
```

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Epoch 19/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0220
- val_loss: 0.9700
Epoch 20/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0153
- val_loss: 0.9641
[1m33/33[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 921us/step
Encoding Dimension: 1, Loss: [1.2831521034240723, 1.2611310482025146,
1.242155909538269, 1.2254847288131714, 1.2104400396347046, 1.1961543560028076,
1.1820470094680786, 1.167638897895813, 1.1521997451782227, 1.1363461017608643,
1.1200652122497559, 1.1037242412567139, 1.087790846824646, 1.0731830596923828,
1.060219407081604, 1.0485895872116089, 1.0384330749511719, 1.0295852422714233,
1.0219604969024658, 1.015328049659729]
Epoch 1/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2ms/step - loss: 1.2512
- val_loss: 1.1696
Epoch 2/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2222
- val_loss: 1.1436
Epoch 3/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1958
- val_loss: 1.1190
Epoch 4/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1704
- val_loss: 1.0952
Epoch 5/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1457
- val_loss: 1.0711
Epoch 6/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1203
- val_loss: 1.0461
Epoch 7/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0931
- val_loss: 1.0210
Epoch 8/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0659
- val_loss: 0.9969
Epoch 9/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0404
- val_loss: 0.9749
Epoch 10/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0177
- val_loss: 0.9560
Epoch 11/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9980
- val_loss: 0.9394
Epoch 12/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9814
- val_loss: 0.9258
Epoch 13/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9679
- val_loss: 0.9148
Epoch 14/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9566
- val_loss: 0.9056
Epoch 15/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9476
- val_loss: 0.8982
Epoch 16/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9404
- val_loss: 0.8921
Epoch 17/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9345
- val_loss: 0.8873
Epoch 18/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9296
- val_loss: 0.8830
Epoch 19/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9255
- val_loss: 0.8791
```

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Epoch 20/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9221
- val_loss: 0.8763
[1m33/33[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step
Encoding Dimension: 2, Loss: [1.251167893409729, 1.2222402095794678,
1.1958192586898804, 1.170384168624878, 1.1456682682037354, 1.1202806234359741,
1.0931165218353271, 1.065946340560913, 1.0403627157211304, 1.0177333354949951,
0.9980093836784363, 0.9814159274101257, 0.9678815007209778, 0.9565631151199341,
0.9476122856140137, 0.9404034614562988, 0.9344808459281921, 0.9295568466186523,
0.9255173802375793, 0.9221017956733704]
Epoch 1/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2ms/step - loss: 1.3033
- val_loss: 1.2059
Epoch 2/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2658
- val_loss: 1.1747
Epoch 3/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2327
- val_loss: 1.1478
Epoch 4/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2021
- val_loss: 1.1230
Epoch 5/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1727
- val_loss: 1.0985
Epoch 6/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1446
- val_loss: 1.0754
Epoch 7/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1184
- val_loss: 1.0542
Epoch 8/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0954
- val_loss: 1.0349
Epoch 9/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0748
- val_loss: 1.0167
Epoch 10/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0566
- val_loss: 1.0007
Epoch 11/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0408
- val_loss: 0.9865
Epoch 12/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0273
- val_loss: 0.9739
Epoch 13/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0156
- val_loss: 0.9631
Epoch 14/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0055
- val_loss: 0.9533
Epoch 15/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9966
- val_loss: 0.9447
Epoch 16/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9887
- val_loss: 0.9369
Epoch 17/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9815
- val_loss: 0.9297
Epoch 18/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9747
- val_loss: 0.9229
Epoch 19/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9685
- val_loss: 0.9167
Epoch 20/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9626
- val_loss: 0.9112
```

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[1m33/33[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 919us/step
Encoding Dimension: 3, Loss: [1.3032701015472412, 1.265808343887329,
1.2327265739440918, 1.2021225690841675, 1.172741413116455, 1.1446104049682617,
1.1184163093566895, 1.0954279899597168, 1.0747706890106201, 1.0565791130065918,
1.0407543182373047, 1.0272631645202637, 1.015642523765564, 1.0055080652236938,
0.9966239929199219, 0.9886893630027771, 0.9814791083335876, 0.9747150540351868,
0.9684500098228455, 0.9626489281654358]
Epoch 1/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 3ms/step - loss: 1.2692
- val_loss: 1.1875
Epoch 2/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2315
- val_loss: 1.1521
Epoch 3/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1963
- val_loss: 1.1182
Epoch 4/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1613
- val_loss: 1.0838
Epoch 5/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1242
- val_loss: 1.0485
Epoch 6/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0859
- val_loss: 1.0115
Epoch 7/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0473
- val_loss: 0.9752
Epoch 8/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0111
- val_loss: 0.9429
Epoch 9/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9801
- val_loss: 0.9161
Epoch 10/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9549
- val_loss: 0.8942
Epoch 11/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9347
- val_loss: 0.8771
Epoch 12/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9190
- val_loss: 0.8629
Epoch 13/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9062
- val_loss: 0.8515
Epoch 14/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8958
- val_loss: 0.8420
Epoch 15/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8875
- val_loss: 0.8341
Epoch 16/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8804
- val_loss: 0.8272
Epoch 17/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8743
- val_loss: 0.8214
Epoch 18/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8688
- val_loss: 0.8163
Epoch 19/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8640
- val_loss: 0.8120
Epoch 20/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8596
- val_loss: 0.8076
[1m33/33[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 948us/step
Encoding Dimension: 4, Loss: [1.2692148685455322, 1.2314589023590088,
1.1962578296661377, 1.1612668037414455, 1.124210238456726, 1.0859355926513672,
```

```
1.0472582578659058, 1.0111247301101685, 0.9801482558250427, 0.9549389481544495,
0.9346714615821838, 0.9189833998680115, 0.9062225818634033, 0.8958492279052734,
0.8874610066413879, 0.8803602457046509, 0.8742563128471375, 0.8688479661941528,
0.864011824131012, 0.8595812320709229]
Epoch 1/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2ms/step - loss: 1.2697
- val_loss: 1.1801
Epoch 2/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2280
- val_loss: 1.1435
Epoch 3/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1900
- val_loss: 1.1098
Epoch 4/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1543
- val_loss: 1.0776
Epoch 5/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1209
- val_loss: 1.0477
Epoch 6/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0899
- val_loss: 1.0198
Epoch 7/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0621
- val_loss: 0.9945
Epoch 8/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0361
- val_loss: 0.9705
Epoch 9/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0115
- val_loss: 0.9474
Epoch 10/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9883
- val_loss: 0.9257
Epoch 11/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9662
- val_loss: 0.9050
Epoch 12/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9453
- val_loss: 0.8863
Epoch 13/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9269
- val_loss: 0.8699
Epoch 14/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9109
- val_loss: 0.8559
Epoch 15/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8972
- val_loss: 0.8441
Epoch 16/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8856
- val_loss: 0.8342
Epoch 17/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8754
- val_loss: 0.8254
Epoch 18/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8664
- val_loss: 0.8175
Epoch 19/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8580
- val_loss: 0.8105
Epoch 20/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8501
- val_loss: 0.8040
[1m33/33[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step
Encoding Dimension: 5, Loss: [1.2697259187698364, 1.2279988527297974,
1.1899957656860352, 1.1543203592300415, 1.1208827495574951, 1.0899039506912231,
1.0621033906936646, 1.03610360622406, 1.011527419090271, 0.9883061647415161,
0.9661586880683899, 0.9453197717666626, 0.9268538355827332, 0.9109323024749756,
0.8972092866897583, 0.8855556845664978, 0.8753909468650818, 0.8663800358772278,
```

```
0.8580005764961243, 0.8500725030899048]
Epoch 1/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2ms/step - loss: 1.2689
- val_loss: 1.1872
Epoch 2/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.2191
- val_loss: 1.1430
Epoch 3/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1739
- val_loss: 1.1030
Epoch 4/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1305
- val_loss: 1.0641
Epoch 5/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0879
- val_loss: 1.0260
Epoch 6/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0468
- val_loss: 0.9906
Epoch 7/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0095
- val_loss: 0.9575
Epoch 8/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9757
- val_loss: 0.9286
Epoch 9/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9462
- val_loss: 0.9031
Epoch 10/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9209
- val_loss: 0.8818
Epoch 11/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9000
- val_loss: 0.8641
Epoch 12/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8829
- val_loss: 0.8494
Epoch 13/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8690
- val_loss: 0.8372
Epoch 14/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8573
- val_loss: 0.8268
Epoch 15/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8473
- val_loss: 0.8179
Epoch 16/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8387
- val_loss: 0.8100
Epoch 17/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8311
- val_loss: 0.8030
Epoch 18/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8246
- val_loss: 0.7963
Epoch 19/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8186
- val_loss: 0.7908
Epoch 20/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8130
- val_loss: 0.7855
[1m33/33[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step
Encoding Dimension: 6, Loss: [1.268891453742981, 1.2191321849822998,
1.173931360244751, 1.1304678916931152, 1.0878806114196777, 1.0468478202819824,
1.0094624757766724, 0.9757015109062195, 0.946201503276825, 0.9208778142929077,
0.8999965786933899, 0.8829025626182556, 0.8690149784088135, 0.8573118448257446,
0.8473080992698669, 0.8387160301208496, 0.8311342000961304, 0.824552059173584,
0.8185542225837708, 0.8130397200584412]
Epoch 1/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2ms/step - loss: 1.1954
```

```
- val_loss: 1.1067
Epoch 2/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.1404
- val_loss: 1.0555
Epoch 3/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0870
- val_loss: 1.0053
Epoch 4/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 1.0355
- val_loss: 0.9581
Epoch 5/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9879
- val_loss: 0.9176
Epoch 6/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9489
- val_loss: 0.8844
Epoch 7/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9183
- val_loss: 0.8581
Epoch 8/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8944
- val_loss: 0.8371
Epoch 9/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8755
- val_loss: 0.8200
Epoch 10/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8599
- val_loss: 0.8055
Epoch 11/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8466
- val_loss: 0.7930
Epoch 12/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8349
- val_loss: 0.7820
Epoch 13/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8244
- val_loss: 0.7722
Epoch 14/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8151
- val_loss: 0.7633
Epoch 15/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8066
- val_loss: 0.7556
Epoch 16/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7989
- val_loss: 0.7481
Epoch 17/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7919
- val_loss: 0.7416
Epoch 18/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7855
- val_loss: 0.7353
Epoch 19/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7794
- val_loss: 0.7296
Epoch 20/20
[1m52/52[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7737
- val_loss: 0.7244
[1m33/33[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 944us/step
Encoding Dimension: 7, Loss: [1.1954097747802734, 1.140404224395752,
1.0870429277420044, 1.0354678630828857, 0.9878857731819153, 0.9488819241523743,
0.9183225035667419, 0.8943727612495422, 0.8754844069480896, 0.8599272966384888,
0.846598207950592, 0.8348783254623413, 0.824389636516571, 0.8150631785392761,
0.8066068291664124, 0.7989274859428406, 0.791931688785553, 0.7854940891265869,
0.7793994545936584, 0.773716151714325]
```

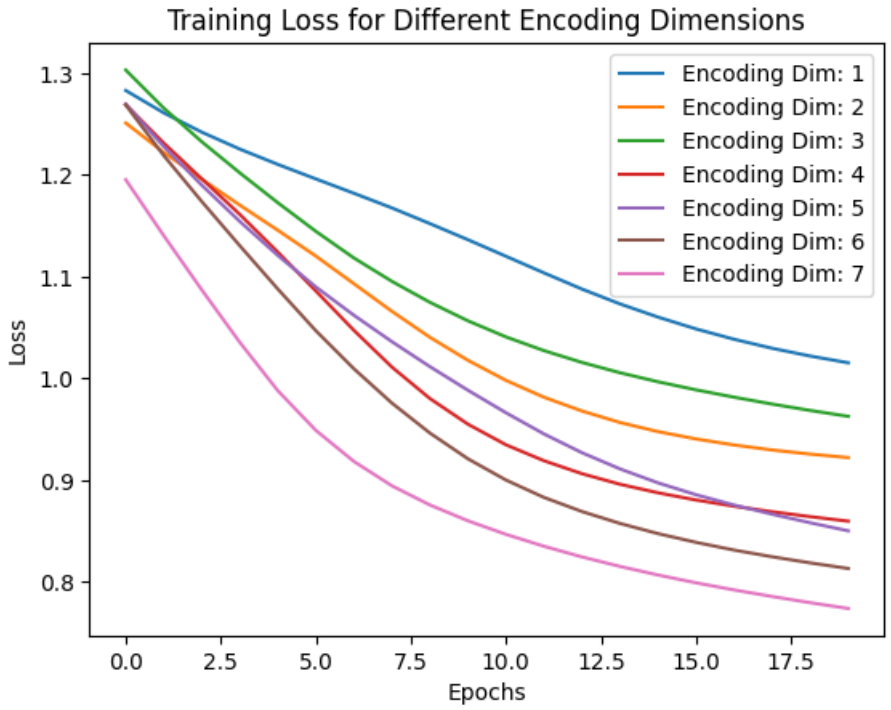
In [38]:
```
loss
```

Out[38]:
```
[[1.2831521034240723,
  1.2611310482025146,
  1.242155909538269,
  1.2254847288131714,
  1.2104400396347046,
  1.1961543560028076,
  1.1820470094680786,
  1.167638897895813,
  1.1521997451782227,
  1.1363461017608643,
  1.1200652122497559,
  1.1037242412567139,
  1.087790846824646,
  1.0731830596923828,
  1.060219407081604,
  1.0485895872116089,
  1.0384330749511719,
  1.0295852422714233,
  1.0219604969024658,
  1.015328049659729],
 [1.251167893409729,
  1.2222402095794678,
  1.1958192586898804,
  1.170384168624878,
  1.1456682682037354,
  1.1202806234359741,
  1.0931165218353271,
  1.065946340560913,
  1.0403627157211304,
  1.0177333354949951,
  0.9980093836784363,
  0.9814159274101257,
  0.9678815007209778,
  0.9565631151199341,
  0.9476122856140137,
  0.9404034614562988,
  0.9344808459281921,
  0.9295568466186523,
  0.9255173802375793,
  0.9221017956733704],
 [1.3032701015472412,
  1.265808343887329,
  1.2327265739440918,
  1.2021225690841675,
  1.172741413116455,
  1.1446104049682617,
  1.1184163093566895,
  1.0954279899597168,
  1.0747706890106201,
  1.0565791130065918,
  1.0407543182373047,
  1.0272631645202637,
  1.015642523765564,
  1.0055080652236938,
  0.9966239929199219,
  0.9886893630027771,
  0.9814791083335876,
  0.9747150540351868,
  0.9684500098228455,
  0.9626489281654358],
 [1.2692148685455322,
  1.2314589023590088,
  1.1962578296661377,
  1.161266803741455,
  1.124210238456726,
  1.0859355926513672,
  1.0472582578659058,
```

```
 1.0111247301101685,
 0.9801482558250427,
 0.9549389481544495,
 0.9346714615821838,
 0.9189833998680115,
 0.9062225818634033,
 0.8958492279052734,
 0.8874610066413879,
 0.8803602457046509,
 0.8742563128471375,
 0.8688479661941528,
 0.864011824131012,
 0.8595812320709229],
[1.2697259187698364,
 1.2279988527297974,
 1.1899957656860352,
 1.1543203592300415,
 1.1208827495574951,
 1.0899039506912231,
 1.0621033906936646,
 1.03610360622406,
 1.011527419090271,
 0.9883061647415161,
 0.9661586880683899,
 0.9453197717666626,
 0.9268538355827332,
 0.9109323024749756,
 0.8972092866897583,
 0.8855556845664978,
 0.8753909468650818,
 0.8663800358772278,
 0.8580005764961243,
 0.8500725030899048],
[1.268891453742981,
 1.2191321849822998,
 1.173931360244751,
 1.1304678916931152,
 1.0878806114196777,
 1.0468478202819824,
 1.0094624757766724,
 0.9757015109062195,
 0.946201503276825,
 0.9208778142929077,
 0.8999965786933899,
 0.8829025626182556,
 0.8690149784088135,
 0.8573118448257446,
 0.8473080992698669,
 0.8387160301208496,
 0.8311342000961304,
 0.824552059173584,
 0.8185542225837708,
 0.8130397200584412],
[1.1954097747802734,
 1.140404224395752,
 1.0870429277420044,
 1.0354678630828857,
 0.9878857731819153,
 0.9488819241523743,
 0.9183225035667419,
 0.8943727612495422,
 0.8754844069480896,
 0.8599272966384888,
 0.846598207950592,
 0.8348783254623413,
 0.824389636516571,
 0.8150631785392761,
 0.8066068291664124,
 0.7989274859428406,
 0.791931688785553,
```

```
0.7854940891265869,
0.7793994545936584,
0.773716151714325]]
```

In [39]:
```
import matplotlib.pyplot as plt

for i in range(len(loss)):
    plt.plot(loss[i], label=f'Encoding Dim: {i+1}')
plt.title('Training Loss for Different Encoding Dimensions')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



In [ ]:

Task 1

- Load California Housing dataset and select 2 features (e.g., Median Income, House Age) and 1 target (Median House Value).
- Normalize inputs and initialize a single-layer NN with random weights and bias.
- Perform forward propagation, calculate prediction error, Squared Error, and MSE.
- Update weights and bias using gradient descent.
- Plot Loss vs Weight, Loss vs Bias, and Error Surface.

In [15]:
```
import pandas as pd
import numpy as np
```

In [16]:
```
X = pd.read_csv('Data\housing.csv')
```

```
<>:1: SyntaxWarning: invalid escape sequence '\h'
<>:1: SyntaxWarning: invalid escape sequence '\h'
C:\Users\Smayan Kulkarni\AppData\Local\Temp\ipykernel_23104\2826990410.py:1:
SyntaxWarning: invalid escape sequence '\h'
  X = pd.read_csv('Data\housing.csv')
```

In [17]:
```
X
```

Out[17]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	populati
0	-122.23	37.88	41.0	880.0	129.0	322.0
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0
2	-122.24	37.85	52.0	1467.0	190.0	496.0
3	-122.25	37.85	52.0	1274.0	235.0	558.0
4	-122.25	37.85	52.0	1627.0	280.0	565.0
...	...	...	...	...	...	...
20635	-121.09	39.48	25.0	1665.0	374.0	845.0
20636	-121.21	39.49	18.0	697.0	150.0	356.0
20637	-121.22	39.43	17.0	2254.0	485.0	1007.0
20638	-121.32	39.43	18.0	1860.0	409.0	741.0
20639	-121.24	39.37	16.0	2785.0	616.0	1387.0

20640 rows × 10 columns

In [18]:
```
y = X[['median_house_value']].values
X = X[['median_income', 'households']].values
```

In [19]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
np.random.seed(42)
weights = np.random.rand(X.shape[1])
bias = np.random.rand(1)
initial_weights = weights.copy()
initial_bias = bias.copy()
```

In [20]:
```
def forwardprop(X,weights,bias):
    layer_input = np.dot(X,weights) + bias
    layer_output = layer_input #Regression
    return layer_output
```

In [21]:
```
from sklearn.metrics import mean_squared_error, mean_absolute_error
y_preds = forwardprop(X_scaled, weights, bias)
pred_errors = y.flatten() - y_preds
squared_errors = pred_errors ** 2

print("Initial Metrics:")
print(f"Sample Prediction Errors: {pred_errors[:5]}")
print(f"Sample Squared Errors: {squared_errors[:5]}")
print(f"Initial MSE: {mean_squared_error(y, y_preds)}")
print(f"Initial MAE: {mean_absolute_error(y, y_preds)}")
```

```
Initial Metrics:
Sample Prediction Errors: [452599.31867632 358496.80683353 352099.4023713
341299.61618881
 342199.87097924]
Sample Squared Errors: [2.04846143e+11 1.28519961e+11 1.23973989e+11
1.16485428e+11
 1.17100752e+11]
Initial MSE: 56104455234.26047
Initial MAE: 206855.08491497295
```

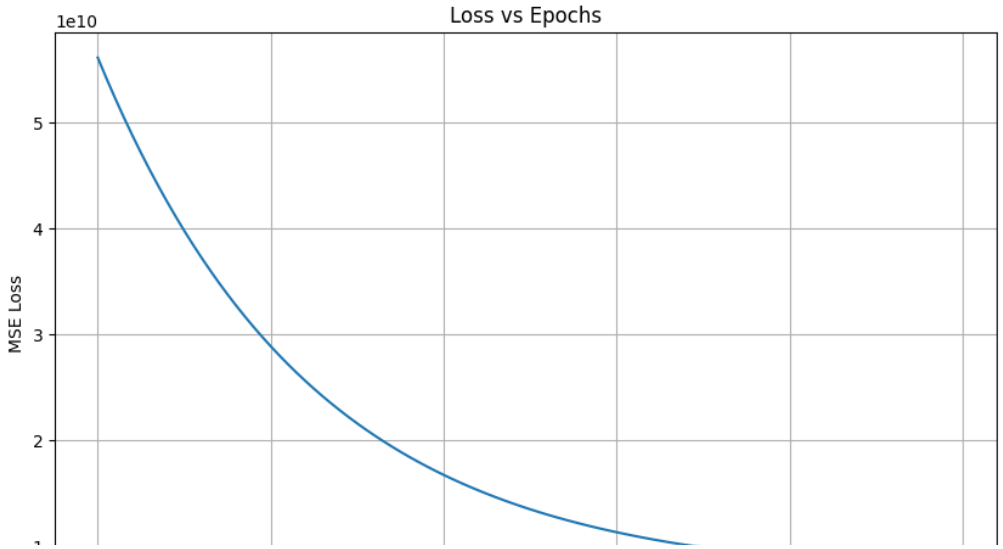
In [22]:

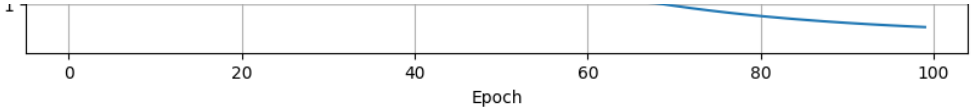
```
epochs = 100
learning_rate = 0.01
loss_history = []
weight_history = []
bias_history = []

for i in range(epochs):
    y_preds = forwardprop(X_scaled, weights, bias)

    error = y.flatten() - y_preds
    dw = (-2/X.shape[0]) * np.dot(X_scaled.T, error)
    db = (-2/X.shape[0]) * np.sum(error)

    weights = weights - learning_rate * dw
    bias = bias - learning_rate * db

    mse = mean_squared_error(y, y_preds)
    loss_history.append(mse)
    weight_history.append(weights.copy())
    bias_history.append(bias.copy())

    if i % 10 == 0:
        mae = mean_absolute_error(y, y_preds)
        print(f'Epoch {i}: MSE={mse:.2f}, MAE={mae:.2f}')

print(f"\nFinal MSE: {loss_history[-1]:.2f}")
print(f"Final Weights: {weights}")

print(f"Final Bias: {bias}")
```

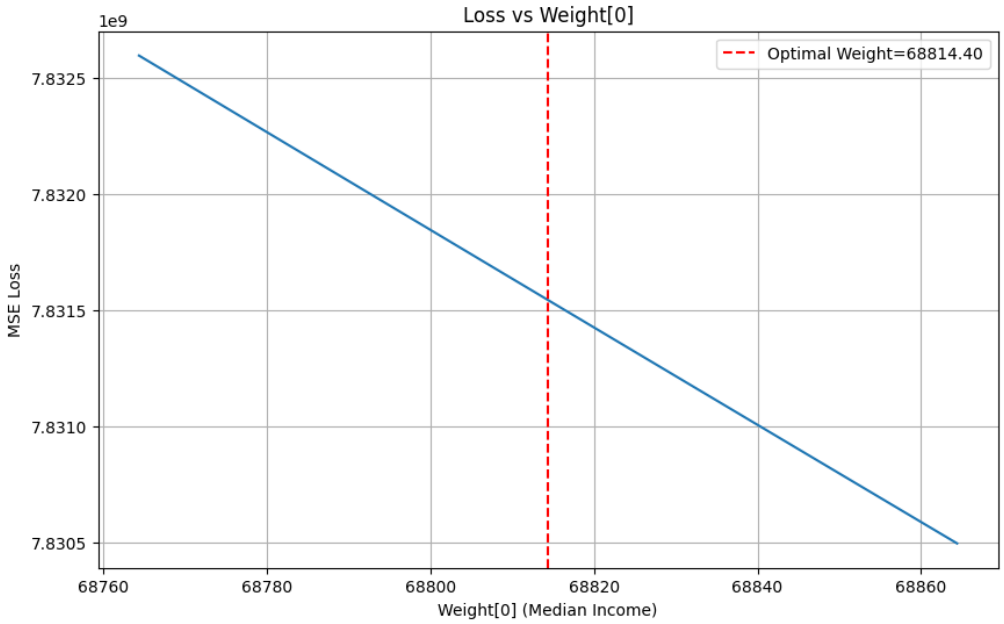
```
Epoch 0: MSE=56104455234.26, MAE=206855.08
Epoch 10: MSE=39768032722.60, MAE=169022.72
Epoch 20: MSE=28863094281.99, MAE=138200.39
Epoch 30: MSE=21583770091.47, MAE=113695.77
Epoch 40: MSE=16724618078.15, MAE=95729.65
Epoch 50: MSE=13480986721.76, MAE=83207.44
Epoch 60: MSE=11315756532.03, MAE=74726.02
Epoch 70: MSE=9870389195.66, MAE=69080.18
Epoch 80: MSE=8905552137.81, MAE=65547.43
Epoch 90: MSE=8261484775.36, MAE=63423.78

Final MSE: 7867146896.05
Final Weights: [68814.40211502  5973.17294627]
Final Bias: [179422.78741292]
```

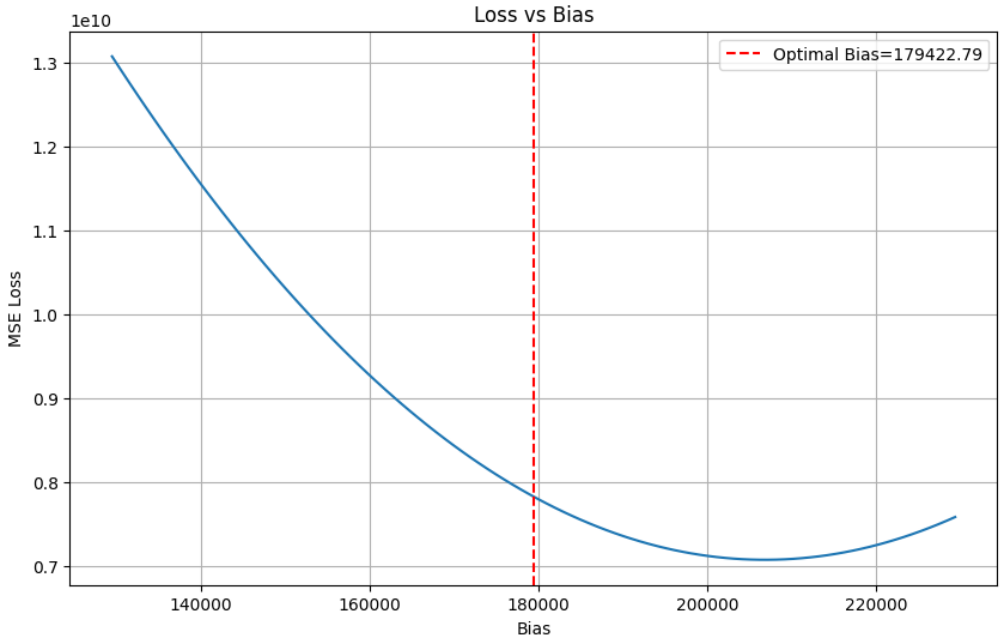
In [23]:

```
import matplotlib.pyplot as plt
# Plot 1: Loss vs Epochs
plt.figure(figsize=(10, 6))
plt.plot(loss_history)
plt.xlabel('Epoch')
plt.ylabel('MSE Loss')
plt.title('Loss vs Epochs')
plt.grid(True)
plt.show()

# Plot 2: Loss vs Weight (for first weight)
def calculate_loss_for_weight(w_val, w_idx):
    temp_weights = weights.copy()
    temp_weights[w_idx] = w_val
    y_pred = forwardprop(X_scaled, temp_weights, bias)
    return mean_squared_error(y, y_pred)

weight_range = np.linspace(weights[0] - 50, weights[0] + 50, 100)
losses_w0 = [calculate_loss_for_weight(w, 0) for w in weight_range]

plt.figure(figsize=(10, 6))
plt.plot(weight_range, losses_w0)
plt.xlabel('Weight[0] (Median Income)')
plt.ylabel('MSE Loss')
plt.title('Loss vs Weight[0]')
plt.axvline(x=weights[0], color='r', linestyle='--', label=f'Optimal
Weight={weights[0]:.2f}')
plt.legend()
plt.grid(True)
plt.show()

# Plot 3: Loss vs Bias
def calculate_loss_for_bias(b_val):
    y_pred = forwardprop(X_scaled, weights, b_val)
    return mean_squared_error(y, y_pred)

bias_range = np.linspace(bias[0] - 50000, bias[0] + 50000, 100)
losses_bias = [calculate_loss_for_bias(b) for b in bias_range]

plt.figure(figsize=(10, 6))
plt.plot(bias_range, losses_bias)
plt.xlabel('Bias')
plt.ylabel('MSE Loss')
plt.title('Loss vs Bias')
plt.axvline(x=bias[0], color='r', linestyle='--', label=f'Optimal
Bias={bias[0]:.2f}')
plt.legend()
plt.grid(True)
plt.show()
```









In [ ]:

Implement Self Organizing Map for anomaly Detection

- Use Credit Card Applications Dataset:
- Detect fraud customers in the dataset using SOM and perform hyperparameter tuning
- Show map and use markers to distinguish frauds

In [1]:
```
data = r'Data\Credit_Card_Applications.csv'
```

In [2]:
```
import pandas as pd
import numpy as np
from minisom import MiniSom
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt

df = pd.read_csv(data)

print("Dataset shape:", df.shape)
print("\nFirst few rows:")
df.head()
```

```
Dataset shape: (690, 16)

First few rows:
```

Out[2]:

	CustomerID	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
0	15776156	1	22.08	11.46	2	4	4	1.585	0	0	0	1	2
1	15739548	0	22.67	7.00	2	8	4	0.165	0	0	0	0	2
2	15662854	0	29.58	1.75	1	4	4	1.250	0	0	0	1	2
3	15687688	0	21.67	11.50	1	5	3	0.000	1	1	11	1	2
4	15715750	1	20.17	8.17	2	6	4	1.960	1	1	14	0	2

In [3]:
```
X = df.drop(columns=df.columns[-1]).values
y = df.iloc[:, -1].values
```

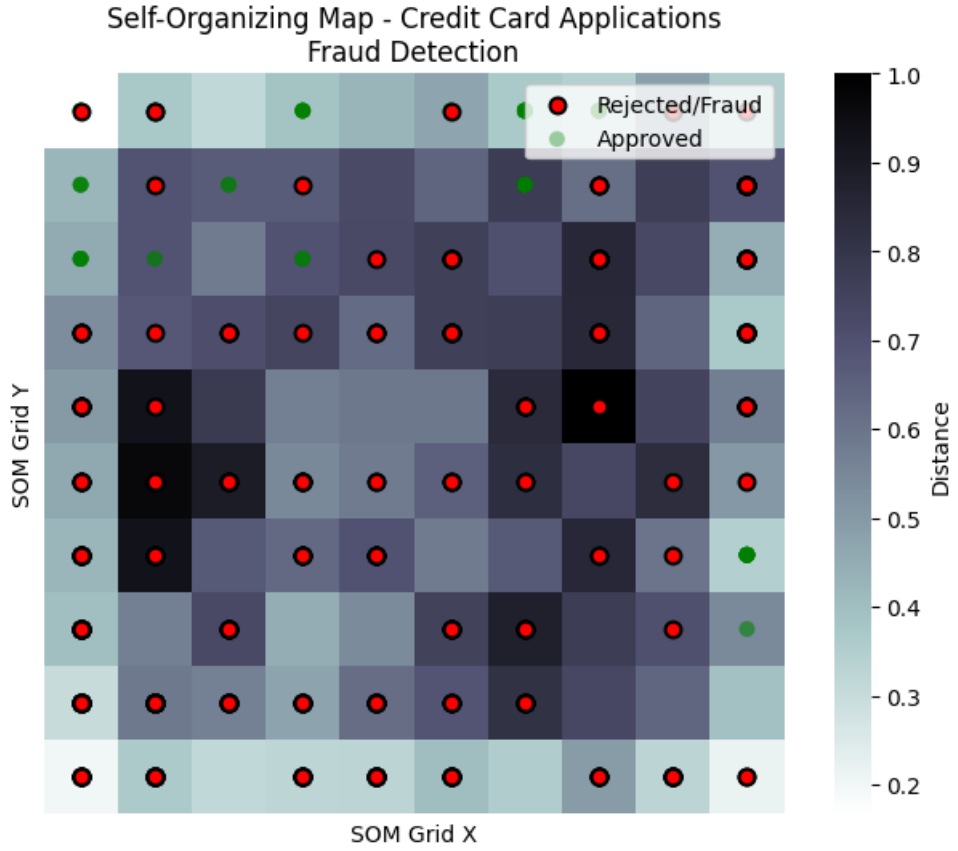
In [4]:
```
scaler = MinMaxScaler(feature_range=(0, 1))
X_scaled = scaler.fit_transform(X)
```

In [5]:
```
som_grid_size = 10
som_sigma = 1.0
som_learning_rate = 0.5
som_iterations = 10000
som = MiniSom(x=som_grid_size, y=som_grid_size,
              input_len=X_scaled.shape[1],
              sigma=som_sigma,
              learning_rate=som_learning_rate,
              random_seed=42)

som.random_weights_init(X_scaled)
som.train_random(X_scaled, som_iterations)
```

In [6]:

```
distance_map = som.distance_map()
fraud_markers = []
normal_markers = []

for i, x in enumerate(X_scaled):
    w = som.winner(x)
    if y[i] == 0:  # Assuming 0 is rejected/fraud
        fraud_markers.append(w)
    else:
        normal_markers.append(w)
```

In [10]:
```
import seaborn as sns

plt.figure(figsize=(8, 6))
sns.heatmap(distance_map.T, cmap='bone_r', cbar_kws={'label': 'Distance'},
            square=True, xticklabels=False, yticklabels=False)

fraud_arr = np.asarray(fraud_markers)
normal_arr = np.asarray(normal_markers)

if fraud_arr.size:
    plt.scatter(fraud_arr[:, 0] + 0.5, fraud_arr[:, 1] + 0.5,
                s=50, c='red', edgecolors='k', linewidths=1.5,
                label='Rejected/Fraud', zorder=3)

if normal_arr.size:
    plt.scatter(normal_arr[:, 0] + 0.5, normal_arr[:, 1] + 0.5,
                s=50, c='green', alpha=0.35, edgecolors='none',
                label='Approved', zorder=2)

plt.legend(loc='upper right')
plt.title('Self-Organizing Map - Credit Card Applications\nFraud Detection')
plt.xlabel('SOM Grid X')
plt.ylabel('SOM Grid Y')
plt.show()

print(f"\nSOM trained with grid size: {som_grid_size}x{som_grid_size}")
print(f"Sigma: {som_sigma}, Learning rate: {som_learning_rate}")
print(f"Number of iterations: {som_iterations}")
```




```
SOM trained with grid size: 10x10
Sigma: 1.0, Learning rate: 0.5
Number of iterations: 10000
```

In [ ]:

Train a small neural network (dataset - MNIST classification)

Compare the optimizers:
1. SGD
2. SGD + Momentum
3. Adam
Plot:
1. Training loss vs epochs
2. Accuracy vs epochs

In [1]:
```
from tensorflow.keras.datasets import mnist
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
2026-01-06 15:42:04.098943: I tensorflow/core/util/port.cc:153] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn
them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2026-01-06 15:42:04.105967: E external/local_xla/xla/stream_executor/cuda/
cuda_fft.cc:467] Unable to register cuFFT factory: Attempting to register
factory for plugin cuFFT when one has already been registered
WARNING: All log messages before absl::InitializeLog() is called are written
to STDERR
E0000 00:00:1767694324.115136  185700 cuda_dnn.cc:8579] Unable to register
cuDNN factory: Attempting to register factory for plugin cuDNN when one has
already been registered
E0000 00:00:1767694324.117636  185700 cuda_blas.cc:1407] Unable to register
cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has
already been registered
W0000 00:00:1767694324.123933  185700 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767694324.123946  185700 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767694324.123947  185700 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767694324.123948  185700 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
2026-01-06 15:42:04.126372: I tensorflow/core/platform/
cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use
available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operations,
rebuild TensorFlow with the appropriate compiler flags.
```

In [2]:
```
data = mnist.load_data()
(train_images, train_labels), (test_images, test_labels) = data
```

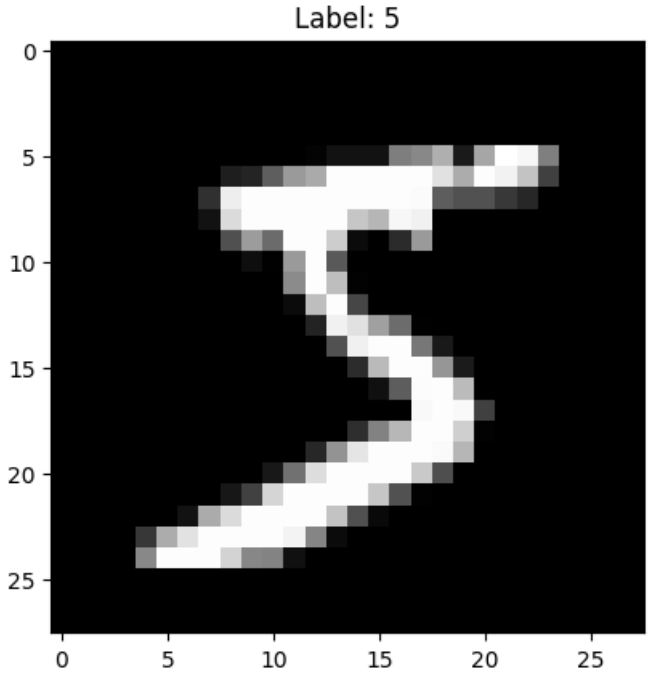
In [3]:
```
img_size =  train_images[0].shape[0]
```

In [4]:
```
num_classes = 10
```

In [5]:
```
train_images = train_images.astype("float32") / 255.0
test_images = test_images.astype("float32") / 255.0
```

In [6]:
```
plt.imshow(train_images[0], cmap='gray')
plt.title(f'Label: {train_labels[0]}')
```

Out[6]:
```
Text(0.5, 1.0, 'Label: 5')
```



In [7]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Input, Flatten
```

In [8]:
```
from tensorflow.keras.optimizers import SGD, Adam
SGD_nomomentum = SGD()
SGD_momentum = SGD(momentum=0.6)
```

```
---------------------------------------------------------------------------
InternalError                             Traceback (most recent call last)
Cell In[8], line 2
      1 from tensorflow.keras.optimizers import SGD, Adam
----> 2 SGD_nomomentum = SGD()
      3 SGD_momentum = SGD(momentum=0.6)

File ~/Desktop/AI-ML-DS/AI-and-ML-Course/.conda/lib/python3.11/site-packages/
keras/src/optimizers/sgd.py:60, in SGD.__init__(self, learning_rate,
momentum, nesterov, weight_decay, clipnorm, clipvalue, global_clipnorm,
use_ema, ema_momentum, ema_overwrite_frequency, loss_scale_factor,
gradient_accumulation_steps, name, **kwargs)
     43 def __init__(
     44     self,
     45     learning_rate=0.01,
   (...)
     58     **kwargs,
     59 ):
---> 60     super().__init__(
     61         learning_rate=learning_rate,
     62         name=name,
     63         weight_decay=weight_decay,
     64         clipnorm=clipnorm,
     65         clipvalue=clipvalue,
     66         global_clipnorm=global_clipnorm,
     67         use_ema=use_ema,
     68         ema_momentum=ema_momentum,
     69         ema_overwrite_frequency=ema_overwrite_frequency,
     70         loss_scale_factor=loss_scale_factor,
     71         gradient_accumulation_steps=gradient_accumulation_steps,
     72         **kwargs,
     73     )
     74     if not isinstance(momentum, float) or momentum < 0 or momentum >
1:
     75         raise ValueError("`momentum` must be a float between [0,
1].")

File ~/Desktop/AI-ML-DS/AI-and-ML-Course/.conda/lib/python3.11/site-packages/
keras/src/backend/tensorflow/optimizer.py:21, in TFOptimizer.__init__(self,
*args, **kwargs)
     20 def __init__(self, *args, **kwargs):
---> 21     super().__init__(*args, **kwargs)
     22     self._distribution_strategy = tf.distribute.get_strategy()

File ~/Desktop/AI-ML-DS/AI-and-ML-Course/.conda/lib/python3.11/site-packages/
keras/src/optimizers/base_optimizer.py:158, in BaseOptimizer.__init__(self,
learning_rate, weight_decay, clipnorm, clipvalue, global_clipnorm, use_ema,
ema_momentum, ema_overwrite_frequency, loss_scale_factor,
gradient_accumulation_steps, name, **kwargs)
    154 # Create iteration variable
    155 # Note: dtype="int" will resolve to int32 in JAX
    156 # (since int64 is disallowed in JAX) and to int64 in TF.
    157 with backend.name_scope(self.name, caller=self):
--> 158     iterations = backend.Variable(
    159         0,
    160         name="iteration",
    161         dtype="int",
    162         trainable=False,
    163         aggregation="only_first_replica",
    164     )
    165 self._track_variable(iterations)
```

```
    166 self._iterations = iterations

File ~/Desktop/AI-ML-DS/AI-and-ML-Course/.conda/lib/python3.11/site-packages/
keras/src/backend/common/variables.py:173, in Variable.__init__(***failed
resolving arguments***)
    166         raise ValueError(
    167             "When creating a Variable from an initializer, "
    168             "the `shape` argument should be specified. "
    169             f"Received: initializer={initializer} "
    170             f"and shape={shape}"
    171         )
    172 else:
--> 173     initializer = self._convert_to_tensor(initializer, dtype=dtype)
    174     # If dtype is None and `initializer` is an array, use its dtype.
    175     if dtype is None:

File ~/Desktop/AI-ML-DS/AI-and-ML-Course/.conda/lib/python3.11/site-packages/
keras/src/backend/tensorflow/core.py:73, in Variable._convert_to_tensor(self,
value, dtype)
     72 def _convert_to_tensor(self, value, dtype=None):
---> 73     return convert_to_tensor(value, dtype=dtype)

File ~/Desktop/AI-ML-DS/AI-and-ML-Course/.conda/lib/python3.11/site-packages/
keras/src/backend/tensorflow/core.py:151, in convert_to_tensor(x, dtype,
sparse, ragged)
    146 if not tf.is_tensor(x):
    147     if dtype == "bool" or is_int_dtype(dtype):
    148         # TensorFlow conversion is stricter than other backends, it
does not
    149         # allow ints for bools or floats for ints. We convert without
dtype
    150         # and cast instead.
--> 151         x = tf.convert_to_tensor(x)
    152         return tf.cast(x, dtype)
    153     return tf.convert_to_tensor(x, dtype=dtype)

File ~/Desktop/AI-ML-DS/AI-and-ML-Course/.conda/lib/python3.11/site-packages/
tensorflow/python/util/traceback_utils.py:153, in
filter_traceback.<locals>.error_handler(*args, **kwargs)
    151 except Exception as e:
    152   filtered_tb = _process_traceback_frames(e.__traceback__)
--> 153   raise e.with_traceback(filtered_tb) from None
    154 finally:
    155   del filtered_tb

File ~/Desktop/AI-ML-DS/AI-and-ML-Course/.conda/lib/python3.11/site-packages/
tensorflow/python/eager/context.py:726, in Context.ensure_initialized(self)
    722   pywrap_tfe.TFE_ContextOptionsSetRunEagerOpAsFunction(opts, True)
    723   pywrap_tfe.TFE_ContextOptionsSetJitCompileRewrite(
    724       opts, self._jit_compile_rewrite
    725   )
--> 726   context_handle = pywrap_tfe.TFE_NewContext(opts)
    727 finally:
    728   pywrap_tfe.TFE_DeleteContextOptions(opts)

InternalError: cudaSetDevice() on GPU:0 failed. Status: out of memory
```

In [ ]:
```
adam_model = Sequential([
    Input(shape =(img_size,img_size) ),
    Flatten(),
    Dense(32, activation='relu'),
    Dense(num_classes, activation='softmax')
])

adam_model.compile(optimizer = 'adam', loss =
'sparse_categorical_crossentropy',metrics=['accuracy'])
adam_history = adam_model.fit(train_images,train_labels, epochs = 15)
```

```
Epoch 1/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 598us/step -
accuracy: 0.8997 - loss: 0.3581
Epoch 2/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 566us/step -
accuracy: 0.9426 - loss: 0.2003
Epoch 3/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 553us/step -
accuracy: 0.9559 - loss: 0.1559
Epoch 4/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 560us/step -
accuracy: 0.9630 - loss: 0.1276
Epoch 5/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 617us/step -
accuracy: 0.9675 - loss: 0.1107
Epoch 6/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 569us/step -
accuracy: 0.9705 - loss: 0.0986
Epoch 7/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 609us/step -
accuracy: 0.9738 - loss: 0.0882
Epoch 8/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 604us/step -
accuracy: 0.9754 - loss: 0.0811
Epoch 9/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 566us/step -
accuracy: 0.9783 - loss: 0.0738
Epoch 10/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 564us/step -
accuracy: 0.9790 - loss: 0.0695
Epoch 11/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 551us/step -
accuracy: 0.9812 - loss: 0.0635
Epoch 12/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 557us/step -
accuracy: 0.9814 - loss: 0.0599
Epoch 13/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 549us/step -
accuracy: 0.9831 - loss: 0.0554
Epoch 14/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 560us/step -
accuracy: 0.9835 - loss: 0.0529
Epoch 15/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 593us/step -
accuracy: 0.9847 - loss: 0.0496
```

In [ ]:
```
SGD_model = Sequential([
    Input(shape =(img_size,img_size) ),
    Flatten(),
    Dense(32, activation='relu'),
    Dense(num_classes, activation='softmax')
])

SGD_model.compile(optimizer =SGD_nomomentum, loss =
'sparse_categorical_crossentropy',metrics=['accuracy'])
SGD_history = SGD_model.fit(train_images,train_labels, epochs = 15)
```

```
Epoch 1/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 550us/step -
accuracy: 0.8143 - loss: 0.7009
Epoch 2/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 557us/step -
accuracy: 0.9014 - loss: 0.3548
Epoch 3/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 548us/step -
accuracy: 0.9131 - loss: 0.3085
Epoch 4/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 531us/step -
accuracy: 0.9200 - loss: 0.2817
Epoch 5/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 519us/step -
accuracy: 0.9255 - loss: 0.2628
Epoch 6/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 515us/step -
accuracy: 0.9296 - loss: 0.2472
Epoch 7/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 508us/step -
accuracy: 0.9340 - loss: 0.2333
Epoch 8/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 523us/step -
accuracy: 0.9377 - loss: 0.2213
Epoch 9/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 519us/step -
accuracy: 0.9409 - loss: 0.2110
Epoch 10/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 515us/step -
accuracy: 0.9428 - loss: 0.2017
Epoch 11/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 513us/step -
accuracy: 0.9453 - loss: 0.1935
Epoch 12/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 518us/step -
accuracy: 0.9469 - loss: 0.1865
Epoch 13/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 516us/step -
accuracy: 0.9495 - loss: 0.1794
Epoch 14/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 511us/step -
accuracy: 0.9505 - loss: 0.1732
Epoch 15/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 518us/step -
accuracy: 0.9529 - loss: 0.1674
```

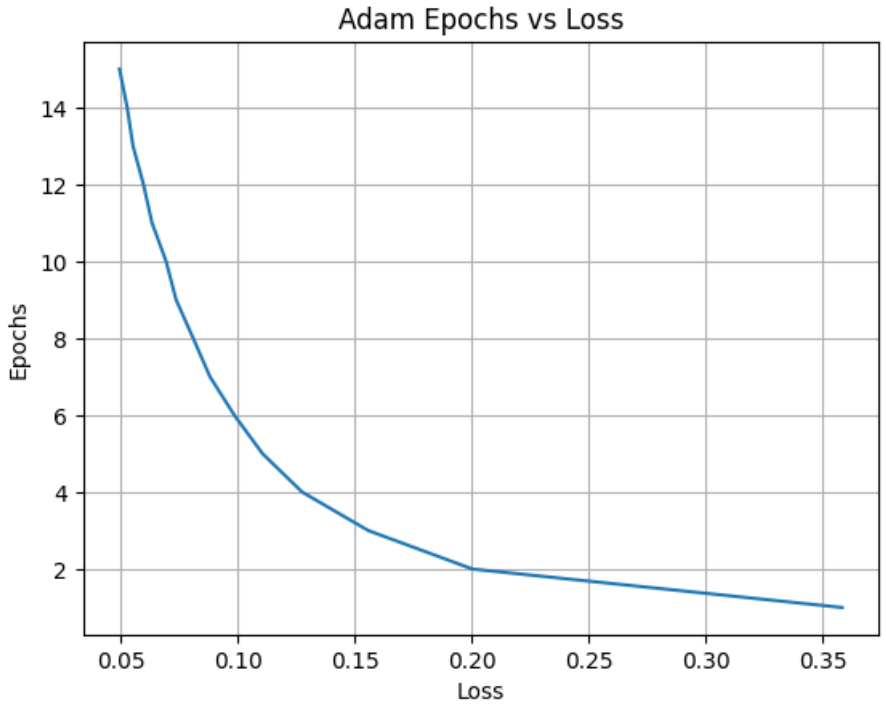
In [ ]:
```
SGD_momentum_model = Sequential([
    Input(shape =(img_size,img_size) ),
    Flatten(),
    Dense(32, activation='relu'),
    Dense(num_classes, activation='softmax')
])

SGD_momentum_model.compile(optimizer =SGD_momentum, loss =
'sparse_categorical_crossentropy',metrics=['accuracy'])
SGD_momentum_history = SGD_momentum_model.fit(train_images,train_labels, epochs = 15)
```

```
Epoch 1/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 531us/step -
accuracy: 0.8680 - loss: 0.4883
Epoch 2/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 530us/step -
accuracy: 0.9208 - loss: 0.2795
Epoch 3/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 520us/step -
accuracy: 0.9338 - loss: 0.2357
Epoch 4/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 511us/step -
accuracy: 0.9409 - loss: 0.2070
Epoch 5/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 519us/step -
accuracy: 0.9469 - loss: 0.1863
Epoch 6/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 514us/step -
accuracy: 0.9512 - loss: 0.1711
Epoch 7/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 517us/step -
accuracy: 0.9553 - loss: 0.1580
Epoch 8/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 534us/step -
accuracy: 0.9589 - loss: 0.1473
Epoch 9/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 519us/step -
accuracy: 0.9613 - loss: 0.1381
Epoch 10/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 530us/step -
accuracy: 0.9636 - loss: 0.1301
Epoch 11/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 529us/step -
accuracy: 0.9650 - loss: 0.1232
Epoch 12/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 529us/step -
accuracy: 0.9676 - loss: 0.1172
Epoch 13/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 1ms/step - accuracy:
0.9686 - loss: 0.1118
Epoch 14/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 547us/step -
accuracy: 0.9703 - loss: 0.1069
Epoch 15/15
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 552us/step -
accuracy: 0.9712 - loss: 0.1029
```

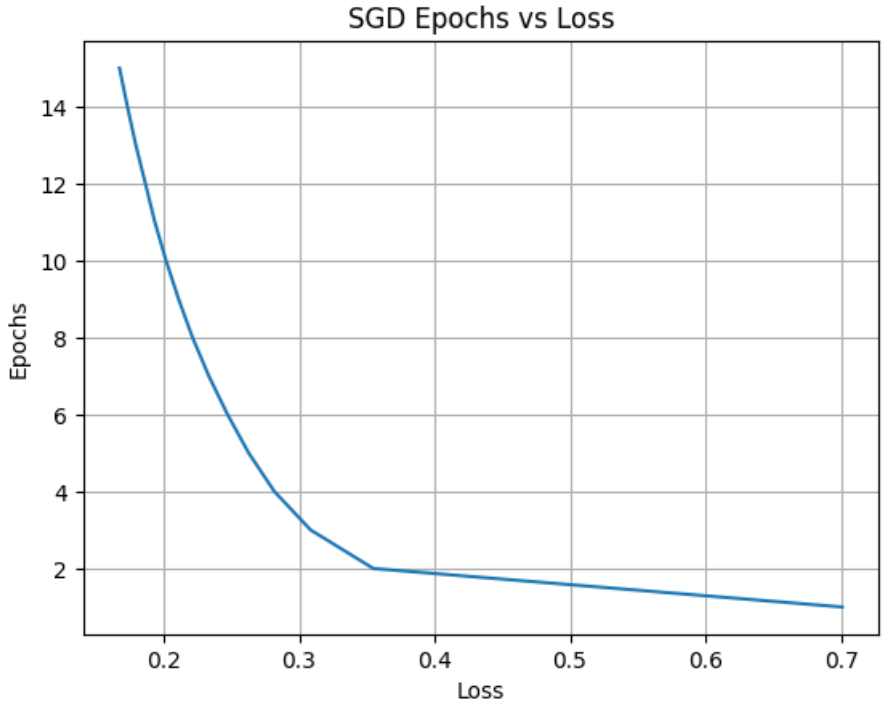
In [ ]:
```
adam_losses = adam_history.history['loss']
SGD_losses = SGD_history.history['loss']
SGD_momentum_losses = SGD_momentum_history.history['loss']
```

In [ ]:
```
x = np.arange(1, 16)
```

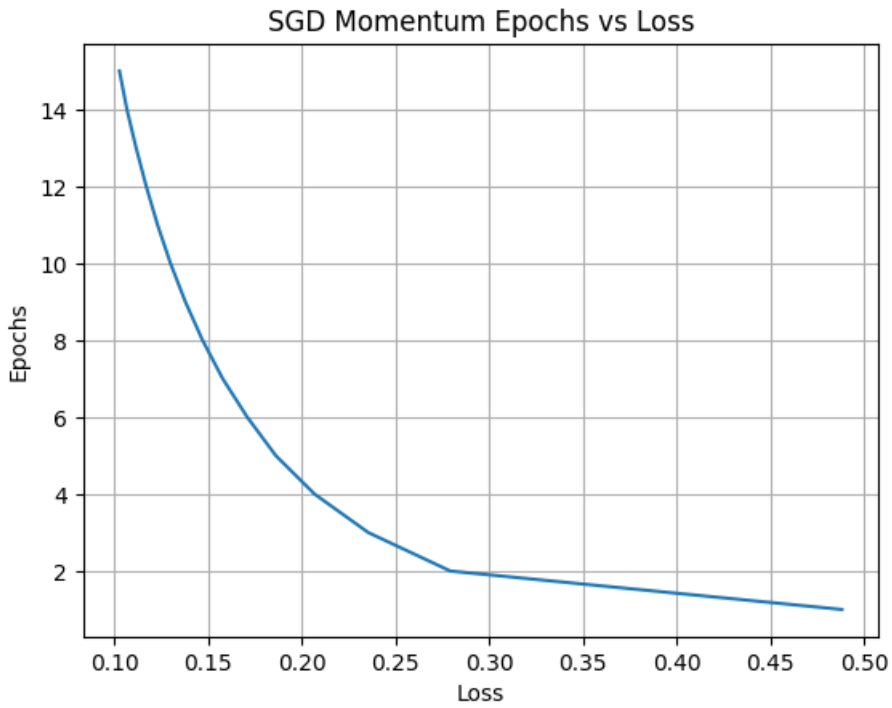
In [ ]:
```
plt.plot(adam_losses, x)
plt.xlabel('Loss')
plt.ylabel('Epochs')
plt.title("Adam Epochs vs Loss")
plt.grid()
```



In [ ]:
```
plt.plot(SGD_losses, x)
plt.xlabel('Loss')
plt.ylabel('Epochs')
plt.title("SGD Epochs vs Loss")
plt.grid()
```

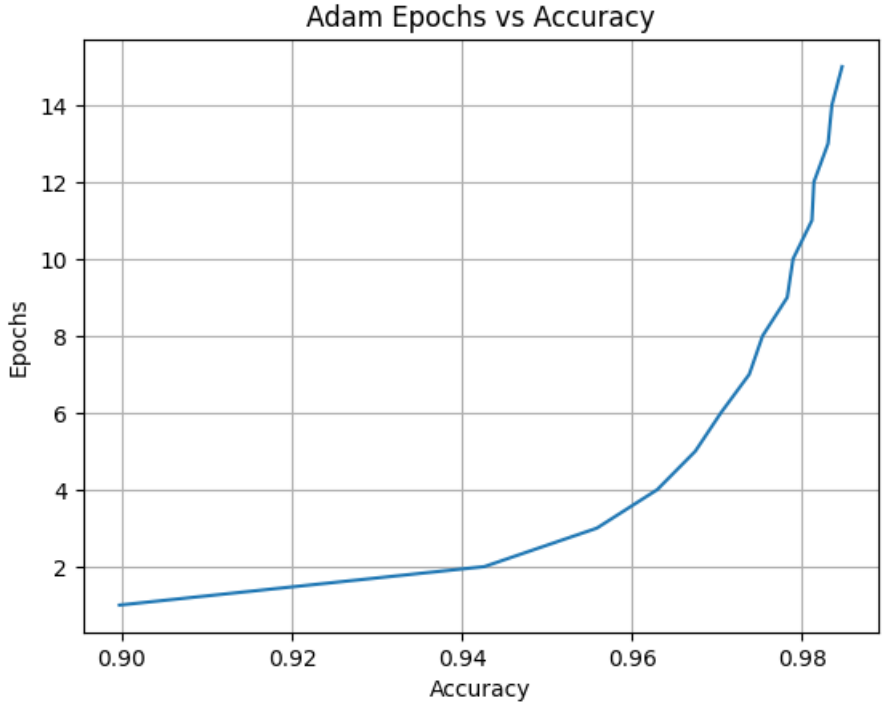


In [ ]:
```
plt.plot(SGD_momentum_losses, x)
plt.xlabel('Loss')
plt.ylabel('Epochs')
plt.title("SGD Momentum Epochs vs Loss")
plt.grid()
```

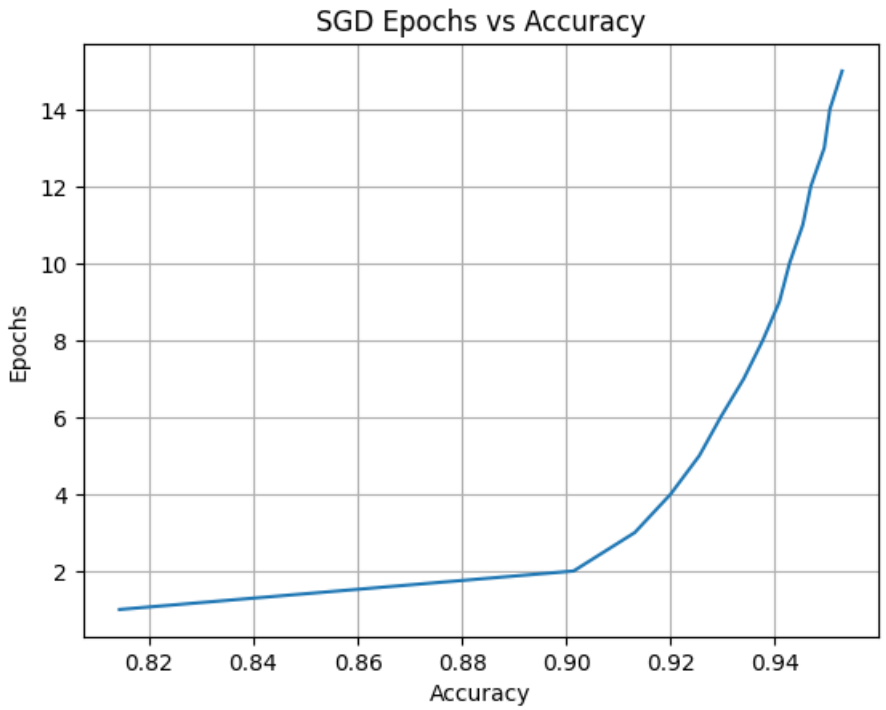


In [ ]:
```
adam_acc = adam_history.history['accuracy']
SGD_acc = SGD_history.history['accuracy']
SGD_momentum_acc = SGD_momentum_history.history['accuracy']
```

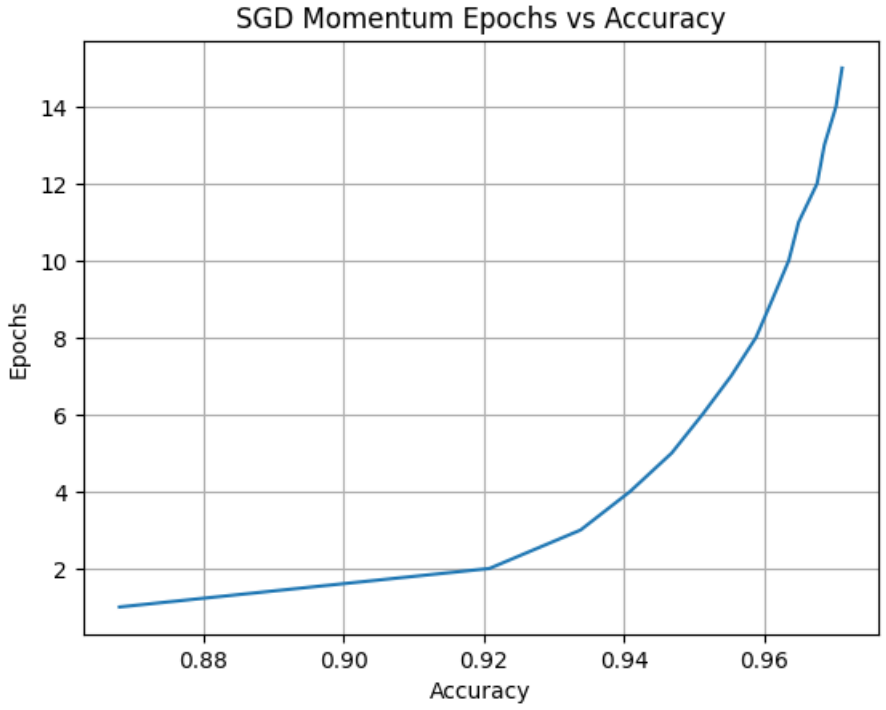
In [ ]:
```
plt.plot(adam_acc, x)
plt.xlabel('Accuracy')
plt.ylabel('Epochs')
plt.title("Adam Epochs vs Accuracy")
plt.grid()
```



In [ ]:
```
plt.plot(SGD_acc, x)
plt.xlabel('Accuracy')
plt.ylabel('Epochs')
plt.title("SGD Epochs vs Accuracy")
plt.grid()
```



In [ ]:
```
plt.plot(SGD_momentum_acc, x)
plt.xlabel('Accuracy')
plt.ylabel('Epochs')
plt.title("SGD Momentum Epochs vs Accuracy")
plt.grid()
```



In [ ]:

```
# Plot ROC AUC Curves for Multi-class Classification (One-vs-Rest)
from sklearn.metrics import roc_curve, auc, roc_auc_score
from sklearn.preprocessing import label_binarize
import numpy as np
import matplotlib.pyplot as plt

# Get probability predictions for all three models
adam_preds = adam_model.predict(test_images)
sgd_preds = SGD_model.predict(test_images)
sgd_momentum_preds = SGD_momentum_model.predict(test_images)

n_classes = 10

# Binarize the test labels for multi-class ROC AUC
y_bin = label_binarize(test_labels, classes=list(range(n_classes)))

# Function to compute and plot ROC curves
def plot_roc_curves(y_pred_proba, y_bin, model_name, n_classes=10):
    fpr = dict()
    tpr = dict()
    roc_auc_dict = dict()

    for i in range(n_classes):
        fpr[i], tpr[i], _ = roc_curve(y_bin[:, i], y_pred_proba[:, i])
        roc_auc_dict[i] = auc(fpr[i], tpr[i])

    # Calculate macro-average AUC
    macro_auc = np.mean(list(roc_auc_dict.values()))

    # Plot ROC curves for each class (showing first 5 classes for clarity)
    plt.figure(figsize=(12, 8))
    colors = plt.cm.tab10(np.linspace(0, 1, n_classes))

    for i in range(min(n_classes, 10)):
        plt.plot(fpr[i], tpr[i], color=colors[i], lw=1.5, alpha=0.7,
                 label=f'Class {i} (AUC = {roc_auc_dict[i]:.3f})')

    plt.plot([0, 1], [0, 1], 'k--', lw=2, label='Random Classifier')

    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate', fontsize=12)
    plt.ylabel('True Positive Rate', fontsize=12)
    plt.title(f'ROC Curves - MNIST with {model_name}\n(Macro-average AUC =
{macro_auc:.4f})',
              fontsize=14, fontweight='bold')
    plt.legend(loc="lower right", fontsize=9)
    plt.grid(True, alpha=0.3)
    plt.tight_layout()
    plt.show()

    return macro_auc, roc_auc_dict

print("\n" + "="*70)
print("ROC AUC ANALYSIS FOR MNIST CLASSIFICATION")
print("="*70)

# Plot ROC for Adam
print("\n1. ADAM OPTIMIZER")
adam_macro_auc, adam_auc_dict = plot_roc_curves(adam_preds, y_bin, 'Adam')
print(f"Macro-average AUC (Adam): {adam_macro_auc:.4f}")

# Plot ROC for SGD
print("\n2. SGD WITHOUT MOMENTUM")
sgd_macro_auc, sgd_auc_dict = plot_roc_curves(sgd_preds, y_bin, 'SGD (No Momentum)')
print(f"Macro-average AUC (SGD): {sgd_macro_auc:.4f}")

# Plot ROC for SGD + Momentum
print("\n3. SGD WITH MOMENTUM")
sgd_momentum_macro_auc, sgd_momentum_auc_dict = plot_roc_curves(sgd_momentum_preds,
```

```
y_bin, 'SGD + Momentum')
print(f"Macro-average AUC (SGD + Momentum): {sgd_momentum_macro_auc:.4f}")

# Comparison plot
print("\n" + "="*70)
print("OPTIMIZER COMPARISON - MACRO-AVERAGE AUC")
print("="*70)
plt.figure(figsize=(10, 6))
optimizers = ['Adam', 'SGD\n(No Momentum)', 'SGD +\nMomentum']
auc_scores = [adam_macro_auc, sgd_macro_auc, sgd_momentum_macro_auc]
colors_bar = ['#FF6B6B', '#4ECDC4', '#45B7D1']

bars = plt.bar(optimizers, auc_scores, color=colors_bar, alpha=0.8,
edgecolor='black', linewidth=2)
plt.ylabel('Macro-average AUC', fontsize=12)
plt.title('MNIST Optimizer Comparison - ROC AUC Score', fontsize=14,
fontweight='bold')
plt.ylim([0, 1.0])
plt.grid(True, alpha=0.3, axis='y')

# Add value labels on bars
for bar, score in zip(bars, auc_scores):
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2., height,
            f'{score:.4f}',
            ha='center', va='bottom', fontsize=12, fontweight='bold')

plt.tight_layout()
plt.show()

print(f"\nBest Optimizer (by AUC): {optimizers[np.argmax(auc_scores)]} with AUC =
{max(auc_scores):.4f}")
```

In [1]:
```
from tensorflow.keras.datasets import mnist
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
d:\Study\ML2\Practicals\.venv\Lib\site-
packages\keras\src\export\tf2onnx_lib.py:8: FutureWarning: In the future
`np.object` will be defined as the corresponding NumPy scalar.
  if not hasattr(np, "object"):
```

In [2]:
```
data = mnist.load_data()
(train_images, train_labels), (test_images, test_labels) = data
```

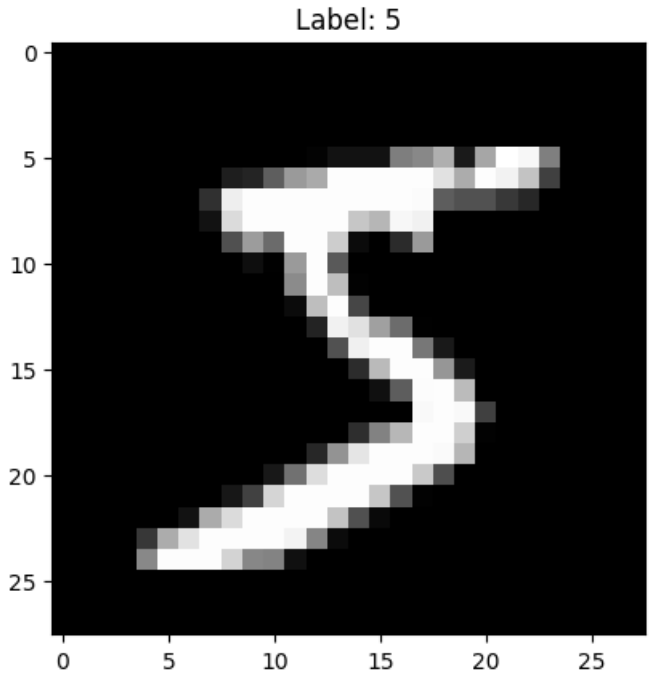
In [3]:
```
img_size =  train_images[0].shape[0]
```

In [4]:
```
num_classes = 10
```

In [5]:
```
train_images = train_images.astype("float32") / 255.0
test_images = test_images.astype("float32") / 255.0
```

In [6]:
```
plt.imshow(train_images[0], cmap='gray')
plt.title(f'Label: {train_labels[0]}')
```

Out[6]: Text(0.5, 1.0, 'Label: 5')



In [7]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Input, Flatten,RandomRotation,
GaussianNoise
```

In [8]:
```
from tensorflow.keras.optimizers import SGD, Adam
```

In [9]:
```
Gen_model = Sequential([
    Input(shape =(img_size,img_size) ),
    RandomRotation(0.1),
    GaussianNoise(0.05),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(32, activation='relu'),
    Dense(num_classes, activation='softmax')
])

Gen_model.compile(optimizer = 'adam', loss =
'sparse_categorical_crossentropy',metrics=['accuracy'])
Gen_history = Gen_model.fit(train_images,train_labels, epochs = 50)
```

```
Epoch 1/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 1ms/step - accuracy:
0.3938 - loss: 1.7054
Epoch 2/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.4798 - loss: 1.4601
Epoch 3/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5083 - loss: 1.3811
Epoch 4/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5291 - loss: 1.3313
Epoch 5/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5398 - loss: 1.2957
Epoch 6/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5440 - loss: 1.2850
Epoch 7/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5451 - loss: 1.2708
Epoch 8/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5602 - loss: 1.2313
Epoch 9/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5610 - loss: 1.2281
Epoch 10/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5728 - loss: 1.1981
Epoch 11/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5705 - loss: 1.2038
Epoch 12/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5727 - loss: 1.1991
Epoch 13/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5790 - loss: 1.1842
Epoch 14/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 1ms/step - accuracy:
0.5786 - loss: 1.1856
Epoch 15/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m6s[0m 3ms/step - accuracy:
0.5743 - loss: 1.1883
Epoch 16/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.5725 - loss: 1.1940
Epoch 17/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m11s[0m 3ms/step -
accuracy: 0.5872 - loss: 1.1574
Epoch 18/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5897 - loss: 1.1496
Epoch 19/50
```

```
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5861 - loss: 1.1570
Epoch 20/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5861 - loss: 1.1479
Epoch 21/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5925 - loss: 1.1452
Epoch 22/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5919 - loss: 1.1437
Epoch 23/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5925 - loss: 1.1472
Epoch 24/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5900 - loss: 1.1542
Epoch 25/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5982 - loss: 1.1285
Epoch 26/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5911 - loss: 1.1443
Epoch 27/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5961 - loss: 1.1337
Epoch 28/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5957 - loss: 1.1276
Epoch 29/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5977 - loss: 1.1221
Epoch 30/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6000 - loss: 1.1242
Epoch 31/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5894 - loss: 1.1514
Epoch 32/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6029 - loss: 1.1165
Epoch 33/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6114 - loss: 1.0892
Epoch 34/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5997 - loss: 1.1240
Epoch 35/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6125 - loss: 1.0880
Epoch 36/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6073 - loss: 1.1020
Epoch 37/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6128 - loss: 1.0876
Epoch 38/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6019 - loss: 1.1106
Epoch 39/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6105 - loss: 1.0882
Epoch 40/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6041 - loss: 1.1055
Epoch 41/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6065 - loss: 1.1052
Epoch 42/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
```

```
0.6087 - loss: 1.0956
Epoch 43/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6043 - loss: 1.1026
Epoch 44/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6150 - loss: 1.0815
Epoch 45/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6099 - loss: 1.0965
Epoch 46/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6083 - loss: 1.0938
Epoch 47/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6087 - loss: 1.0910
Epoch 48/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6047 - loss: 1.0979
Epoch 49/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6123 - loss: 1.0816
Epoch 50/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6183 - loss: 1.0709
```

Without Generalization

In [10]:
```
data = mnist.load_data()
(train_images, train_labels), (test_images, test_labels) = data
img_size =  train_images[0].shape[0]
num_classes = 10
```

In [11]:
```
NonGen_model = Sequential([
    Input(shape =(img_size,img_size) ),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(32, activation='relu'),
    Dense(num_classes, activation='softmax')
])
callbacks = tensorflow.k
NonGen_model.compile(optimizer = 'adam', loss =
'sparse_categorical_crossentropy',metrics=['accuracy'])
NonGen_history = NonGen_model.fit(train_images,train_labels, epochs = 50)
```

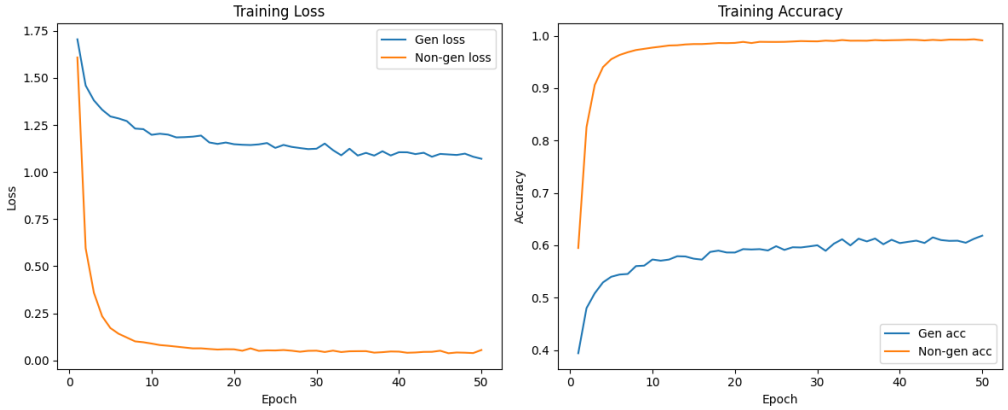
```
Epoch 1/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 807us/step -
accuracy: 0.5947 - loss: 1.6090
Epoch 2/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 956us/step -
accuracy: 0.8255 - loss: 0.5957
Epoch 3/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m4s[0m 2ms/step - accuracy:
0.9061 - loss: 0.3591
Epoch 4/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m6s[0m 3ms/step - accuracy:
0.9401 - loss: 0.2342
Epoch 5/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m6s[0m 3ms/step - accuracy:
0.9553 - loss: 0.1715
Epoch 6/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m9s[0m 3ms/step - accuracy:
0.9633 - loss: 0.1411
Epoch 7/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 782us/step -
accuracy: 0.9685 - loss: 0.1208
Epoch 8/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 777us/step -
accuracy: 0.9728 - loss: 0.1006
Epoch 9/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 773us/step -
accuracy: 0.9751 - loss: 0.0959
Epoch 10/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 776us/step -
accuracy: 0.9774 - loss: 0.0889
Epoch 11/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 776us/step -
accuracy: 0.9793 - loss: 0.0810
Epoch 12/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 809us/step -
accuracy: 0.9814 - loss: 0.0773
Epoch 13/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 800us/step -
accuracy: 0.9819 - loss: 0.0726
Epoch 14/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 851us/step -
accuracy: 0.9834 - loss: 0.0680
Epoch 15/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 817us/step -
accuracy: 0.9842 - loss: 0.0632
Epoch 16/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 845us/step -
accuracy: 0.9842 - loss: 0.0635
Epoch 17/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 831us/step -
accuracy: 0.9851 - loss: 0.0601
Epoch 18/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 820us/step -
accuracy: 0.9862 - loss: 0.0571
Epoch 19/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 839us/step -
accuracy: 0.9859 - loss: 0.0589
```

```
Epoch 20/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 822us/step -
accuracy: 0.9864 - loss: 0.0583
Epoch 21/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 831us/step -
accuracy: 0.9883 - loss: 0.0507
Epoch 22/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 774us/step -
accuracy: 0.9861 - loss: 0.0634
Epoch 23/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 808us/step -
accuracy: 0.9884 - loss: 0.0502
Epoch 24/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 855us/step -
accuracy: 0.9883 - loss: 0.0527
Epoch 25/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 2ms/step - accuracy:
0.9882 - loss: 0.0523
Epoch 26/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m6s[0m 2ms/step - accuracy:
0.9884 - loss: 0.0546
Epoch 27/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 838us/step -
accuracy: 0.9891 - loss: 0.0510
Epoch 28/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m4s[0m 2ms/step - accuracy:
0.9899 - loss: 0.0455
Epoch 29/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m6s[0m 2ms/step - accuracy:
0.9895 - loss: 0.0504
Epoch 30/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 2ms/step - accuracy:
0.9894 - loss: 0.0511
Epoch 31/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.9907 - loss: 0.0441
Epoch 32/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m4s[0m 2ms/step - accuracy:
0.9901 - loss: 0.0514
Epoch 33/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m7s[0m 3ms/step - accuracy:
0.9918 - loss: 0.0438
Epoch 34/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m10s[0m 3ms/step -
accuracy: 0.9906 - loss: 0.0480
Epoch 35/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m4s[0m 2ms/step - accuracy:
0.9907 - loss: 0.0485
Epoch 36/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m6s[0m 3ms/step - accuracy:
0.9905 - loss: 0.0487
Epoch 37/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m10s[0m 3ms/step -
accuracy: 0.9918 - loss: 0.0406
Epoch 38/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m11s[0m 3ms/step -
accuracy: 0.9911 - loss: 0.0431
Epoch 39/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.9915 - loss: 0.0469
Epoch 40/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.9918 - loss: 0.0461
Epoch 41/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.9924 - loss: 0.0400
Epoch 42/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.9922 - loss: 0.0415
Epoch 43/50
```

```
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 778us/step -
accuracy: 0.9911 - loss: 0.0446
Epoch 44/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.9922 - loss: 0.0450
Epoch 45/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.9913 - loss: 0.0509
Epoch 46/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m8s[0m 1ms/step - accuracy:
0.9926 - loss: 0.0375
Epoch 47/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 814us/step -
accuracy: 0.9926 - loss: 0.0415
Epoch 48/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 868us/step -
accuracy: 0.9925 - loss: 0.0404
Epoch 49/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 794us/step -
accuracy: 0.9933 - loss: 0.0384
Epoch 50/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 777us/step -
accuracy: 0.9913 - loss: 0.0547
```

In [12]:

```
import matplotlib.pyplot as plt
epochs = range(1, len(NonGen_history.history['loss']) + 1)

plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.plot(epochs, Gen_history.history['loss'], label='Gen loss')
plt.plot(epochs, NonGen_history.history['loss'], label='Non-gen loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training Loss')
plt.legend()

plt.subplot(1,2,2)
plt.plot(epochs, Gen_history.history['accuracy'], label='Gen acc')
plt.plot(epochs, NonGen_history.history['accuracy'], label='Non-gen acc')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Training Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



SimCLR on CIFAR10 (with vs without augmentations)

In [19]:
```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
tf.random.set_seed(42)
np.random.seed(42)
```

In [ ]:
```
# Load cifar10 and keep a small subset for speed
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()

subset = 12000
x_train_small = x_train[:subset]
y_train_small = y_train[:subset]
input_shape = x_train_small.shape[1:]
num_classes = 10
```

In [29]:
```
# Augmentation builders
strong_aug = tf.keras.Sequential([
    tf.keras.layers.Rescaling(1./255),
    tf.keras.layers.RandomFlip('horizontal'),
    tf.keras.layers.RandomRotation(0.15),
    tf.keras.layers.RandomTranslation(0.1, 0.1),
    tf.keras.layers.RandomContrast(0.2),
    tf.keras.layers.GaussianNoise(0.05),
])

def identity_aug(x):
    return x
```

In [22]:
```
AUTOTUNE = tf.data.AUTOTUNE
batch_size = 256
temperature = 0.1
epochs = 6

def make_simclr_ds(images, aug_fn):
    ds = tf.data.Dataset.from_tensor_slices(images)
    ds = ds.shuffle(10000)
    ds = ds.map(lambda x: (aug_fn(x, training=True), aug_fn(x, training=True)),
num_parallel_calls=AUTOTUNE)
    ds = ds.batch(batch_size).prefetch(AUTOTUNE)
    return ds

ds_aug = make_simclr_ds(x_train_small, strong_aug)
ds_plain = make_simclr_ds(x_train_small, lambda x, training=True: identity_aug(x))
```

In [23]:
```
def build_encoder():
    return tf.keras.Sequential([
        tf.keras.layers.Input(shape=input_shape),
        tf.keras.layers.Conv2D(32, 3, padding='same', activation='relu'),
        tf.keras.layers.Conv2D(64, 3, padding='same', strides=2, activation='relu'),
        tf.keras.layers.Conv2D(128, 3, padding='same', strides=2, activation='relu'),
        tf.keras.layers.GlobalAveragePooling2D(),
])

def build_projector():
    return tf.keras.Sequential([
        tf.keras.layers.Input(shape=(128,)),
        tf.keras.layers.Dense(128, activation='relu'),
        tf.keras.layers.Dense(64),
])
```

In [24]:
```
def nt_xent(z1, z2, temperature=0.1):
    z1 = tf.math.l2_normalize(z1, axis=1)
    z2 = tf.math.l2_normalize(z2, axis=1)
    z = tf.concat([z1, z2], axis=0)  # (2B, d)
    sim = tf.matmul(z, z, transpose_b=True) / temperature
    batch_size = tf.shape(z1)[0] * 2
    diag_mask = tf.eye(batch_size)
    sim = sim - 1e9 * diag_mask  # remove self-similarity
    # Positive mask: pairs (i, i+B) and (i+B, i)
    b = tf.shape(z1)[0]
    pos_mask_top = tf.concat([tf.zeros((b, b)), tf.eye(b)], axis=1)
    pos_mask_bottom = tf.concat([tf.eye(b), tf.zeros((b, b))], axis=1)
    pos_mask = tf.concat([pos_mask_top, pos_mask_bottom], axis=0)
    exp_sim = tf.exp(sim)
    log_prob = tf.math.log(tf.reduce_sum(exp_sim * pos_mask, axis=1) /
tf.reduce_sum(exp_sim, axis=1))
    loss = -tf.reduce_mean(log_prob)
    return loss
```

In [25]:
```
@tf.function
def train_step(encoder, projector, optimizer, x1, x2):
    with tf.GradientTape() as tape:
        h1 = encoder(x1, training=True)
        h2 = encoder(x2, training=True)
        z1 = projector(h1, training=True)
        z2 = projector(h2, training=True)
        loss = nt_xent(z1, z2, temperature)
    grads = tape.gradient(loss, encoder.trainable_variables +
projector.trainable_variables)
    optimizer.apply_gradients(zip(grads, encoder.trainable_variables +
projector.trainable_variables))
    return loss
```

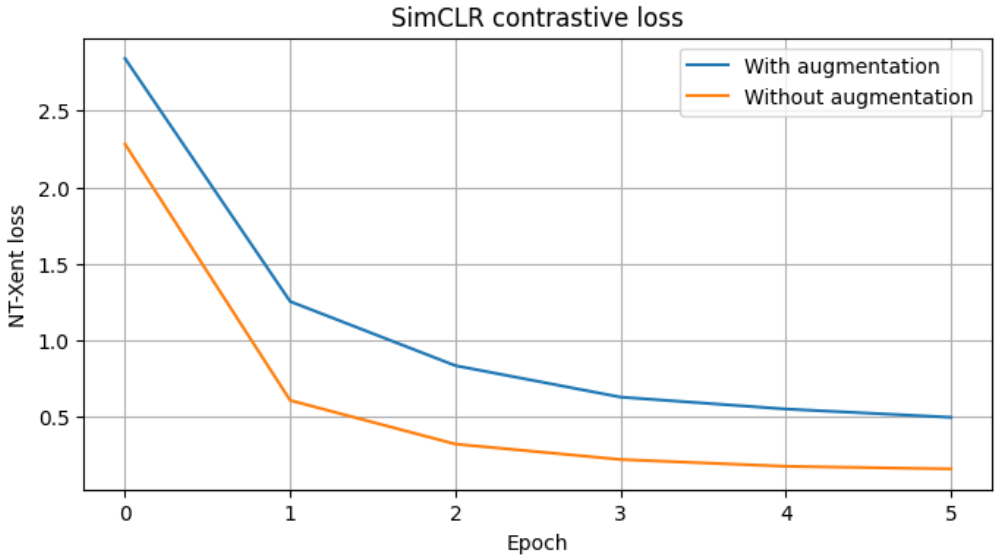
In [26]:

```
def train_simclr(ds):
    encoder = build_encoder()
    projector = build_projector()
    # build variables once to avoid creation inside tf.function
    dummy = tf.zeros((1,) + input_shape)
    h_dummy = encoder(dummy, training=False)
    _ = projector(h_dummy, training=False)
    optimizer = tf.keras.optimizers.Adam(1e-3)
    optimizer.build(encoder.trainable_variables + projector.trainable_variables)

    @tf.function
    def train_step(x1, x2):
        with tf.GradientTape() as tape:
            h1 = encoder(x1, training=True)
            h2 = encoder(x2, training=True)
            z1 = projector(h1, training=True)
            z2 = projector(h2, training=True)
            loss = nt_xent(z1, z2, temperature)
        grads = tape.gradient(loss, encoder.trainable_variables +
projector.trainable_variables)
        optimizer.apply_gradients(zip(grads, encoder.trainable_variables +
projector.trainable_variables))
        return loss

    history = []
    for epoch in range(epochs):
        losses = []
        for x1, x2 in ds:
            loss = train_step(x1, x2)
            losses.append(loss.numpy())
        history.append(np.mean(losses))
        print(f"Epoch {epoch+1}/{epochs} - loss: {history[-1]:.4f}")
    return encoder, projector, history

encoder_aug, projector_aug, loss_aug = train_simclr(ds_aug)
encoder_plain, projector_plain, loss_plain = train_simclr(ds_plain)
```

```
I0000 00:00:1767669726.375784   14063 cuda_dnn.cc:529] Loaded cuDNN version
91701
2026-01-06 08:52:10.607340: I tensorflow/core/framework/
local_rendezvous.cc:407] Local rendezvous is aborting with status:
OUT_OF_RANGE: End of sequence

Epoch 1/6 - loss: 2.8415

2026-01-06 08:52:12.817609: I tensorflow/core/framework/
local_rendezvous.cc:407] Local rendezvous is aborting with status:
OUT_OF_RANGE: End of sequence

Epoch 2/6 - loss: 1.2538
Epoch 3/6 - loss: 0.8349

2026-01-06 08:52:17.230441: I tensorflow/core/framework/
local_rendezvous.cc:407] Local rendezvous is aborting with status:
OUT_OF_RANGE: End of sequence

Epoch 4/6 - loss: 0.6292
Epoch 5/6 - loss: 0.5514
Epoch 6/6 - loss: 0.4972
Epoch 1/6 - loss: 2.2822

2026-01-06 08:52:22.860149: I tensorflow/core/framework/
local_rendezvous.cc:407] Local rendezvous is aborting with status:
OUT_OF_RANGE: End of sequence
```

```
Epoch 2/6 - loss: 0.6077
Epoch 3/6 - loss: 0.3224
Epoch 4/6 - loss: 0.2217
Epoch 5/6 - loss: 0.1771
Epoch 6/6 - loss: 0.1601
```

In [27]:
```
plt.figure(figsize=(8,4))
plt.plot(loss_aug, label='With augmentation')
plt.plot(loss_plain, label='Without augmentation')
plt.xlabel('Epoch')
plt.ylabel('NT-Xent loss')
plt.title('SimCLR contrastive loss')
plt.legend()
plt.grid(True)
plt.show()
```



Transfer learning on Intel Image dataset (frozen vs fine-tuned MobileNetV2)

In [9]:
```
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras.preprocessing import image_dataset_from_directory
tf.random.set_seed(42)
```

In [10]:
```
data_dir = 'Data/Intel Image Data/seg_train/seg_train'
img_size = (160, 160)
batch_size = 32

train_ds = image_dataset_from_directory(
    data_dir,
    validation_split=0.2,
    subset='training',
    seed=42,
    image_size=img_size,
    batch_size=batch_size
)

val_ds = image_dataset_from_directory(
    'Data/Intel Image Data/seg_test/seg_test',
    validation_split=0.2,
    subset='validation',
    seed=42,
    image_size=img_size,
    batch_size=batch_size
)

class_names = train_ds.class_names
num_classes = len(class_names)
class_names
```

```
Found 14034 files belonging to 6 classes.
Using 11228 files for training.
Found 3000 files belonging to 6 classes.
Using 600 files for validation.
```

Out[10]:
```
['buildings', 'forest', 'glacier', 'mountain', 'sea', 'street']
```

In [11]:
```
data_augmentation = tf.keras.Sequential([
    tf.keras.layers.RandomFlip('horizontal'),
    tf.keras.layers.RandomRotation(0.1),
    tf.keras.layers.RandomZoom(0.1),
])

train_ds = train_ds.map(lambda x, y: (data_augmentation(x, training=True), y))
```

In [12]:
```
# ----- Model 1: Frozen MobileNetV2 encoder (Sequential) -----
base_model_frozen = tf.keras.applications.MobileNetV2(
    input_shape=img_size + (3,),
    include_top=False,
    weights='imagenet'
)
base_model_frozen.trainable = False

model_frozen = tf.keras.Sequential([
    base_model_frozen,
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(num_classes, activation='softmax')
])

model_frozen.compile(
    optimizer=tf.keras.optimizers.Adam(1e-3),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy'],
 )
model_frozen.summary()
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
mobilenetv2_1.00_160 (Functional)	(None, 5, 5, 1280)	2,257,984
global_average_pooling2d_2 (GlobalAveragePooling2D)	(None, 1280)	0
dense_2 (Dense)	(None, 128)	163,968
dense_3 (Dense)	(None, 64)	8,256
dense_4 (Dense)	(None, 6)	390

Total params: 2,430,598 (9.27 MB)

Trainable params: 172,614 (674.27 KB)

Non-trainable params: 2,257,984 (8.61 MB)

In [13]:
```
history_frozen = model_frozen.fit(train_ds,
                                  epochs=5,
                                  validation_data=val_ds)
eval_frozen = model_frozen.evaluate(val_ds)
print('Frozen encoder val loss/acc:', eval_frozen)
```

```
Epoch 1/5


 2026-01-06 15:53:23.591990: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_4111', 204 bytes spill stores, 204 bytes
 spill loads

 2026-01-06 15:53:23.611544: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_4111_0', 464 bytes spill stores, 1372
 bytes spill loads

 2026-01-06 15:53:23.754766: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_4111', 5616 bytes spill stores, 5612
 bytes spill loads

 2026-01-06 15:53:23.920548: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_6374', 32 bytes spill stores, 32 bytes
 spill loads

 2026-01-06 15:53:24.040219: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_4118', 4 bytes spill stores, 4 bytes
 spill loads

 2026-01-06 15:53:24.072467: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_4118', 12 bytes spill stores, 12 bytes
 spill loads

 2026-01-06 15:53:24.198828: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_4111', 5340 bytes spill stores, 5324
 bytes spill loads

 2026-01-06 15:53:24.373166: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_6374', 20 bytes spill stores, 20 bytes
 spill loads


[1m350/351[0m [32m━━━━━━━━━━━━━━━━━━━[0m[37m━[0m [1m0s[0m 54ms/step - accuracy:
0.5834 - loss: 1.0374

 2026-01-06 15:53:45.353960: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_4118', 12 bytes spill stores, 12 bytes
 spill loads

 2026-01-06 15:53:45.570445: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_4111', 220 bytes spill stores, 220 bytes
 spill loads

 2026-01-06 15:53:45.570575: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_4111_0', 444 bytes spill stores, 1384
 bytes spill loads

 2026-01-06 15:53:45.679481: I external/local_xla/xla/stream_executor/cuda/
```

```
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_4118', 4 bytes spill stores, 4 bytes
spill loads

2026-01-06 15:53:45.735091: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_4111', 5524 bytes spill stores, 5564
bytes spill loads

2026-01-06 15:53:46.013096: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_4111', 8 bytes spill stores, 8 bytes
spill loads

2026-01-06 15:53:46.203628: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_6374', 32 bytes spill stores, 32 bytes
spill loads

2026-01-06 15:53:46.281159: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_4111', 5388 bytes spill stores, 5392
bytes spill loads

2026-01-06 15:53:46.330587: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_6374', 20 bytes spill stores, 20 bytes
spill loads


[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 63ms/step - accuracy:
0.5837 - loss: 1.0369

2026-01-06 15:53:50.651100: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_1171', 8 bytes spill stores, 8 bytes
spill loads

2026-01-06 15:53:50.763657: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_1171_0', 444 bytes spill stores, 1384
bytes spill loads

2026-01-06 15:53:50.864129: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_1178', 4 bytes spill stores, 4 bytes
spill loads

2026-01-06 15:53:50.898621: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_1178', 12 bytes spill stores, 12 bytes
spill loads

2026-01-06 15:53:50.979706: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_1171', 220 bytes spill stores, 220 bytes
spill loads

2026-01-06 15:53:51.058526: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_1171', 5388 bytes spill stores, 5392
bytes spill loads

2026-01-06 15:53:51.215065: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_1171', 5524 bytes spill stores, 5564
bytes spill loads
```

```
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m31s[0m 76ms/step - accuracy:
0.5839 - loss: 1.0365 - val_accuracy: 0.7250 - val_loss: 0.7427
Epoch 2/5
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m19s[0m 54ms/step - accuracy:
0.7234 - loss: 0.7379 - val_accuracy: 0.7367 - val_loss: 0.7354
Epoch 3/5
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m19s[0m 54ms/step - accuracy:
0.7462 - loss: 0.6656 - val_accuracy: 0.7250 - val_loss: 0.6690
Epoch 4/5
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m19s[0m 54ms/step - accuracy:
0.7567 - loss: 0.6413 - val_accuracy: 0.7583 - val_loss: 0.6643
Epoch 5/5
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m19s[0m 54ms/step - accuracy:
0.7678 - loss: 0.6216 - val_accuracy: 0.7600 - val_loss: 0.6640
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - accuracy:
0.7651 - loss: 0.6497
Frozen encoder val loss/acc: [0.6640393733978271, 0.7599999904632568]
```

In [14]:
```
# ----- Model 2: Separate model for fine-tuning (Sequential) -----
base_model_ft = tf.keras.applications.MobileNetV2(
    input_shape=img_size + (3,),
    include_top=False,
    weights='imagenet'
)
base_model_ft.trainable = True

# Freeze most of the encoder; fine-tune only the last ~30 layers
fine_tune_at = len(base_model_ft.layers) - 30
for layer in base_model_ft.layers[:fine_tune_at]:
    layer.trainable = False

model_ft = tf.keras.Sequential([
    base_model_ft,
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(num_classes, activation='softmax')
])

model_ft.compile(
    optimizer=tf.keras.optimizers.Adam(1e-4),
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy'],
 )

history_ft = model_ft.fit(
    train_ds,
    epochs=5,
    validation_data=val_ds,
 )
eval_ft = model_ft.evaluate(val_ds)
print('Fine-tuned val loss/acc:', eval_ft)
```

```
Epoch 1/5
```

```
2026-01-06 15:55:13.325723: W external/local_xla/xla/tsl/framework/
bfc_allocator.cc:310] Allocator (GPU_0_bfc) ran out of memory trying to
allocate 691.98MiB with freed_by_count=0. The caller indicates that this is
not a failure, but this may mean that there could be performance gains if
more memory were available.
2026-01-06 15:55:13.351853: W external/local_xla/xla/tsl/framework/
bfc_allocator.cc:310] Allocator (GPU_0_bfc) ran out of memory trying to
allocate 919.91MiB with freed_by_count=0. The caller indicates that this is
not a failure, but this may mean that there could be performance gains if
more memory were available.
```

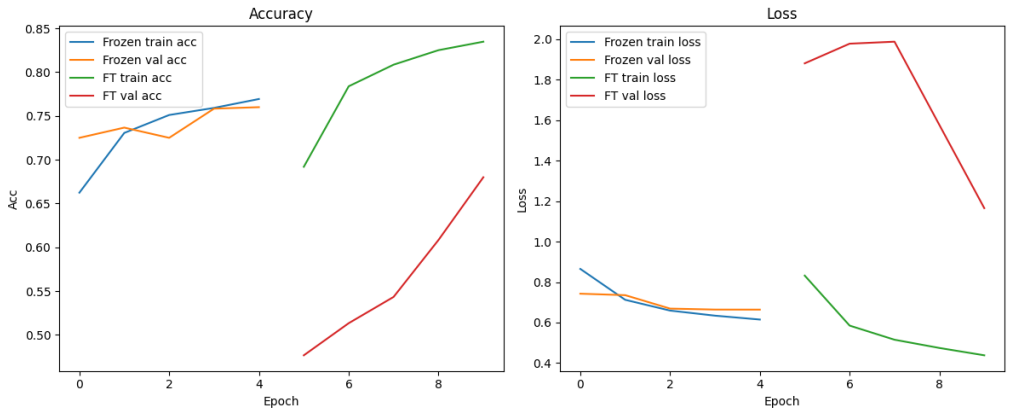
```
[1m350/351[0m [32m━━━━━━━━━━━━━━━━━━━[0m[37m━[0m [1m0s[0m 54ms/step - accuracy:
0.5973 - loss: 1.0740
```

```
2026-01-06 15:55:35.404618: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_6330', 12 bytes spill stores, 12 bytes
spill loads

2026-01-06 15:55:35.601672: W external/local_xla/xla/tsl/framework/
bfc_allocator.cc:310] Allocator (GPU_0_bfc) ran out of memory trying to
allocate 691.85MiB with freed_by_count=0. The caller indicates that this is
not a failure, but this may mean that there could be performance gains if
more memory were available.
2026-01-06 15:55:35.629058: W external/local_xla/xla/tsl/framework/
bfc_allocator.cc:310] Allocator (GPU_0_bfc) ran out of memory trying to
allocate 919.42MiB with freed_by_count=0. The caller indicates that this is
not a failure, but this may mean that there could be performance gains if
more memory were available.
```

```
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m32s[0m 74ms/step - accuracy:
0.5979 - loss: 1.0726 - val_accuracy: 0.4767 - val_loss: 1.8813
Epoch 2/5
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m19s[0m 54ms/step - accuracy:
0.7749 - loss: 0.6032 - val_accuracy: 0.5133 - val_loss: 1.9785
Epoch 3/5
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m19s[0m 54ms/step - accuracy:
0.8016 - loss: 0.5349 - val_accuracy: 0.5433 - val_loss: 1.9884
Epoch 4/5
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m19s[0m 54ms/step - accuracy:
0.8230 - loss: 0.4787 - val_accuracy: 0.6083 - val_loss: 1.5767
Epoch 5/5
[1m351/351[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m19s[0m 54ms/step - accuracy:
0.8344 - loss: 0.4383 - val_accuracy: 0.6800 - val_loss: 1.1656
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step - accuracy:
0.6811 - loss: 1.1385
Fine-tuned val loss/acc: [1.165554165840149, 0.6800000071525574]
```

In [15]:

```
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.plot(history_frozen.history['accuracy'], label='Frozen train acc')
plt.plot(history_frozen.history['val_accuracy'], label='Frozen val acc')
plt.plot([None]*len(history_frozen.history['accuracy']) +
history_ft.history['accuracy'], label='FT train acc')
plt.plot([None]*len(history_frozen.history['val_accuracy']) +
history_ft.history['val_accuracy'], label='FT val acc')
plt.title('Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Acc')
plt.legend()

plt.subplot(1,2,2)
plt.plot(history_frozen.history['loss'], label='Frozen train loss')
plt.plot(history_frozen.history['val_loss'], label='Frozen val loss')
plt.plot([None]*len(history_frozen.history['loss']) + history_ft.history['loss'],
label='FT train loss')
plt.plot([None]*len(history_frozen.history['val_loss']) +
history_ft.history['val_loss'], label='FT val loss')
plt.title('Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.tight_layout()
plt.show()
```



In [16]:

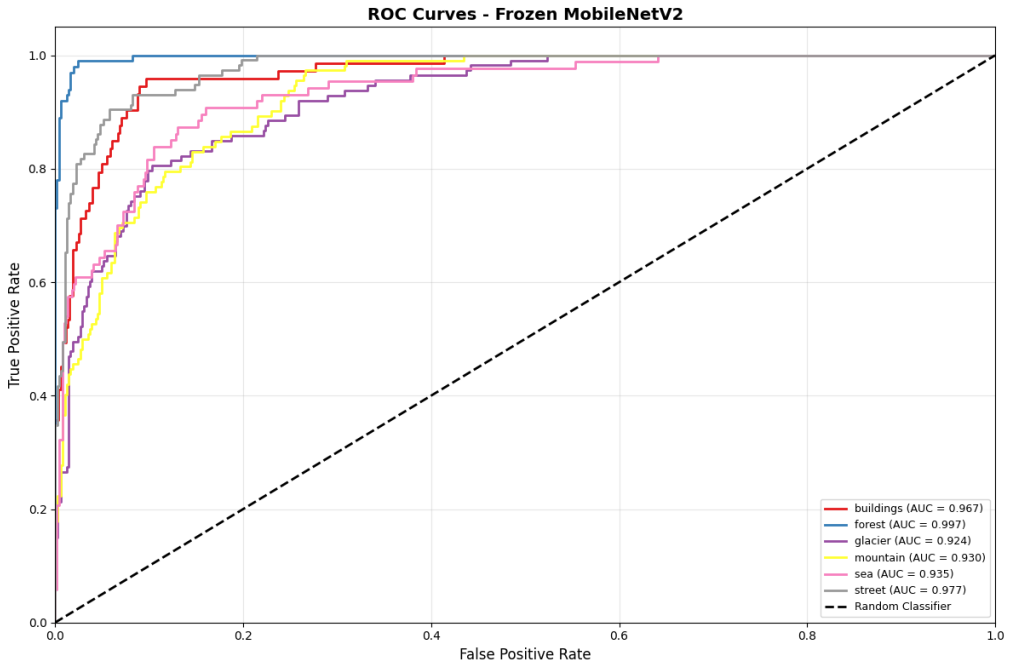
```
# Plot ROC AUC Curves for Multi-class Classification (One-vs-Rest)
from sklearn.metrics import roc_curve, auc, roc_auc_score
from sklearn.preprocessing import label_binarize
import numpy as np
import matplotlib.pyplot as plt

# Get predictions from both models
y_true_list = []
y_frozen_proba = []
y_ft_proba = []

for x, y in val_ds:
    y_true_list.extend(y.numpy())
    y_frozen_proba.extend(model_frozen.predict(x, verbose=0))
    y_ft_proba.extend(model_ft.predict(x, verbose=0))

y_true = np.array(y_true_list)
y_frozen_proba = np.array(y_frozen_proba)
y_ft_proba = np.array(y_ft_proba)

# Binarize the output for multi-class ROC AUC
n_classes = num_classes
y_bin = label_binarize(y_true, classes=list(range(n_classes)))

# Function to compute and plot ROC curves
def plot_roc_multiclass(y_pred_proba, y_bin, model_name, n_classes, class_names):
    fpr = dict()
    tpr = dict()
    roc_auc_dict = dict()
    colors = plt.cm.Set1(np.linspace(0, 1, n_classes))

    plt.figure(figsize=(12, 8))

    for i in range(n_classes):
        fpr[i], tpr[i], _ = roc_curve(y_bin[:, i], y_pred_proba[:, i])
        roc_auc_dict[i] = auc(fpr[i], tpr[i])
        plt.plot(fpr[i], tpr[i], color=colors[i], lw=2,
                 label=f'{class_names[i]} (AUC = {roc_auc_dict[i]:.3f})')

    # Plot random classifier baseline
    plt.plot([0, 1], [0, 1], 'k--', lw=2, label='Random Classifier')

    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate', fontsize=12)
    plt.ylabel('True Positive Rate', fontsize=12)
    plt.title(f'ROC Curves - {model_name}', fontsize=14, fontweight='bold')
    plt.legend(loc="lower right", fontsize=9)
    plt.grid(True, alpha=0.3)
    plt.tight_layout()
    plt.show()

    # Calculate macro and weighted averages
    macro_auc = np.mean(list(roc_auc_dict.values()))
    weights = np.bincount(y_true) / len(y_true)
    weighted_auc = np.average([roc_auc_dict[i] for i in range(n_classes)],
weights=weights)

    return macro_auc, weighted_auc, roc_auc_dict

print("\n" + "="*70)
print("ROC AUC ANALYSIS - TRANSFER LEARNING MODELS")
print("="*70)

# Plot ROC for Frozen Model
print("\n1. FROZEN MOBILENETV2 ENCODER")
frozen_macro_auc, frozen_weighted_auc, frozen_auc_dict = plot_roc_multiclass(
    y_frozen_proba, y_bin, 'Frozen MobileNetV2', n_classes, class_names)
print(f"Macro-average AUC: {frozen_macro_auc:.4f}")
print(f"Weighted-average AUC: {frozen_weighted_auc:.4f}")
```

```
# Plot ROC for Fine-tuned Model
print("\n2. FINE-TUNED MOBILENETV2")
ft_macro_auc, ft_weighted_auc, ft_auc_dict = plot_roc_multiclass(
    y_ft_proba, y_bin, 'Fine-tuned MobileNetV2', n_classes, class_names)
print(f"Macro-average AUC: {ft_macro_auc:.4f}")
print(f"Weighted-average AUC: {ft_weighted_auc:.4f}")

# Comparison plot
print("\n" + "="*70)
print("MODEL COMPARISON - AUC SCORES")
print("="*70)

fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# Macro-average comparison
models = ['Frozen', 'Fine-tuned']
macro_auc_scores = [frozen_macro_auc, ft_macro_auc]
colors_bar = ['#FF6B6B', '#45B7D1']

axes[0].bar(models, macro_auc_scores, color=colors_bar, alpha=0.8, edgecolor='black',
linewidth=2)
axes[0].set_ylabel('Macro-average AUC', fontsize=12)
axes[0].set_title('Macro-average AUC Comparison', fontsize=12, fontweight='bold')
axes[0].set_ylim([0, 1.0])
axes[0].grid(True, alpha=0.3, axis='y')

# Add value labels
for i, (model, score) in enumerate(zip(models, macro_auc_scores)):
    axes[0].text(i, score + 0.02, f'{score:.4f}', ha='center', fontsize=11,
fontweight='bold')

# Weighted-average comparison
weighted_auc_scores = [frozen_weighted_auc, ft_weighted_auc]

axes[1].bar(models, weighted_auc_scores, color=colors_bar, alpha=0.8,
edgecolor='black', linewidth=2)
axes[1].set_ylabel('Weighted-average AUC', fontsize=12)
axes[1].set_title('Weighted-average AUC Comparison', fontsize=12, fontweight='bold')
axes[1].set_ylim([0, 1.0])
axes[1].grid(True, alpha=0.3, axis='y')

# Add value labels
for i, (model, score) in enumerate(zip(models, weighted_auc_scores)):
    axes[1].text(i, score + 0.02, f'{score:.4f}', ha='center', fontsize=11,
fontweight='bold')

plt.tight_layout()
plt.show()

# Determine winner
if ft_macro_auc > frozen_macro_auc:
    print(f"\n✓ Fine-tuned model performs better with macro-average AUC =
{ft_macro_auc:.4f}")
else:
    print(f"\n✓ Frozen model performs better with macro-average AUC =
{frozen_macro_auc:.4f}")
```

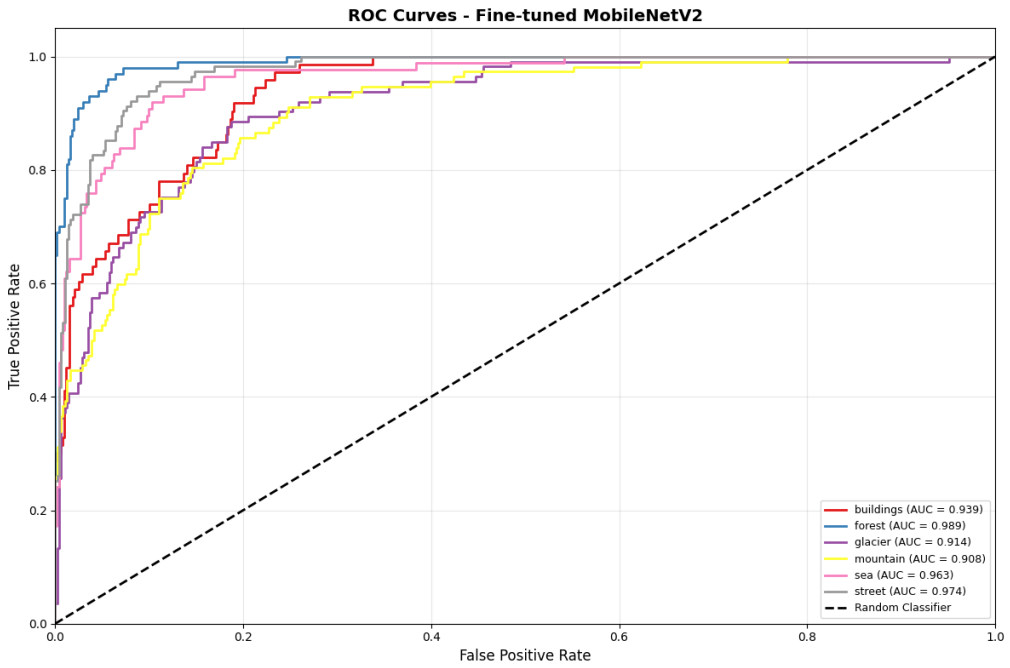
```
WARNING:tensorflow:5 out of the last 39 calls to <function
TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at
0x7e575cf4c5e0> triggered tf.function retracing. Tracing is expensive and the
excessive number of tracings could be due to (1) creating @tf.function repeatedly
in a loop, (2) passing tensors with different shapes, (3) passing Python objects
instead of tensors. For (1), please define your @tf.function outside of the loop.
For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary
retracing. For (3), please refer to https://www.tensorflow.org/guide/
function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/
function for  more details.
```

```
2026-01-06 15:57:06.928535: I tensorflow/core/framework/
local_rendezvous.cc:407] Local rendezvous is aborting with status:
OUT_OF_RANGE: End of sequence
```

```
======================================================================
ROC AUC ANALYSIS - TRANSFER LEARNING MODELS
======================================================================

1. FROZEN MOBILENETV2 ENCODER
```

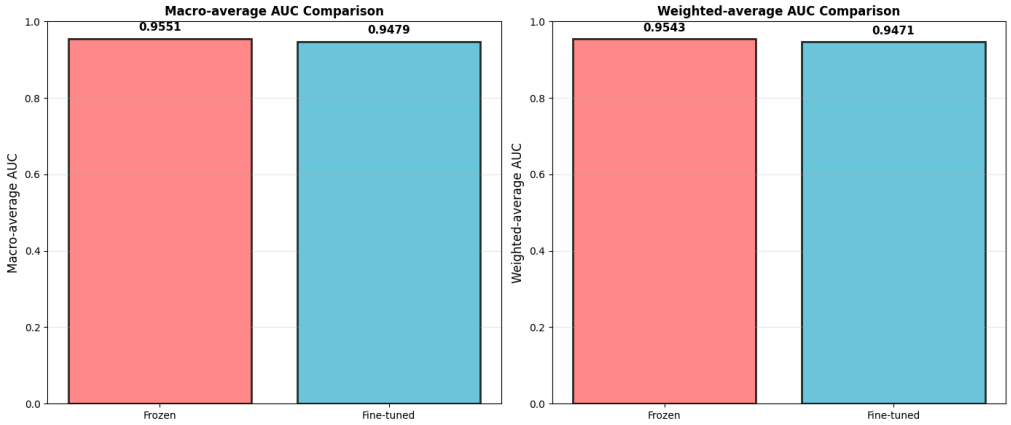



```
Macro-average AUC: 0.9551
Weighted-average AUC: 0.9543

2. FINE-TUNED MOBILENETV2
```




```
Macro-average AUC: 0.9479
Weighted-average AUC: 0.9471

======================================================================
```

```
MODEL COMPARISON - AUC SCORES
======================================================================
```




```
✓ Frozen model performs better with macro-average AUC = 0.9551
```

Choose two datasets with different distributions (dogs &cats , cars).

1. Resize images to the required input size of the chosen pre-trained model.
2. Load Pre-trained Model (LeNet-5 or VGG-16 or MobileNetV2 or Resnet50 or AlexNet)
. Compare the performances of all the models and visualize
4. Write down your observations and conclusions

In [1]:
```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

```
2026-01-06 10:22:56.204440: I tensorflow/core/util/port.cc:153] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn
them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2026-01-06 10:22:56.211499: E external/local_xla/xla/stream_executor/cuda/
cuda_fft.cc:467] Unable to register cuFFT factory: Attempting to register
factory for plugin cuFFT when one has already been registered
WARNING: All log messages before absl::InitializeLog() is called are written
to STDERR
E0000 00:00:1767675176.219594  113805 cuda_dnn.cc:8579] Unable to register
cuDNN factory: Attempting to register factory for plugin cuDNN when one has
already been registered
E0000 00:00:1767675176.222006  113805 cuda_blas.cc:1407] Unable to register
cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has
already been registered
W0000 00:00:1767675176.228296  113805 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767675176.228306  113805 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767675176.228307  113805 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767675176.228308  113805 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
2026-01-06 10:22:56.230633: I tensorflow/core/platform/
cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use
available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operations,
rebuild TensorFlow with the appropriate compiler flags.
```

In [2]:
```
data = tf.keras.datasets.cifar10.load_data()
```

In [3]:
```
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()
```

In [4]:
```
from tensorflow.keras.applications.resnet_v2 import ResNet50V2
```

In [5]:
```
base_model_resnet = ResNet50V2(input_shape=(32,32,3),
weights='imagenet',include_top=False )
```

```
I0000 00:00:1767675179.651980  113805 gpu_device.cc:2019] Created device /
job:localhost/replica:0/task:0/device:GPU:0 with 9172 MB memory:  -> device:
0, name: NVIDIA GeForce RTX 4070 SUPER, pci bus id: 0000:01:00.0, compute
capability: 8.9
```

In [6]:
```
base_model_resnet
```

Out[6]: <Functional name=resnet50v2, built=True>

In [7]:
```
base_model_resnet.trainable = False
```

In [8]:
```
main_model_resnet = tf.keras.Sequential([
    base_model_resnet,
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(10, activation='softmax')
])
```

In [9]:
```
main_model_resnet.compile(optimizer = 'adam', loss='sparse_categorical_crossentropy',
metrics=['accuracy'])
```

In [10]:
```
main_model_resnet.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
resnet50v2 (Functional)	(None, 1, 1, 2048)	23,564,800
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
dense (Dense)	(None, 128)	262,272
dense_1 (Dense)	(None, 64)	8,256
dense_2 (Dense)	(None, 10)	650

Total params: 23,835,978 (90.93 MB)

Trainable params: 271,178 (1.03 MB)

Non-trainable params: 23,564,800 (89.89 MB)

In [11]:
```
main_model_resnet.fit(x_train, y_train, epochs=10, validation_data=(x_test, y_test))
resnet_losses = main_model_resnet.history.history['loss']
res_acc = main_model_resnet.history.history['accuracy']
```

```
Epoch 1/10


 WARNING: All log messages before absl::InitializeLog() is called are written
 to STDERR
 I0000 00:00:1767675182.742734  113984 service.cc:152] XLA service
 0x78cbd40027f0 initialized for platform CUDA (this does not guarantee that
 XLA will be used). Devices:
 I0000 00:00:1767675182.742746  113984 service.cc:160]   StreamExecutor device
 (0): NVIDIA GeForce RTX 4070 SUPER, Compute Capability 8.9
 2026-01-06 10:23:02.807298: I tensorflow/compiler/mlir/tensorflow/utils/
 dump_mlir_util.cc:269] disabling MLIR crash reproducer, set env var
 `MLIR_CRASH_REPRODUCER_DIRECTORY` to enable.
 I0000 00:00:1767675183.372177  113984 cuda_dnn.cc:529] Loaded cuDNN version
 91701
 2026-01-06 10:23:03.926094: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_4946', 204 bytes spill stores, 204 bytes
 spill loads

 2026-01-06 10:23:04.085252: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_7425', 32 bytes spill stores, 32 bytes
 spill loads

 2026-01-06 10:23:04.115513: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_4946_0', 396 bytes spill stores, 2300
 bytes spill loads

 2026-01-06 10:23:04.137504: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_4953', 12 bytes spill stores, 12 bytes
 spill loads

 2026-01-06 10:23:04.141450: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_4946', 3940 bytes spill stores, 3920
 bytes spill loads

 2026-01-06 10:23:04.301632: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_4946', 992 bytes spill stores, 992 bytes
 spill loads

 2026-01-06 10:23:04.457317: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_4953', 4 bytes spill stores, 4 bytes
 spill loads

 2026-01-06 10:23:04.807844: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_7425', 20 bytes spill stores, 20 bytes
 spill loads


[1m  64/1563[0m [37m━━━━━━━━━━━━━━━━━━━━[0m [1m3s[0m 2ms/step - accuracy: 0.1074
- loss: 36.0356

 I0000 00:00:1767675186.483376  113984 device_compiler.h:188] Compiled cluster
 using XLA!  This line is logged at most once for the lifetime of the process.

[1m1543/1563[0m [32m━━━━━━━━━━━━━━━━━━━[0m[37m━[0m [1m0s[0m 2ms/step - accuracy:
0.1041 - loss: 5.3288
```

```
2026-01-06 10:23:11.196165: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_4946', 4 bytes spill stores, 4 bytes
spill loads

2026-01-06 10:23:11.417148: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_4946', 116 bytes spill stores, 116 bytes
spill loads

2026-01-06 10:23:11.680364: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_4946', 3940 bytes spill stores, 3920
bytes spill loads

2026-01-06 10:23:11.965342: I external/local_xla/xla/stream_executor/cuda/
subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
memory in function 'gemm_fusion_dot_4946', 992 bytes spill stores, 992 bytes
spill loads
```

```
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m16s[0m 6ms/step -
accuracy: 0.1040 - loss: 5.2950 - val_accuracy: 0.1000 - val_loss: 2.3023
Epoch 2/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m4s[0m 3ms/step - accuracy:
0.0950 - loss: 2.3029 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 3/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.0946 - loss: 2.3028 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 4/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m4s[0m 3ms/step - accuracy:
0.1003 - loss: 2.3027 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 5/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m4s[0m 3ms/step - accuracy:
0.0988 - loss: 2.3028 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 6/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m4s[0m 3ms/step - accuracy:
0.0970 - loss: 2.3027 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 7/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m4s[0m 3ms/step - accuracy:
0.0958 - loss: 2.3027 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 8/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.0997 - loss: 2.3028 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 9/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.0971 - loss: 2.3028 - val_accuracy: 0.1000 - val_loss: 2.3027
Epoch 10/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.0972 - loss: 2.3027 - val_accuracy: 0.1000 - val_loss: 2.3027
```

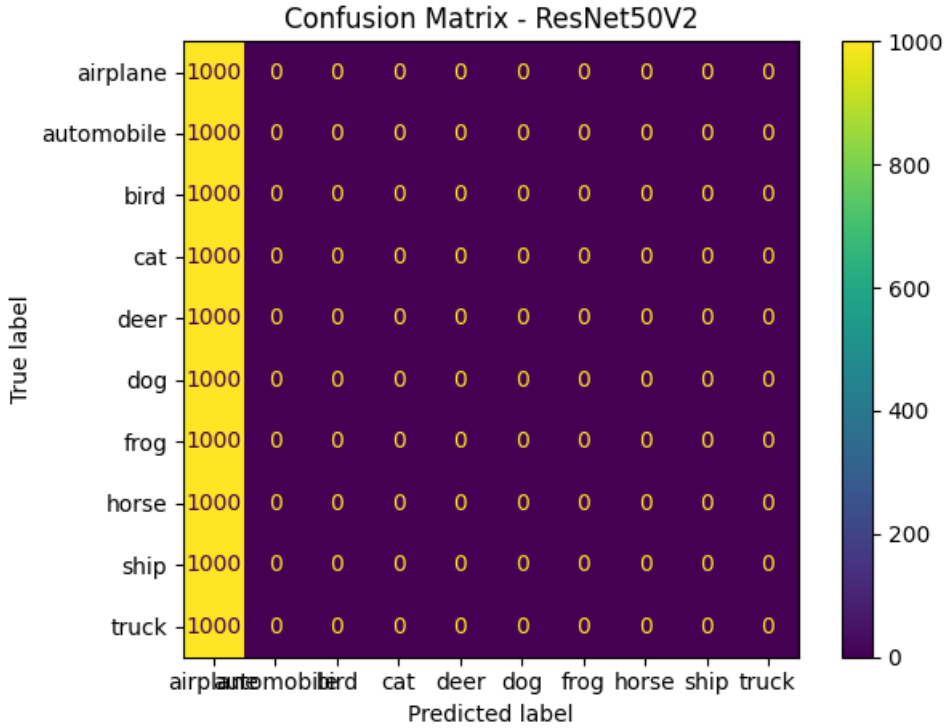
In [12]:
```
test_loss, test_acc = main_model_resnet.evaluate(x_test, y_test)
print(f"Test accuracy: {test_acc}")
```

```
[1m313/313[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 2ms/step - accuracy:
0.1001 - loss: 2.3027
Test accuracy: 0.10000000149011612
```

In [13]:
```
preds = main_model_resnet.predict(x_test)
```

```
[1m313/313[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 6ms/step
```

In [14]:
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog',
'horse', 'ship', 'truck']
true_labels = y_test.flatten()

predicted_labels = np.argmax(preds, axis=1)

cm = confusion_matrix(true_labels, predicted_labels)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_names)
disp.plot()
plt.title('Confusion Matrix - ResNet50V2')
plt.tight_layout()
plt.show()
```



In [15]:
```
import gc
tf.keras.backend.clear_session()
gc.collect()
```

Out[15]: 0

In [16]:
```
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()
from tensorflow.keras.applications.mobilenet_v2 import MobileNetV2

base_model_mobilenet = MobileNetV2(input_shape=(32,32,3),
weights='imagenet',include_top=False )
base_model_mobilenet
base_model_mobilenet.trainable = False
main_model_mobilenet = tf.keras.Sequential([
    base_model_mobilenet,
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(10, activation='softmax')
])

main_model_mobilenet.compile(optimizer = 'adam',
loss='sparse_categorical_crossentropy', metrics=['accuracy'])
main_model_mobilenet.summary()
main_model_mobilenet.fit(x_train, y_train, epochs=10, validation_data=(x_test,
y_test))

mobilenet_losses = main_model_mobilenet.history.history['loss']
mobilenet_acc = main_model_mobilenet.history.history['accuracy']
test_loss, test_acc = main_model_mobilenet.evaluate(x_test, y_test)
print(f"Test accuracy: {test_acc}")
```

```
/tmp/ipykernel_113805/2946216259.py:4: UserWarning: `input_shape` is
undefined or non-square, or `rows` is not in [96, 128, 160, 192, 224].
Weights for input shape (224, 224) will be loaded as the default.
  base_model_mobilenet = MobileNetV2(input_shape=(32,32,3),
weights='imagenet',include_top=False )
```

Model: "sequential"

Layer (type)	Output Shape	Param #
mobilenetv2_1.00_224 (Functional)	(None, 1, 1, 1280)	2,257,984
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1280)	0
dense (Dense)	(None, 128)	163,968
dense_1 (Dense)	(None, 64)	8,256
dense_2 (Dense)	(None, 10)	650

Total params: 2,430,858 (9.27 MB)

Trainable params: 172,874 (675.29 KB)

Non-trainable params: 2,257,984 (8.61 MB)

```
Epoch 1/10

2026-01-06 10:24:08.581006: E external/local_xla/xla/stream_executor/cuda/
cuda_timer.cc:86] Delay kernel timed out: measured time has sub-optimal
accuracy. There may be a missing warmup execution, please investigate in
Nsight Systems.
2026-01-06 10:24:08.659660: E external/local_xla/xla/stream_executor/cuda/
cuda_timer.cc:86] Delay kernel timed out: measured time has sub-optimal
accuracy. There may be a missing warmup execution, please investigate in
Nsight Systems.

[1m1552/1563[0m [32m━━━━━━━━━━━━━━━━━━━[0m[37m━[0m [1m0s[0m 2ms/step - accuracy:
0.2035 - loss: 2.1513
```

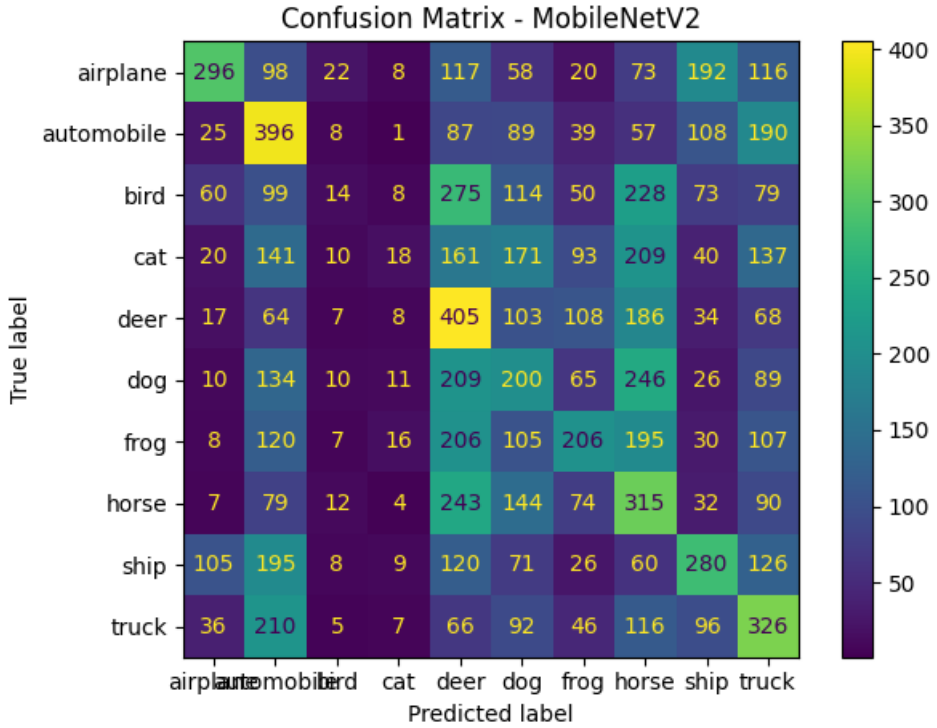
```
2026-01-06 10:24:15.805457: E external/local_xla/xla/stream_executor/cuda/
cuda_timer.cc:86] Delay kernel timed out: measured time has sub-optimal
accuracy. There may be a missing warmup execution, please investigate in
Nsight Systems.
2026-01-06 10:24:15.883491: E external/local_xla/xla/stream_executor/cuda/
cuda_timer.cc:86] Delay kernel timed out: measured time has sub-optimal
accuracy. There may be a missing warmup execution, please investigate in
Nsight Systems.
2026-01-06 10:24:15.961956: E external/local_xla/xla/stream_executor/cuda/
cuda_timer.cc:86] Delay kernel timed out: measured time has sub-optimal
accuracy. There may be a missing warmup execution, please investigate in
Nsight Systems.
2026-01-06 10:24:16.040595: E external/local_xla/xla/stream_executor/cuda/
cuda_timer.cc:86] Delay kernel timed out: measured time has sub-optimal
accuracy. There may be a missing warmup execution, please investigate in
Nsight Systems.
2026-01-06 10:24:16.119446: E external/local_xla/xla/stream_executor/cuda/
cuda_timer.cc:86] Delay kernel timed out: measured time has sub-optimal
accuracy. There may be a missing warmup execution, please investigate in
Nsight Systems.
```

```
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m16s[0m 7ms/step -
accuracy: 0.2036 - loss: 2.1510 - val_accuracy: 0.2386 - val_loss: 2.0665
Epoch 2/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 2ms/step - accuracy:
0.2345 - loss: 2.0730 - val_accuracy: 0.2437 - val_loss: 2.0557
Epoch 3/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 2ms/step - accuracy:
0.2374 - loss: 2.0567 - val_accuracy: 0.2410 - val_loss: 2.0524
Epoch 4/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 2ms/step - accuracy:
0.2442 - loss: 2.0431 - val_accuracy: 0.2449 - val_loss: 2.0501
Epoch 5/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 2ms/step - accuracy:
0.2496 - loss: 2.0296 - val_accuracy: 0.2452 - val_loss: 2.0509
Epoch 6/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 2ms/step - accuracy:
0.2490 - loss: 2.0263 - val_accuracy: 0.2443 - val_loss: 2.0477
Epoch 7/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 2ms/step - accuracy:
0.2535 - loss: 2.0145 - val_accuracy: 0.2467 - val_loss: 2.0466
Epoch 8/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 2ms/step - accuracy:
0.2557 - loss: 2.0164 - val_accuracy: 0.2453 - val_loss: 2.0524
Epoch 9/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 2ms/step - accuracy:
0.2587 - loss: 1.9978 - val_accuracy: 0.2483 - val_loss: 2.0499
Epoch 10/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 2ms/step - accuracy:
0.2628 - loss: 1.9940 - val_accuracy: 0.2456 - val_loss: 2.0605
[1m313/313[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 2ms/step - accuracy:
0.2421 - loss: 2.0658
Test accuracy: 0.24560000002384186
```

In [18]:
```
preds = main_model_mobilenet.predict(x_test, batch_size=32)
```

```
[1m313/313[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 6ms/step
```

In [19]:
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog',
'horse', 'ship', 'truck']
true_labels = y_test.flatten()

predicted_labels = np.argmax(preds, axis=1)

cm = confusion_matrix(true_labels, predicted_labels)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_names)
disp.plot()
plt.title('Confusion Matrix - MobileNetV2')
plt.tight_layout()
plt.show()
```



In [22]:
```
import gc
tf.keras.backend.clear_session()
gc.collect()
```

Out[22]: 0

In [23]:
```
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()
from tensorflow.keras.applications.vgg16 import VGG16

base_model_vgg16 = VGG16(input_shape=(32,32,3), weights='imagenet',include_top=False
)
base_model_vgg16
base_model_vgg16.trainable = False
main_model_vgg16 = tf.keras.Sequential([
    base_model_vgg16,
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(10, activation='softmax')
])

main_model_vgg16.compile(optimizer = 'adam', loss='sparse_categorical_crossentropy',
metrics=['accuracy'])
main_model_vgg16.summary()
main_model_vgg16.fit(x_train, y_train, epochs=10, validation_data=(x_test, y_test))

vgg16_losses = main_model_vgg16.history.history['loss']
vgg16_acc = main_model_vgg16.history.history['accuracy']

test_loss, test_acc = main_model_vgg16.evaluate(x_test, y_test)
print(f"Test accuracy: {test_acc}")
```

Model: "sequential"

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 1, 1, 512)	14,714,688
global_average_pooling2d (GlobalAveragePooling2D)	(None, 512)	0
dense (Dense)	(None, 128)	65,664
dense_1 (Dense)	(None, 64)	8,256
dense_2 (Dense)	(None, 10)	650

Total params: 14,789,258 (56.42 MB)

Trainable params: 74,570 (291.29 KB)

Non-trainable params: 14,714,688 (56.13 MB)

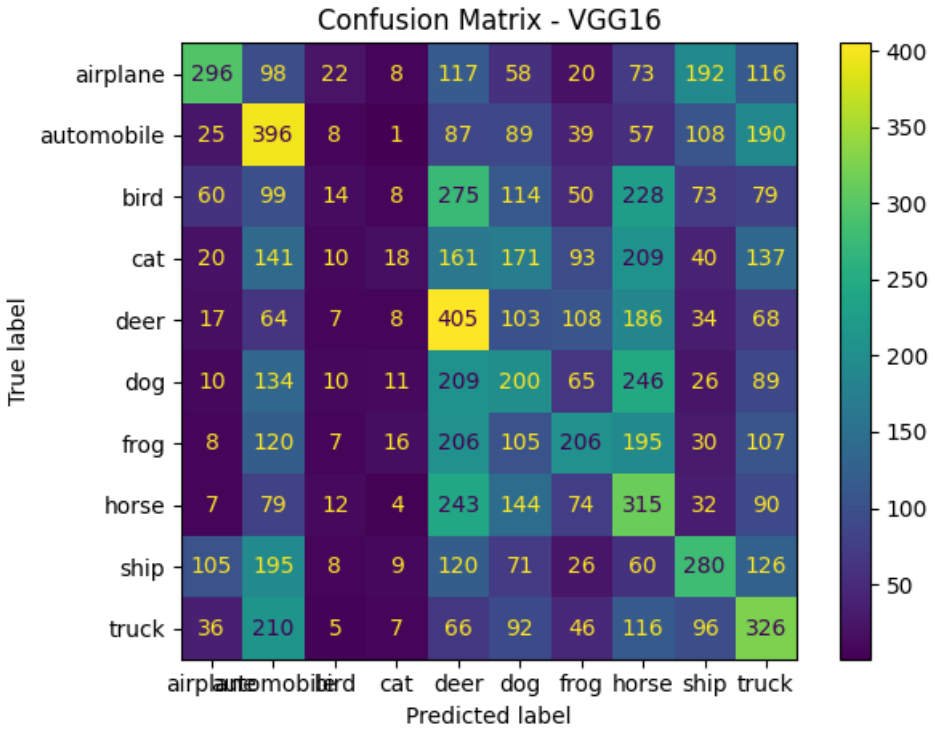
```
Epoch 1/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m8s[0m 4ms/step - accuracy:
0.3823 - loss: 2.6111 - val_accuracy: 0.5578 - val_loss: 1.2806
Epoch 2/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.5827 - loss: 1.2063 - val_accuracy: 0.5968 - val_loss: 1.1964
Epoch 3/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.6200 - loss: 1.0882 - val_accuracy: 0.5978 - val_loss: 1.1834
Epoch 4/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.6449 - loss: 1.0264 - val_accuracy: 0.6131 - val_loss: 1.1532
Epoch 5/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.6622 - loss: 0.9643 - val_accuracy: 0.6058 - val_loss: 1.1836
Epoch 6/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.6828 - loss: 0.9117 - val_accuracy: 0.6144 - val_loss: 1.1677
Epoch 7/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.6978 - loss: 0.8662 - val_accuracy: 0.6132 - val_loss: 1.1984
Epoch 8/10
```

```
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.7151 - loss: 0.8108 - val_accuracy: 0.6066 - val_loss: 1.2251
Epoch 9/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.7301 - loss: 0.7707 - val_accuracy: 0.6112 - val_loss: 1.2390
Epoch 10/10
[1m1563/1563[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.7452 - loss: 0.7289 - val_accuracy: 0.5999 - val_loss: 1.3358
[1m313/313[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 2ms/step - accuracy:
0.5957 - loss: 1.3562
Test accuracy: 0.5999000072479248
```

In [25]:
```
y_preds = main_model_vgg16.predict(x_test, batch_size=32)
```

```
[1m313/313[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 3ms/step
```

In [26]:
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog',
'horse', 'ship', 'truck']
true_labels = y_test.flatten()

predicted_labels = np.argmax(preds, axis=1)

cm = confusion_matrix(true_labels, predicted_labels)

disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_names)
disp.plot()
plt.title('Confusion Matrix - VGG16')
plt.tight_layout()
plt.show()
```

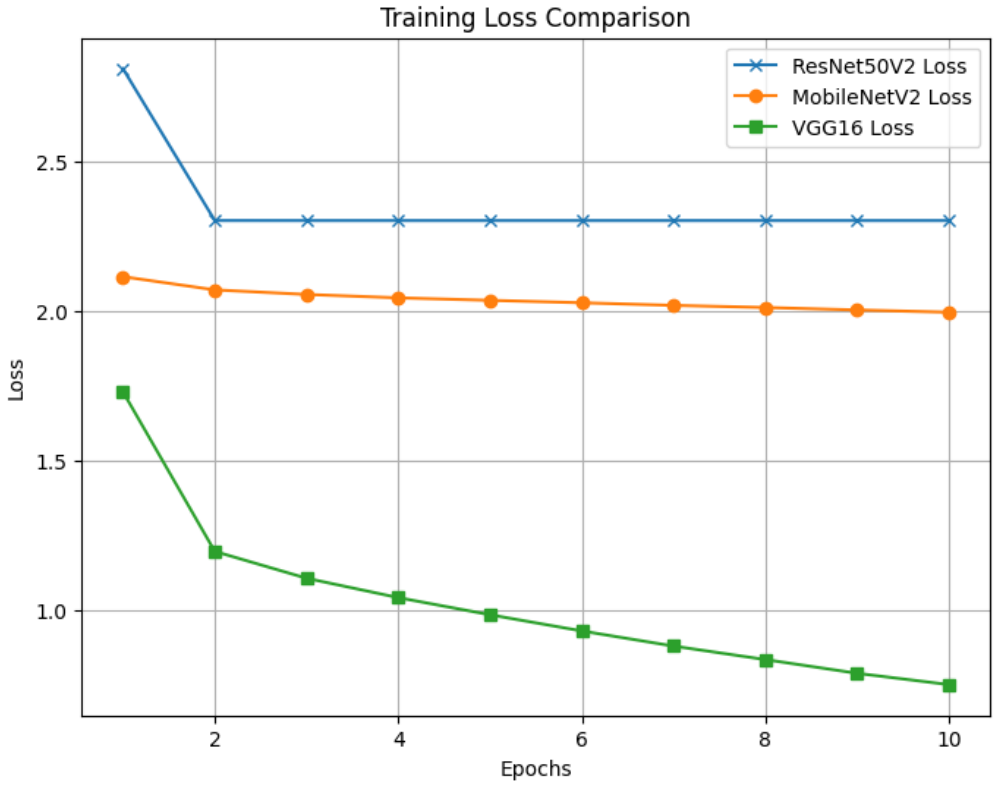


In [27]:
```
import gc
tf.keras.backend.clear_session()
gc.collect()
```

Out[27]: 0

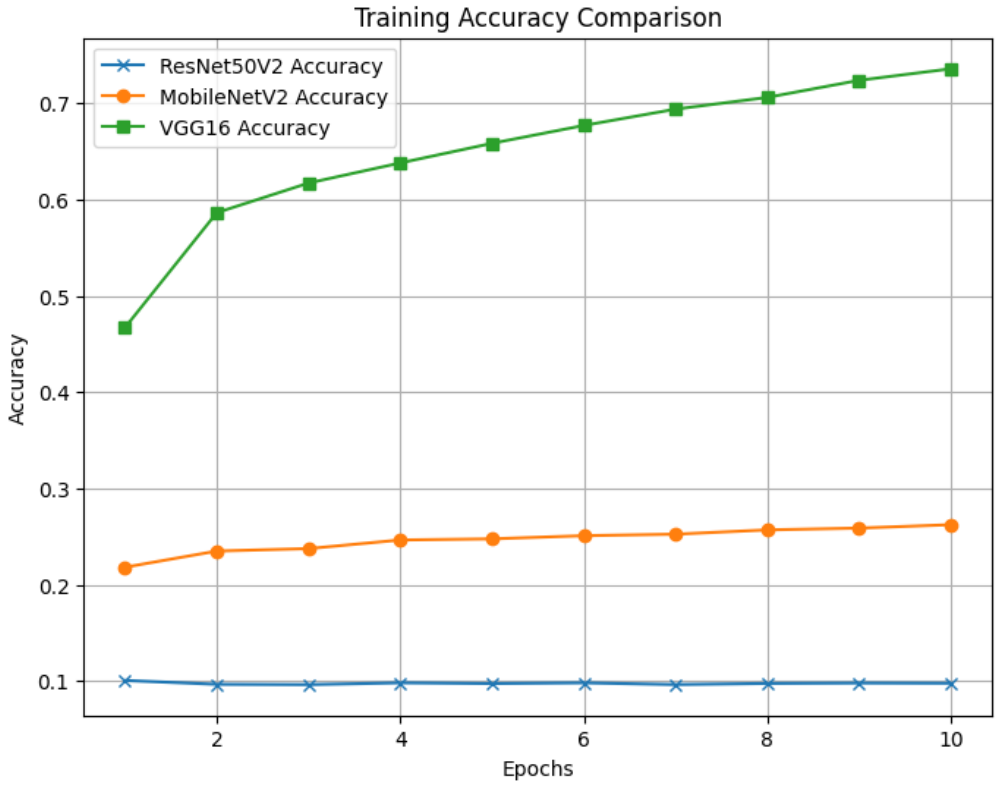
In [54]:
```
x = range(1, 11)
plt.figure(figsize=(8,6))
plt.plot(x,resnet_losses, label='ResNet50V2 Loss', marker='x')
plt.plot(x,mobilenet_losses, label='MobileNetV2 Loss', marker='o')
plt.plot(x,vgg16_losses, label='VGG16 Loss', marker='s')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training Loss Comparison')
plt.legend()
plt.grid()
plt.title('Training Loss Comparison')
```

Out[54]: `Text(0.5, 1.0, 'Training Loss Comparison')`



In [53]:
```
x = range(1, 11)
plt.figure(figsize=(8,6))
plt.plot(x,res_acc, label='ResNet50V2 Accuracy', marker='x')
plt.plot(x,mobilenet_acc, label='MobileNetV2 Accuracy', marker='o')
plt.plot(x,vgg16_acc, label='VGG16 Accuracy', marker='s')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Training Accuracy Comparison')
plt.legend(loc='upper left')
plt.grid()
plt.title('Training Accuracy Comparison')
```

Out[53]: `Text(0.5, 1.0, 'Training Accuracy Comparison')`



In [ ]:

Task 1

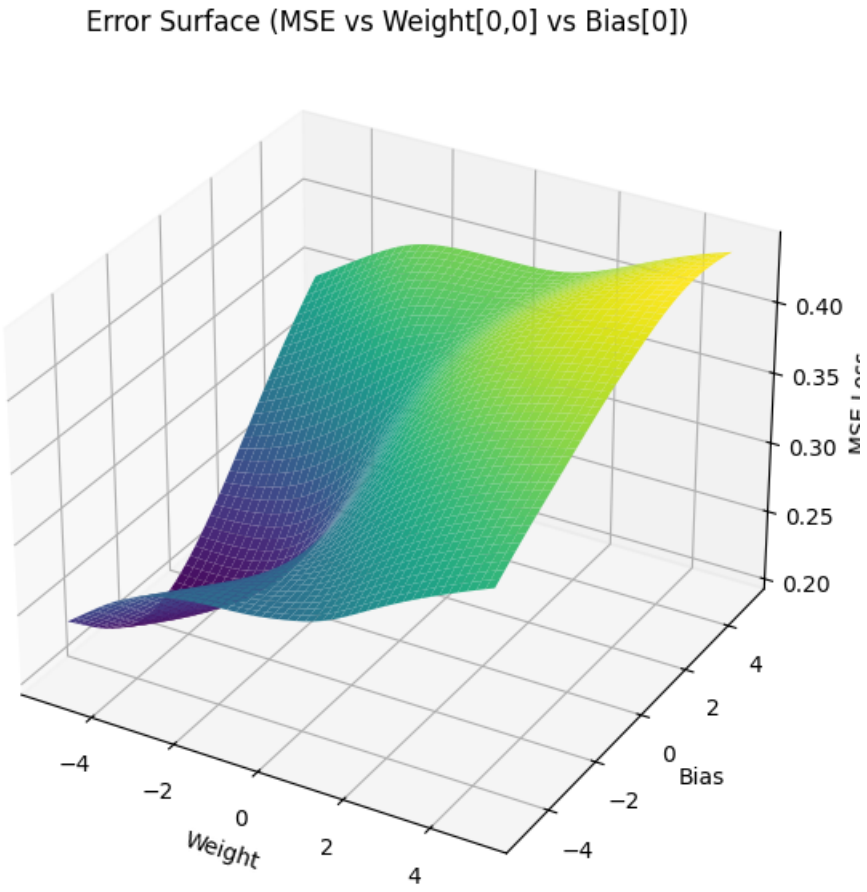
1. Take the dataset of Iris.
2. Initialize a neural network with random weights.
3. Calculate output of Neural Network:
4. Calculate MSE
5. Plot error surface using loss function verses weight, bias
6. Perform this cycle in step c for every input output pair
7. Perform 10 epochs of step d
8. Update weights accordingly using stochastic gradient descend.
9. Plot the mean squared error for each iteration in stochastic Gradient Descent.
10. Similarly plot accuracy for iteration and note the results

In [27]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from mpl_toolkits.mplot3d import Axes3D

# 1. Take the dataset of Iris
iris = load_iris()
X = iris.data
y = iris.target.reshape(-1, 1)
print(X.shape, y.shape)
# Preprocessing
encoder = OneHotEncoder(sparse_output=False)
y_onehot = encoder.fit_transform(y)

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split (using full dataset for training as implied by "dataset of Iris")
X_train, y_train = X_scaled, y_onehot
```

```
(150, 4) (150, 1)
```

In [28]:
```
# 2. Initialize a neural network with random weights
# Simple architecture: 4 Inputs -> 3 Outputs (Linear layer + Sigmoid activation)
input_size = 4
output_size = 3

np.random.seed(42)
weights = np.random.randn(input_size, output_size)
bias = np.random.randn(output_size)

def sigmoid(x):
    return 1 / (1 + np.exp(-x))

def sigmoid_derivative(x):
    return x * (1 - x)

def predict(inputs, w, b):
    # 3. Calculate output of Neural Network
    return sigmoid(np.dot(inputs, w) + b)

def calculate_mse(y_true, y_pred):
    # 4. Calculate MSE
    return np.mean((y_true - y_pred) ** 2)
```

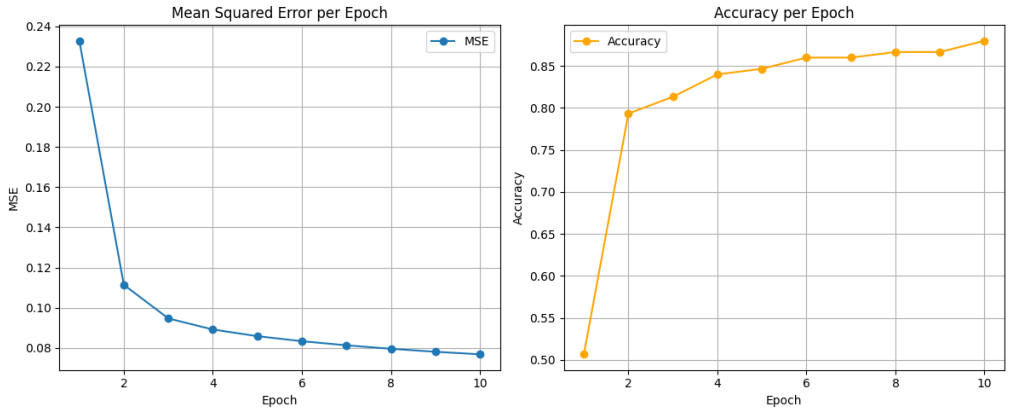
In [29]:
```
# 5. Plot error surface using loss function verses weight, bias
# We pick one weight (w[0,0]) and one bias (b[0]) to vary for visualization
w_range = np.linspace(-5, 5, 50)
b_range = np.linspace(-5, 5, 50)
W_grid, B_grid = np.meshgrid(w_range, b_range)
loss_grid = np.zeros_like(W_grid)

w_temp = weights.copy()
b_temp = bias.copy()

for i in range(len(w_range)):
    for j in range(len(b_range)):
        w_temp[0, 0] = W_grid[i, j]
        b_temp[0] = B_grid[i, j]
        # Compute total MSE for dataset with these parameters
        y_out = predict(X_train, w_temp, b_temp)
        loss_grid[i, j] = calculate_mse(y_train, y_out)

fig = plt.figure(figsize=(10, 7))
ax = fig.add_subplot(111, projection='3d')
ax.plot_surface(W_grid, B_grid, loss_grid, cmap='viridis')
ax.set_title('Error Surface (MSE vs Weight[0,0] vs Bias[0])')
ax.set_xlabel('Weight')
ax.set_ylabel('Bias')
ax.set_zlabel('MSE Loss')
plt.show()
```



In [30]:
```
# Training loop parameters
learning_rate = 0.1
epochs = 10
mse_history = []
accuracy_history = []

print("Starting training...")

for epoch in range(epochs):
    epoch_errors = []
    correct_predictions = 0

    # 6. Perform this cycle in step c for every input output pair
    for i in range(len(X_train)):
        x_sample = X_train[i].reshape(1, -1)
        y_sample = y_train[i].reshape(1, -1)

        output = predict(x_sample, weights, bias)

        error = y_sample - output
        sample_mse = np.mean(error ** 2)
        epoch_errors.append(sample_mse)

        # Accuracy check
        if np.argmax(output) == np.argmax(y_sample):
            correct_predictions += 1


        d_output = error * sigmoid_derivative(output)

        weights += learning_rate * np.dot(x_sample.T, d_output)
        bias += learning_rate * np.sum(d_output, axis=0)

    avg_mse = np.mean(epoch_errors)
    epoch_acc = correct_predictions / len(X_train)

    mse_history.append(avg_mse)
    accuracy_history.append(epoch_acc)

    print(f"Epoch {epoch+1}/{epochs} - MSE: {avg_mse:.4f} - Accuracy:
{epoch_acc:.4f}")
```

```
Starting training...
Epoch 1/10 - MSE: 0.2328 - Accuracy: 0.5067
Epoch 2/10 - MSE: 0.1114 - Accuracy: 0.7933
Epoch 3/10 - MSE: 0.0947 - Accuracy: 0.8133
Epoch 4/10 - MSE: 0.0892 - Accuracy: 0.8400
Epoch 5/10 - MSE: 0.0858 - Accuracy: 0.8467
Epoch 6/10 - MSE: 0.0833 - Accuracy: 0.8600
Epoch 7/10 - MSE: 0.0813 - Accuracy: 0.8600
Epoch 8/10 - MSE: 0.0796 - Accuracy: 0.8667
Epoch 9/10 - MSE: 0.0781 - Accuracy: 0.8667
Epoch 10/10 - MSE: 0.0768 - Accuracy: 0.8800
```

In [31]:
```
# 9. Plot the mean squared error for each iteration (epoch)
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(range(1, epochs + 1), mse_history, marker='o', label='MSE')
plt.title('Mean Squared Error per Epoch')
plt.xlabel('Epoch')
plt.ylabel('MSE')
plt.grid(True)
plt.legend()

# 10. Similarly plot accuracy for iteration and note the results
plt.subplot(1, 2, 2)
plt.plot(range(1, epochs + 1), accuracy_history, marker='o', color='orange',
label='Accuracy')
plt.title('Accuracy per Epoch')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.grid(True)
plt.legend()

plt.tight_layout()
plt.show()
```



In [ ]:

Task 1

1. Implement batch gradient descent optimizer function Take the dataset of Titanic
2. Initialize a neural network with random weights.
3. Calculate output of Neural Network:
4. Calculate squared error loss
5. Update network parameter using batch gradient descent optimizer function Implementation.
6. Display updated weight and bias values
7. Plot loss w.r.t. Iterations

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# 1. Load Titanic dataset
titanic = pd.read_csv('/media/smayan/500GB SSD/Study/ML2/Practicals/Data/
titanic.csv')

# Preprocessing
# Select relevant features and handle missing values
# Adjust column names based on actual CSV (common Titanic datasets use 'Pclass',
'Sex', 'Age', 'SibSp', 'Parch', 'Fare', 'Survived')
df = titanic.copy()

# Standardize column names to lowercase for consistency
df.columns = df.columns.str.lower()

# Select relevant features - use actual column names from the dataset
feature_cols = ['pclass', 'sex', 'age', 'siblings/spouses aboard', 'parents/children
aboard', 'fare']
target_col = 'survived'

# Keep only necessary columns
df = df[feature_cols + [target_col]].copy()

# Handle missing values
df['age'].fillna(df['age'].median(), inplace=True)
df['fare'].fillna(df['fare'].median(), inplace=True)
df.dropna(inplace=True)

# Encode categorical variable
df['sex'] = df['sex'].map({'male': 0, 'female': 1, 'Male': 0, 'Female': 1})

# Separate features and target
X = df[feature_cols].values
y = df[target_col].values.reshape(-1, 1)

# Standardize features
scaler = StandardScaler()
X = scaler.fit_transform(X)

print(f"Dataset shape: X={X.shape}, y={y.shape}")
print(f"Features: {feature_cols}")
```

```
Dataset shape: X=(887, 6), y=(887, 1)
Features: ['pclass', 'sex', 'age', 'siblings/spouses aboard', 'parents/children
aboard', 'fare']


  /tmp/ipykernel_192595/1743091619.py:26: FutureWarning: A value is trying to
  be set on a copy of a DataFrame or Series through chained assignment using an
  inplace method.
  The behavior will change in pandas 3.0. This inplace method will never work
  because the intermediate object on which we are setting values always behaves
  as a copy.

  For example, when doing 'df[col].method(value, inplace=True)', try using
  'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
  instead, to perform the operation inplace on the original object.


    df['age'].fillna(df['age'].median(), inplace=True)
  /tmp/ipykernel_192595/1743091619.py:27: FutureWarning: A value is trying to
  be set on a copy of a DataFrame or Series through chained assignment using an
  inplace method.
  The behavior will change in pandas 3.0. This inplace method will never work
  because the intermediate object on which we are setting values always behaves
  as a copy.
```

```
For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['fare'].fillna(df['fare'].median(), inplace=True)
```

In [2]:

```
# 2. Initialize a neural network with random weights
input_size = X.shape[1]  # 6 features
hidden_size = 4
output_size = 1  # Binary classification (survived or not)

np.random.seed(42)

# Initialize weights and biases
W1 = np.random.randn(input_size, hidden_size) * 0.01
b1 = np.zeros((1, hidden_size))
W2 = np.random.randn(hidden_size, output_size) * 0.01
b2 = np.zeros((1, output_size))

print("Initial Weights and Biases:")
print(f"W1 shape: {W1.shape}")
print(f"b1 shape: {b1.shape}")
print(f"W2 shape: {W2.shape}")
print(f"b2 shape: {b2.shape}")
```

```
Initial Weights and Biases:
W1 shape: (6, 4)
b1 shape: (1, 4)
W2 shape: (4, 1)
b2 shape: (1, 1)
```

In [3]:

```
# Activation functions
def sigmoid(z):
    return 1 / (1 + np.exp(-np.clip(z, -500, 500)))

def sigmoid_derivative(a):
    return a * (1 - a)

# 3. Forward pass - Calculate output of Neural Network
def forward_propagation(X, W1, b1, W2, b2):
    """
    Perform forward propagation through the network
    Returns: output predictions and intermediate values for backprop
    """
    # Hidden layer
    Z1 = np.dot(X, W1) + b1
    A1 = sigmoid(Z1)

    # Output layer
    Z2 = np.dot(A1, W2) + b2
    A2 = sigmoid(Z2)

    cache = {'Z1': Z1, 'A1': A1, 'Z2': Z2, 'A2': A2}
    return A2, cache
```

In [4]:

```
# 4. Calculate squared error loss
def compute_loss(y_true, y_pred):
    """
    Compute mean squared error loss
    """
    m = y_true.shape[0]
    loss = (1 / (2 * m)) * np.sum((y_pred - y_true) ** 2)
    return loss

# Backward propagation
def backward_propagation(X, y, cache, W1, W2):
    """
    Compute gradients using backpropagation
    """
    m = X.shape[0]

    A1 = cache['A1']
    A2 = cache['A2']

    # Output layer gradients
    dZ2 = (A2 - y) * sigmoid_derivative(A2)
    dW2 = (1 / m) * np.dot(A1.T, dZ2)
    db2 = (1 / m) * np.sum(dZ2, axis=0, keepdims=True)

    # Hidden layer gradients
    dZ1 = np.dot(dZ2, W2.T) * sigmoid_derivative(A1)
    dW1 = (1 / m) * np.dot(X.T, dZ1)
    db1 = (1 / m) * np.sum(dZ1, axis=0, keepdims=True)

    gradients = {'dW1': dW1, 'db1': db1, 'dW2': dW2, 'db2': db2}
    return gradients
```

In [5]:

```
# 5. Implement Batch Gradient Descent Optimizer with Momentum
def batch_gradient_descent(X, y, W1, b1, W2, b2, learning_rate=0.01, iterations=1000,
momentum=0.0):
    """
    Batch Gradient Descent Optimizer with Momentum
    Updates weights using gradients computed on the entire dataset

    Parameters:
    - momentum: momentum coefficient (0 = no momentum, typically 0.9)
    """
    loss_history = []

    # Initialize velocity terms for momentum
    vW1 = np.zeros_like(W1)
    vb1 = np.zeros_like(b1)
    vW2 = np.zeros_like(W2)
    vb2 = np.zeros_like(b2)

    for i in range(iterations):
        # Forward propagation
        y_pred, cache = forward_propagation(X, W1, b1, W2, b2)

        # Compute loss
        loss = compute_loss(y, y_pred)
        loss_history.append(loss)

        # Backward propagation
        gradients = backward_propagation(X, y, cache, W1, W2)

        # Update velocities with momentum
        vW1 = momentum * vW1 + (1-momentum) * learning_rate * gradients['dW1']
        vb1 = momentum * vb1 + (1-momentum) * learning_rate * gradients['db1']
        vW2 = momentum * vW2 + (1-momentum) * learning_rate * gradients['dW2']
        vb2 = momentum * vb2 + (1-momentum) * learning_rate * gradients['db2']

        # Update parameters using velocity
        W1 = W1 - vW1
        b1 = b1 - vb1
        W2 = W2 - vW2
        b2 = b2 - vb2

        # Print progress every 100 iterations
        if (i + 1) % 100 == 0:
            print(f"Iteration {i+1}/{iterations}, Loss: {loss:.4f}")

    parameters = {'W1': W1, 'b1': b1, 'W2': W2, 'b2': b2}
    return parameters, loss_history

# Train the network
print("Training Neural Network with Batch Gradient Descent...")
print("="*60)
parameters, loss_history = batch_gradient_descent(
    X, y, W1, b1, W2, b2,
    learning_rate=0.5,
    iterations=1000,
    momentum=0.9
)
```

```
Training Neural Network with Batch Gradient Descent...
============================================================
Iteration 100/1000, Loss: 0.1175
Iteration 200/1000, Loss: 0.1145
Iteration 300/1000, Loss: 0.1067
Iteration 400/1000, Loss: 0.0942
Iteration 500/1000, Loss: 0.0837
Iteration 600/1000, Loss: 0.0780
Iteration 700/1000, Loss: 0.0751
Iteration 800/1000, Loss: 0.0735
Iteration 900/1000, Loss: 0.0725
```

```
Iteration 1000/1000, Loss: 0.0719
```

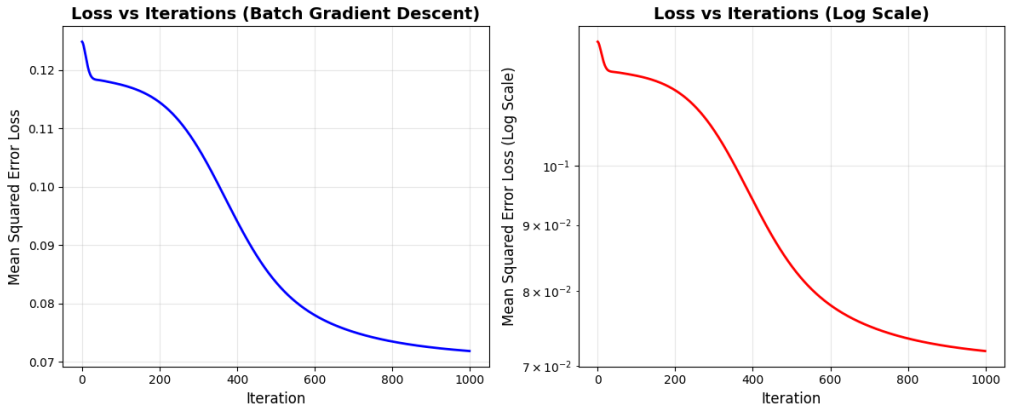
In [6]:

```
# 6. Display updated weight and bias values
print("\n" + "="*60)
print("UPDATED WEIGHTS AND BIASES AFTER TRAINING")
print("="*60)

print("\nLayer 1 (Input -> Hidden):")
print(f"W1 (shape {parameters['W1'].shape}):")
print(parameters['W1'])
print(f"\nb1 (shape {parameters['b1'].shape}):")
print(parameters['b1'])

print("\nLayer 2 (Hidden -> Output):")
print(f"W2 (shape {parameters['W2'].shape}):")
print(parameters['W2'])
print(f"\nb2 (shape {parameters['b2'].shape}):")
print(parameters['b2'])

print("\n" + "="*60)
print(f"Final Loss: {loss_history[-1]:.4f}")
print(f"Initial Loss: {loss_history[0]:.4f}")
print(f"Loss Reduction: {loss_history[0] - loss_history[-1]:.4f}")
print("="*60)
```

```
============================================================
UPDATED WEIGHTS AND BIASES AFTER TRAINING
============================================================

Layer 1 (Input -> Hidden):
W1 (shape (6, 4)):
[[ 0.69950357  0.66294884  0.68142935  0.69198676]
 [-1.09974381 -1.04589364 -1.0509746  -1.06117579]
 [ 0.40781088  0.38332246  0.38422636  0.39143606]
 [ 0.31408378  0.2721496   0.28220892  0.29990137]
 [ 0.08592423  0.08911212  0.07754505  0.07745004]
 [-0.18397521 -0.19922252 -0.20039973 -0.20825874]]

b1 (shape (1, 4)):
[[-0.00080815 -0.01965122 -0.01563361 -0.01166341]]

Layer 2 (Hidden -> Output):
W2 (shape (4, 1)):
[[-1.28403791]
 [-1.17514227]
 [-1.19913486]
 [-1.22908447]]

b2 (shape (1, 1)):
[[1.80390387]]

============================================================
Final Loss: 0.0719
Initial Loss: 0.1248
Loss Reduction: 0.0530
============================================================
```

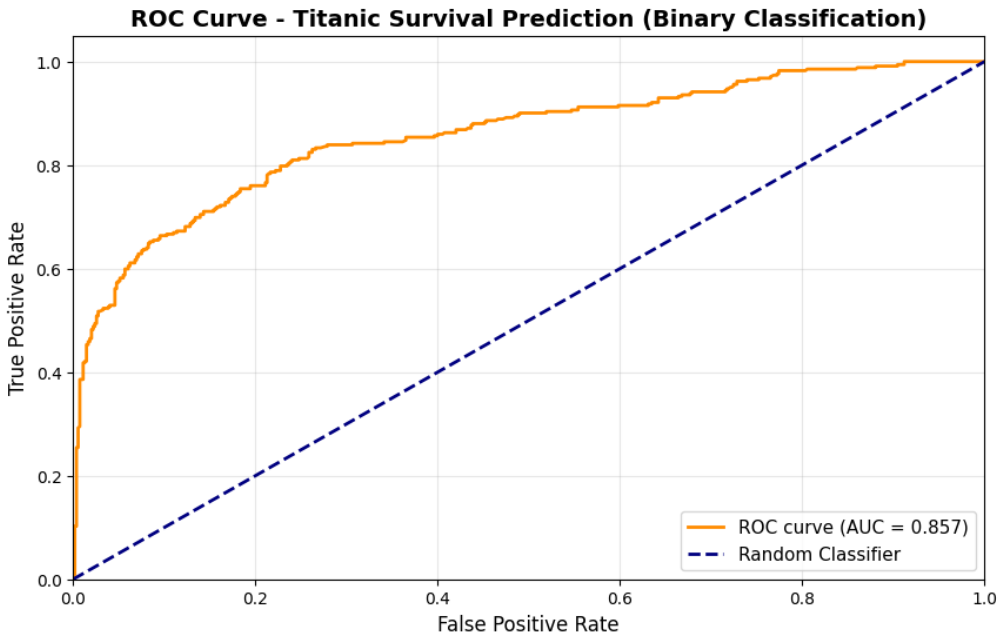
In [7]:

```
# 7. Plot loss w.r.t. Iterations
plt.figure(figsize=(12, 5))

# Plot 1: Loss over all iterations
plt.subplot(1, 2, 1)
plt.plot(loss_history, linewidth=2, color='blue')
plt.title('Loss vs Iterations (Batch Gradient Descent)', fontsize=14,
fontweight='bold')
plt.xlabel('Iteration', fontsize=12)
plt.ylabel('Mean Squared Error Loss', fontsize=12)
plt.grid(True, alpha=0.3)

# Plot 2: Loss over iterations (log scale for better visualization)
plt.subplot(1, 2, 2)
plt.plot(loss_history, linewidth=2, color='red')
plt.title('Loss vs Iterations (Log Scale)', fontsize=14, fontweight='bold')
plt.xlabel('Iteration', fontsize=12)
plt.ylabel('Mean Squared Error Loss (Log Scale)', fontsize=12)
plt.yscale('log')
plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

# Calculate accuracy
final_predictions, _ = forward_propagation(X, parameters['W1'], parameters['b1'],
                                           parameters['W2'], parameters['b2'])
predicted_classes = (final_predictions > 0.5).astype(int)
accuracy = np.mean(predicted_classes == y) * 100

print(f"\nFinal Model Accuracy: {accuracy:.2f}%")
```




```
Final Model Accuracy: 79.93%
```

In [8]:
```
# Plot ROC AUC Curve
from sklearn.metrics import roc_curve, auc, roc_auc_score

# Get probability predictions
y_pred_proba, _ = forward_propagation(X, parameters['W1'], parameters['b1'],
                                      parameters['W2'], parameters['b2'])

# Calculate ROC curve
fpr, tpr, thresholds = roc_curve(y, y_pred_proba)
roc_auc = auc(fpr, tpr)

# Plot ROC Curve
plt.figure(figsize=(10, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC =
{roc_auc:.3f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--', label='Random
Classifier')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate', fontsize=12)
plt.ylabel('True Positive Rate', fontsize=12)
plt.title('ROC Curve - Titanic Survival Prediction (Binary Classification)',
fontsize=14, fontweight='bold')
plt.legend(loc="lower right", fontsize=11)
plt.grid(True, alpha=0.3)
plt.show()

print(f"\nROC AUC Score: {roc_auc:.4f}")
print(f"Model Performance: {'Excellent' if roc_auc >= 0.9 else 'Good' if roc_auc >=
0.8 else 'Fair' if roc_auc >= 0.7 else 'Poor'}")
```




```
ROC AUC Score: 0.8570
Model Performance: Good
```

Task 1.

Implement the NOR Boolean logic gate using perceptron Neural Network. Inputs = x1, x2 and bias, weights should be fed into the perceptron with single Output = y. Display final weights and bias of each perceptron.

Task 2

Take the dataset of Diabetes 2
- Initialize a neural network with random weights.
- Calculate output of Neural Network:
1. Calculate squared error loss
2. Update network parameter using batch Mini Batch gradient descent optimizer function Implementation.
3. Display updated weight and bias values
4. Plot loss w.r.t. bias values

In [74]:
```
import numpy as np
import matplotlib.pyplot as plt

# Task 1: Implement NOR Boolean Logic Gate using Perceptron

print("="*60)
print("TASK 1: NOR GATE USING PERCEPTRON")
print("="*60)

# NOR Truth Table:
# x1  x2  | y
# 0   0   | 1
# 0   1   | 0
# 1   0   | 0
# 1   1   | 0

X = np.array([
    [0, 0],
    [0, 1],
    [1, 0],
    [1, 1]
])
y = np.array([1, 0, 0, 0])

print("\nNOR Truth Table:")
print("x1  x2  |  y")
print("-"*15)
for i in range(len(X)):
    print(f"{X[i][0]}   {X[i][1]}   |  {y[i]}")
```

```
============================================================
TASK 1: NOR GATE USING PERCEPTRON
============================================================

NOR Truth Table:
x1  x2  |  y
---------------
0   0   |  1
0   1   |  0
1   0   |  0
1   1   |  0
```

In [75]:

```
# Step activation function
def step(z):
    return 1 if z >= 0 else 0

# Initialize weights and bias randomly
np.random.seed(42)
w = np.random.rand(2)
b = np.random.rand(1)

print(f"\nInitial weights: {w}")
print(f"Initial bias: {b}")

# Training parameters
epochs = 100
learning_rate = 0.1

print("\nTraining NOR Perceptron...")

# Training loop
for epoch in range(epochs):
    total_error = 0
    for i in range(X.shape[0]):
        # Forward pass
        z = np.dot(w, X[i]) + b
        y_pred = step(z)

        # Calculate error
        error = y[i] - y_pred
        total_error += abs(error)

        # Update weights and bias
        w += learning_rate * error * X[i]
        b += learning_rate * error

    # Stop if converged
    if total_error == 0:
        print(f"Converged at epoch {epoch + 1}")
        break
```

```
Initial weights: [0.37454012 0.95071431]
Initial bias: [0.73199394]

Training NOR Perceptron...
Converged at epoch 10
```

In [76]:
```
# Display final weights and bias
print("\n" + "="*60)
print("FINAL WEIGHTS AND BIAS FOR NOR PERCEPTRON")
print("="*60)
print(f"\nTrained weights: {w}")
print(f"Trained bias: {b}")

# Test the trained perceptron
print("\nTesting NOR Perceptron:")
print("x1  x2  | Predicted | Actual")
print("-"*35)
for i in range(len(X)):
    z = np.dot(w, X[i]) + b
    prediction = step(z)
    print(f"{X[i][0]}   {X[i][1]}   |     {prediction}     |   {y[i]}")

# Verify all predictions are correct
correct = sum([step(np.dot(w, X[i]) + b) == y[i] for i in range(len(X))])
print(f"\nAccuracy: {correct}/{len(X)} = {(correct/len(X))*100:.0f}%")
```

```
============================================================
FINAL WEIGHTS AND BIAS FOR NOR PERCEPTRON
============================================================

Trained weights: [-0.22545988 -0.04928569]
Trained bias: [0.03199394]

Testing NOR Perceptron:
x1  x2  | Predicted | Actual
-----------------------------------
0   0   |     1     |   1
0   1   |     0     |   0
1   0   |     0     |   0
1   1   |     0     |   0

Accuracy: 4/4 = 100%
```

In [77]:
```
print("\n" + "="*60)
print("TASK 2: DIABETES DATASET WITH MINI-BATCH GRADIENT DESCENT")
print("="*60)

import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import load_diabetes

# Load Diabetes dataset
diabetes = load_diabetes()
X_diabetes = diabetes.data
y_diabetes = diabetes.target.reshape(-1, 1)

# Standardize features (already somewhat standardized, but ensuring consistency)
scaler_X = StandardScaler()
X_diabetes = scaler_X.fit_transform(X_diabetes)

# Standardize target for better training
scaler_y = StandardScaler()
y_diabetes = scaler_y.fit_transform(y_diabetes)

print(f"\nDataset shape: X={X_diabetes.shape}, y={y_diabetes.shape}")
print(f"Number of features: {X_diabetes.shape[1]}")
print(f"Number of samples: {X_diabetes.shape[0]}")
print(f"Feature names: {diabetes.feature_names}")
```

```
============================================================
TASK 2: DIABETES DATASET WITH MINI-BATCH GRADIENT DESCENT
============================================================

Dataset shape: X=(442, 10), y=(442, 1)
Number of features: 10
Number of samples: 442
Feature names: ['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6']
```

In [78]:
```
# Initialize Neural Network with random weights
input_size = X_diabetes.shape[1]  # 10 features
hidden_size = 8
output_size = 1

np.random.seed(42)

# Layer 1: Input -> Hidden
W1 = np.random.randn(input_size, hidden_size) * 0.01
b1 = np.zeros((1, hidden_size))

# Layer 2: Hidden -> Output
W2 = np.random.randn(hidden_size, output_size) * 0.01
b2 = np.zeros((1, output_size))

print("\nInitial Network Architecture:")
print(f"Input Layer: {input_size} neurons")
print(f"Hidden Layer: {hidden_size} neurons")
print(f"Output Layer: {output_size} neuron")
print(f"\nW1 shape: {W1.shape}")
print(f"b1 shape: {b1.shape}")
print(f"W2 shape: {W2.shape}")
print(f"b2 shape: {b2.shape}")
```

```
Initial Network Architecture:
Input Layer: 10 neurons
Hidden Layer: 8 neurons
Output Layer: 1 neuron

W1 shape: (10, 8)
b1 shape: (1, 8)
W2 shape: (8, 1)
b2 shape: (1, 1)
```

In [79]:

```
# Define activation functions
def relu(z):
    return np.maximum(0, z)

def relu_derivative(z):
    return (z > 0).astype(float)

# Forward propagation
def forward_pass(X, W1, b1, W2, b2):
    Z1 = np.dot(X, W1) + b1
    A1 = relu(Z1)
    Z2 = np.dot(A1, W2) + b2
    A2 = Z2  # Linear activation for regression

    cache = {'Z1': Z1, 'A1': A1, 'Z2': Z2, 'A2': A2}
    return A2, cache

# Calculate squared error loss (MSE)
def compute_loss(y_true, y_pred):
    m = y_true.shape[0]
    loss = (1 / (2 * m)) * np.sum((y_pred - y_true) ** 2)
    return loss

# Backward propagation
def backward_pass(X, y, cache, W1, W2):
    m = X.shape[0]

    A1 = cache['A1']
    A2 = cache['A2']
    Z1 = cache['Z1']

    # Output layer gradients
    dZ2 = (A2 - y)
    dW2 = (1 / m) * np.dot(A1.T, dZ2)
    db2 = (1 / m) * np.sum(dZ2, axis=0, keepdims=True)

    # Hidden layer gradients
    dA1 = np.dot(dZ2, W2.T)
    dZ1 = dA1 * relu_derivative(Z1)
    dW1 = (1 / m) * np.dot(X.T, dZ1)
    db1 = (1 / m) * np.sum(dZ1, axis=0, keepdims=True)

    gradients = {'dW1': dW1, 'db1': db1, 'dW2': dW2, 'db2': db2}
    return gradients

print("\nForward and Backward propagation functions defined.")
```

```
Forward and Backward propagation functions defined.
```

In [80]:

```
# Mini-Batch Gradient Descent Optimizer with Momentum
def mini_batch_gradient_descent(X, y, W1, b1, W2, b2, batch_size=32,
learning_rate=0.01, epochs=100, momentum=0.9):
    """
    Mini-Batch Gradient Descent Optimizer with Momentum
    Updates weights using gradients computed on mini-batches of data
    """
    m = X.shape[0]
    loss_history = []

    # Initialize velocity for momentum
    vW1 = np.zeros_like(W1)
    vb1 = np.zeros_like(b1)
    vW2 = np.zeros_like(W2)
    vb2 = np.zeros_like(b2)

    print("\nTraining with Mini-Batch Gradient Descent with Momentum...")
    print(f"Batch size: {batch_size}")
    print(f"Learning rate: {learning_rate}")
    print(f"Momentum: {momentum}")
    print(f"Epochs: {epochs}")
    print("-" * 60)

    for epoch in range(epochs):
        # Shuffle the data at the start of each epoch
        indices = np.random.permutation(m)
        X_shuffled = X[indices]
        y_shuffled = y[indices]

        epoch_loss = 0
        num_batches = 0

        # Process mini-batches
        for i in range(0, m, batch_size):
            # Get mini-batch
            X_batch = X_shuffled[i:i+batch_size]
            y_batch = y_shuffled[i:i+batch_size]

            # Forward propagation
            y_pred, cache = forward_pass(X_batch, W1, b1, W2, b2)

            # Compute loss
            batch_loss = compute_loss(y_batch, y_pred)
            epoch_loss += batch_loss
            num_batches += 1

            # Backward propagation
            gradients = backward_pass(X_batch, y_batch, cache, W1, W2)

            # Update velocity with momentum
            vW1 = momentum * vW1 - (1-momentum) * learning_rate * gradients['dW1']
            vb1 = momentum * vb1 - (1-momentum) * learning_rate * gradients['db1']
            vW2 = momentum * vW2 - (1-momentum) * learning_rate * gradients['dW2']
            vb2 = momentum * vb2 - (1-momentum) * learning_rate * gradients['db2']

            # Update parameters
            W1 += vW1
            b1 += vb1
            W2 += vW2
            b2 += vb2

        # Calculate average loss for the epoch
        avg_loss = epoch_loss / num_batches
        loss_history.append(avg_loss)

        # Print progress every 10 epochs
        if (epoch + 1) % 10 == 0:
            print(f"Epoch {epoch+1}/{epochs}, Loss: {avg_loss:.6f}")

    parameters = {'W1': W1, 'b1': b1, 'W2': W2, 'b2': b2}
```

```
    return parameters, loss_history

# Train the network with momentum
trained_params, loss_history = mini_batch_gradient_descent(
    X_diabetes, y_diabetes, W1, b1, W2, b2,
    batch_size=32,
    learning_rate=0.01,
    epochs=100,
    momentum=0.9
)
```

```
Training with Mini-Batch Gradient Descent with Momentum...
Batch size: 32
Learning rate: 0.01
Momentum: 0.9
Epochs: 100
------------------------------------------------------------
Epoch 10/100, Loss: 0.502542
Epoch 20/100, Loss: 0.494495
Epoch 30/100, Loss: 0.482979
Epoch 40/100, Loss: 0.410845
Epoch 50/100, Loss: 0.300766
Epoch 60/100, Loss: 0.259209
Epoch 70/100, Loss: 0.246893
Epoch 80/100, Loss: 0.241139
Epoch 90/100, Loss: 0.236405
Epoch 100/100, Loss: 0.235396
```

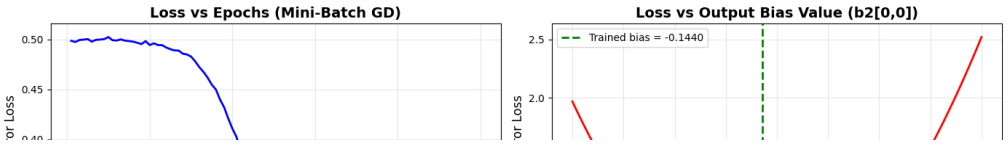
In [81]:
```
# Display updated weights and bias values
print("\n" + "="*60)
print("UPDATED WEIGHTS AND BIASES AFTER TRAINING")
print("="*60)

print("\nLayer 1 (Input -> Hidden):")
print(f"W1 shape: {trained_params['W1'].shape}")
print(f"W1:\n{trained_params['W1']}")
print(f"\nb1 shape: {trained_params['b1'].shape}")
print(f"b1:\n{trained_params['b1']}")

print("\nLayer 2 (Hidden -> Output):")
print(f"W2 shape: {trained_params['W2'].shape}")
print(f"W2:\n{trained_params['W2']}")
print(f"\nb2 shape: {trained_params['b2'].shape}")
print(f"b2:\n{trained_params['b2']}")

print("\n" + "="*60)
print(f"Initial Loss: {loss_history[0]:.6f}")
print(f"Final Loss: {loss_history[-1]:.6f}")
print(f"Loss Reduction: {loss_history[0] - loss_history[-1]:.6f}")
print("="*60)
```

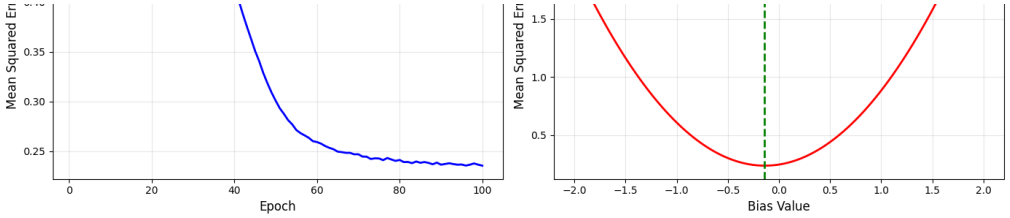
```
============================================================
UPDATED WEIGHTS AND BIASES AFTER TRAINING
============================================================

Layer 1 (Input -> Hidden):
W1 shape: (10, 8)
W1:
[[ 2.47342365e-02  1.28146223e-01  7.28478797e-03  2.91099200e-02
   2.59524287e-03  5.71769578e-02  2.14592242e-02  8.90493460e-03]
 [ 5.21467753e-02 -5.09483827e-02 -4.34969289e-03 -9.84868394e-03
   2.90145134e-02  1.61151871e-01 -1.55273897e-02 -4.53354771e-03]
 [-8.27471376e-02  4.85567088e-01 -3.15270329e-03  2.55053325e-02
  -1.76396623e-02 -2.14073554e-01  1.45929960e-02 -6.41571912e-03]
 [-3.85875790e-02  3.08167459e-01 -5.38085601e-03  2.79910522e-02
  -3.02718144e-02 -1.01180669e-01  3.54565249e-03  2.42816327e-02]
 [ 7.84345964e-04 -3.53513473e-02  1.06785430e-02 -1.86928742e-02
   3.41757099e-04 -2.37532289e-02 -1.38561420e-02  2.21928722e-03]
 [ 2.07599606e-02 -8.89996479e-02  8.52199391e-04 -1.62507773e-02
  -8.93091303e-03  3.39767186e-02 -5.91731211e-03  9.93522915e-03]
 [ 6.94875424e-02 -9.85802493e-02 -2.87789859e-03 -1.02952966e-02
   1.51782026e-02  1.80000957e-01  6.03910820e-04  5.57776995e-03]
 [-5.15245774e-02  6.84998519e-02  9.03726018e-03  1.30102660e-02
  -1.92691765e-02 -1.13672352e-01 -3.50361051e-03 -9.65482081e-03]
 [-1.00237102e-01  3.16674820e-01  7.68250356e-03  3.70585331e-02
  -4.28593217e-02 -3.24007915e-01  1.83540105e-02  2.23959808e-02]
 [-2.62553115e-03  1.64989562e-01 -2.13832095e-02  2.07345087e-02
  -2.98493949e-03 -5.88338550e-03  7.42584208e-03 -1.80666919e-02]]

b1 shape: (1, 8)
b1:
[[ 0.08075549  0.18981778 -0.00384552  0.01771259  0.02497907  0.23765902
   0.00519341  0.00028168]]

Layer 2 (Hidden -> Output):
W2 shape: (8, 1)
W2:
[[-0.18848261]
 [ 0.72997806]
 [ 0.00240609]
 [ 0.06689957]
 [-0.06830435]
 [-0.53888969]
 [ 0.02534389]
 [ 0.01349131]]
```

```
b2 shape: (1, 1)
b2:
[[-0.14396657]]

============================================================
Initial Loss: 0.498773
Final Loss: 0.235396
Loss Reduction: 0.263377
============================================================
```

In [82]:
```
# Plot loss w.r.t. bias values
# We'll vary one bias value and see how loss changes

print("\nGenerating loss surface with respect to bias values...")

# Select one bias from b2 to vary (output layer bias)
bias_range = np.linspace(-2, 2, 100)
loss_vs_bias = []

# Keep all parameters constant except one bias value
W1_temp = trained_params['W1'].copy()
b1_temp = trained_params['b1'].copy()
W2_temp = trained_params['W2'].copy()
b2_temp = trained_params['b2'].copy()

# Store original bias value
original_bias = b2_temp[0, 0]

for bias_val in bias_range:
    # Set the bias to test value
    b2_temp[0, 0] = bias_val

    # Forward pass with this bias
    y_pred, _ = forward_pass(X_diabetes, W1_temp, b1_temp, W2_temp, b2_temp)

    # Compute loss
    loss = compute_loss(y_diabetes, y_pred)
    loss_vs_bias.append(loss)

# Restore original bias
b2_temp[0, 0] = original_bias

# Create the plot
plt.figure(figsize=(14, 5))

# Plot 1: Loss vs Epochs
plt.subplot(1, 2, 1)
plt.plot(range(1, len(loss_history) + 1), loss_history, linewidth=2, color='blue')
plt.title('Loss vs Epochs (Mini-Batch GD)', fontsize=14, fontweight='bold')
plt.xlabel('Epoch', fontsize=12)
plt.ylabel('Mean Squared Error Loss', fontsize=12)
plt.grid(True, alpha=0.3)

# Plot 2: Loss vs Bias Value
plt.subplot(1, 2, 2)
plt.plot(bias_range, loss_vs_bias, linewidth=2, color='red')
plt.axvline(x=original_bias, color='green', linestyle='--', linewidth=2,
label=f'Trained bias = {original_bias:.4f}')
plt.title('Loss vs Output Bias Value (b2[0,0])', fontsize=14, fontweight='bold')
plt.xlabel('Bias Value', fontsize=12)
plt.ylabel('Mean Squared Error Loss', fontsize=12)
plt.legend()
plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print(f"\nOptimal bias value (after training): {original_bias:.6f}")
print(f"Loss at optimal bias: {compute_loss(y_diabetes, forward_pass(X_diabetes,
trained_params['W1'], trained_params['b1'], trained_params['W2'],
trained_params['b2'])[0]):.6f}")
```

```
Generating loss surface with respect to bias values...
```






```
Optimal bias value (after training): -0.143967
Loss at optimal bias: 0.235860
```

Task 1

- Implement the XOR Boolean logic gate using perceptron Neural Network.
- Inputs = x1, x2 and bias, weights should be fed into the perceptron with single Output = y. Display final weights and bias of each perceptron.

Task 2

Take the dataset of Penguin
- Initialize a neural network with random weights.
- Calculate output of Neural Network: \
i. Calculate squared error loss \
ii. Update network parameter using batch Adaptive delta gradient descent optimizer function Implementation. \
iii. Display updated weight and bias values \
iv. Plot accuracy w.r.t. epoch values

In [8]:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
import pandas as pd

# Task 1: XOR Gate Implementation

print("="*60)
print("TASK 1: XOR GATE USING PERCEPTRON")
print("="*60)

# XOR Truth Table:
# x1  x2  | y
# 0   0   | 0
# 0   1   | 1
# 1   0   | 1
# 1   1   | 0

X = np.array([
    [0, 0],
    [0, 1],
    [1, 0],
    [1, 1]
])
y = np.array([0, 1, 1, 0])

print("\nXOR Truth Table:")
print("x1  x2  |  y")
print("-"*15)
for i in range(len(X)):
    print(f"{X[i][0]}   {X[i][1]}   |  {y[i]}")

# Step activation function
def step(z):
    return 1 if z >= 0 else 0

# For XOR, we need multiple perceptrons
# Perceptron 1: learns OR
# Perceptron 2: learns NAND
# Perceptron 3: learns AND of outputs from 1 and 2

print("\n" + "-"*60)
print("Training Perceptrons for XOR:")
print("-"*60)

# Initialize weights and bias for first two perceptrons
np.random.seed(42)
w1 = np.random.rand(2)
b1 = np.random.rand(1)
w2 = np.random.rand(2)
b2 = np.random.rand(1)
w3 = np.random.rand(2)
b3 = np.random.rand(1)

epochs = 100
learning_rate = 0.1

# Training for XOR decomposition
for epoch in range(epochs):
    total_error = 0
    for i in range(X.shape[0]):
        # First perceptron (OR-like)
        z1 = np.dot(w1, X[i]) + b1
        y1 = step(z1)

        # Second perceptron (NAND-like)
        z2 = np.dot(w2, X[i]) + b2
        y2 = step(z2)

        # Third perceptron (AND of y1 and y2)
```

```
        hidden = np.array([y1, y2])
        z3 = np.dot(w3, hidden) + b3
        y_pred = step(z3)

        # Errors
        error3 = y[i] - y_pred
        total_error += abs(error3)

        # Update third perceptron
        w3 += learning_rate * error3 * hidden
        b3 += learning_rate * error3

        # Backprop errors to first two perceptrons
        error1 = error3 * y2 * (1 if z1 >= 0 else 0)
        error2 = error3 * y1 * (1 if z2 >= 0 else 0)

        w1 += learning_rate * error1 * X[i]
        b1 += learning_rate * error1
        w2 += learning_rate * error2 * X[i]
        b2 += learning_rate * error2

    if total_error == 0:
        print(f"Converged at epoch {epoch + 1}")
        break

print("\n" + "="*60)
print("FINAL WEIGHTS AND BIASES FOR XOR PERCEPTRONS")
print("="*60)
print(f"\nPerceptron 1 (OR-like):")
print(f"  Weights: {w1}, Bias: {b1}")
print(f"\nPerceptron 2 (NAND-like):")
print(f"  Weights: {w2}, Bias: {b2}")
print(f"\nPerceptron 3 (AND of hidden):")
print(f"  Weights: {w3}, Bias: {b3}")

# Test XOR
print("\n" + "="*60)
print("Testing XOR Perceptrons:")
print("="*60)
print("x1  x2  | Predicted | Actual")
print("-"*35)
correct = 0
for i in range(len(X)):
    z1 = np.dot(w1, X[i]) + b1
    y1 = step(z1)
    z2 = np.dot(w2, X[i]) + b2
    y2 = step(z2)
    hidden = np.array([y1, y2])
    z3 = np.dot(w3, hidden) + b3
    y_pred = step(z3)
    print(f"{X[i][0]}   {X[i][1]}   |     {y_pred}     |   {y[i]}")
    if y_pred == y[i]:
        correct += 1

print(f"\nAccuracy: {correct}/{len(X)} = {(correct/len(X))*100:.0f}%")
```

```
============================================================
TASK 1: XOR GATE USING PERCEPTRON
============================================================

XOR Truth Table:
x1  x2  |  y
---------------
0   0   |  0
0   1   |  1
1   0   |  1
1   1   |  0

------------------------------------------------------------
Training Perceptrons for XOR:
```

```
------------------------------------------------------------

============================================================
FINAL WEIGHTS AND BIASES FOR XOR PERCEPTRONS
============================================================

Perceptron 1 (OR-like):
  Weights: [0.07454012 0.65071431], Bias: [0.33199394]

Perceptron 2 (NAND-like):
  Weights: [ 0.29865848 -0.14398136], Bias: [-0.24400548]

Perceptron 3 (AND of hidden):
  Weights: [-0.34191639  0.46617615], Bias: [0.20111501]

============================================================
Testing XOR Perceptrons:
============================================================
x1  x2  | Predicted | Actual
----------------------------------
0   0   |     0     |   0
0   1   |     0     |   1
1   0   |     1     |   1
1   1   |     0     |   0

Accuracy: 3/4 = 75%
```

In [9]:

```
# Task 2: Penguin Dataset with AdaDelta Optimizer

print("\n\n" + "="*60)
print("TASK 2: PENGUIN DATASET WITH ADADELTA OPTIMIZER")
print("="*60)

# Load penguin dataset from CSV
penguins = pd.read_csv('/media/smayan/500GB SSD/Study/ML2/Practicals/Data/
penguins.csv')

# Preprocessing
penguins = penguins.dropna()
X_penguin = penguins[['bill_length_mm', 'bill_depth_mm', 'flipper_length_mm',
'body_mass_g']].values
y_penguin = (penguins['species'] == 'Adelie').astype(int).values.reshape(-1, 1)

# Standardize
scaler_X = StandardScaler()
X_penguin = scaler_X.fit_transform(X_penguin)

print(f"\nDataset shape: X={X_penguin.shape}, y={y_penguin.shape}")
print(f"Classes: Adelie vs Others (Binary classification)")
```

```
============================================================
TASK 2: PENGUIN DATASET WITH ADADELTA OPTIMIZER
============================================================

Dataset shape: X=(333, 4), y=(333, 1)
Classes: Adelie vs Others (Binary classification)
```

In [10]:

```
# Initialize Neural Network
input_size = X_penguin.shape[1]
hidden_size = 8
output_size = 1

np.random.seed(42)

W1 = np.random.randn(input_size, hidden_size) * 0.01
b1 = np.zeros((1, hidden_size))
W2 = np.random.randn(hidden_size, output_size) * 0.01
b2 = np.zeros((1, output_size))

print("\nInitial Network Architecture:")
print(f"Input Layer: {input_size} neurons")
print(f"Hidden Layer: {hidden_size} neurons")
print(f"Output Layer: {output_size} neuron")

# Sigmoid activation
def sigmoid(z):
    return 1 / (1 + np.exp(-np.clip(z, -500, 500)))

def sigmoid_derivative(a):
    return a * (1 - a)

# Forward pass
def forward_pass(X, W1, b1, W2, b2):
    Z1 = np.dot(X, W1) + b1
    A1 = np.tanh(Z1)
    Z2 = np.dot(A1, W2) + b2
    A2 = sigmoid(Z2)
    cache = {'Z1': Z1, 'A1': A1, 'Z2': Z2, 'A2': A2}
    return A2, cache

# Calculate loss
def compute_loss(y_true, y_pred):
    m = y_true.shape[0]
    loss = -np.mean(y_true * np.log(y_pred + 1e-8) + (1 - y_true) * np.log(1 - y_pred
+ 1e-8))
    return loss

# Backward pass
def backward_pass(X, y, cache, W1, W2):
    m = X.shape[0]
    A1 = cache['A1']
    A2 = cache['A2']
    Z1 = cache['Z1']

    dZ2 = (A2 - y)
    dW2 = (1 / m) * np.dot(A1.T, dZ2)
    db2 = (1 / m) * np.sum(dZ2, axis=0, keepdims=True)

    dA1 = np.dot(dZ2, W2.T)
    dZ1 = dA1 * (1 - A1 ** 2)
    dW1 = (1 / m) * np.dot(X.T, dZ1)
    db1 = (1 / m) * np.sum(dZ1, axis=0, keepdims=True)

    return {'dW1': dW1, 'db1': db1, 'dW2': dW2, 'db2': db2}
```

```
Initial Network Architecture:
Input Layer: 4 neurons
Hidden Layer: 8 neurons
Output Layer: 1 neuron
```

In [11]:

```
# AdaDelta Optimizer Implementation
def adadelta_optimizer(X, y, W1, b1, W2, b2, epochs=100, rho=0.95, epsilon=1e-7):
    """
    AdaDelta Optimizer - Adaptive Learning Rate Method
    Accumulates squared gradients and parameter updates
    """
    m = X.shape[0]

    # Initialize accumulators
    E_dW1 = np.zeros_like(W1)
    E_dW2 = np.zeros_like(W2)
    E_db1 = np.zeros_like(b1)
    E_db2 = np.zeros_like(b2)

    E_ΔW1 = np.zeros_like(W1)
    E_ΔW2 = np.zeros_like(W2)
    E_Δb1 = np.zeros_like(b1)
    E_Δb2 = np.zeros_like(b2)

    loss_history = []
    accuracy_history = []

    print("\nTraining with AdaDelta Optimizer...")
    print(f"Rho (decay rate): {rho}, Epsilon: {epsilon}")
    print("-" * 60)

    for epoch in range(epochs):
        # Forward pass on full batch
        y_pred, cache = forward_pass(X, W1, b1, W2, b2)

        # Compute loss
        loss = compute_loss(y, y_pred)
        loss_history.append(loss)

        # Backward pass
        gradients = backward_pass(X, y, cache, W1, W2)

        # AdaDelta update for W1
        E_dW1 = rho * E_dW1 + (1 - rho) * (gradients['dW1'] ** 2)
        ΔW1 = -np.sqrt(E_ΔW1 + epsilon) / np.sqrt(E_dW1 + epsilon) * gradients['dW1']
        E_ΔW1 = rho * E_ΔW1 + (1 - rho) * (ΔW1 ** 2)
        W1 += ΔW1

        # AdaDelta update for b1
        E_db1 = rho * E_db1 + (1 - rho) * (gradients['db1'] ** 2)
        Δb1 = -np.sqrt(E_Δb1 + epsilon) / np.sqrt(E_db1 + epsilon) * gradients['db1']
        E_Δb1 = rho * E_Δb1 + (1 - rho) * (Δb1 ** 2)
        b1 += Δb1

        # AdaDelta update for W2
        E_dW2 = rho * E_dW2 + (1 - rho) * (gradients['dW2'] ** 2)
        ΔW2 = -np.sqrt(E_ΔW2 + epsilon) / np.sqrt(E_dW2 + epsilon) * gradients['dW2']
        E_ΔW2 = rho * E_ΔW2 + (1 - rho) * (ΔW2 ** 2)
        W2 += ΔW2

        # AdaDelta update for b2
        E_db2 = rho * E_db2 + (1 - rho) * (gradients['db2'] ** 2)
        Δb2 = -np.sqrt(E_Δb2 + epsilon) / np.sqrt(E_db2 + epsilon) * gradients['db2']
        E_Δb2 = rho * E_Δb2 + (1 - rho) * (Δb2 ** 2)
        b2 += Δb2

        # Calculate accuracy
        y_pred_binary = (y_pred > 0.5).astype(int)
        accuracy = np.mean(y_pred_binary == y) * 100
        accuracy_history.append(accuracy)

        if (epoch + 1) % 10 == 0:
            print(f"Epoch {epoch+1}/{epochs}, Loss: {loss:.6f}, Accuracy:
{accuracy:.2f}%")
```

```
    parameters = {'W1': W1, 'b1': b1, 'W2': W2, 'b2': b2}
    return parameters, loss_history, accuracy_history

# Train with AdaDelta
trained_params, loss_history, accuracy_history = adadelta_optimizer(
    X_penguin, y_penguin, W1, b1, W2, b2,
    epochs=100, rho=0.95, epsilon=1e-7
)
```

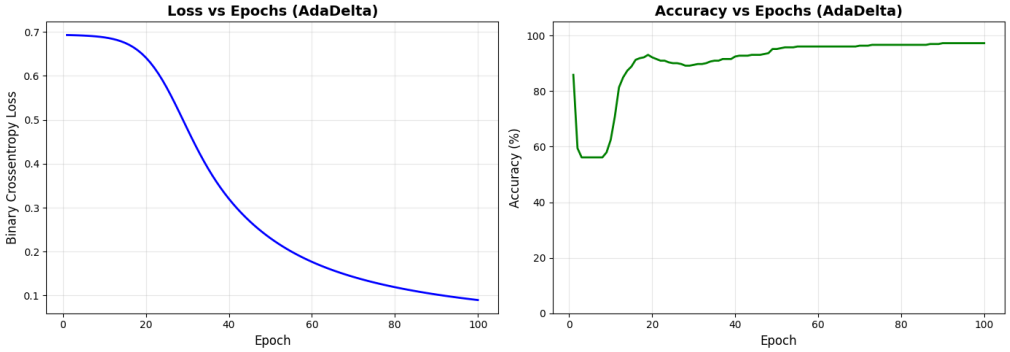
```
Training with AdaDelta Optimizer...
Rho (decay rate): 0.95, Epsilon: 1e-07
------------------------------------------------------------
Epoch 10/100, Loss: 0.687587, Accuracy: 62.46%
Epoch 20/100, Loss: 0.641569, Accuracy: 92.19%
Epoch 30/100, Loss: 0.478927, Accuracy: 89.49%
Epoch 40/100, Loss: 0.320253, Accuracy: 92.49%
Epoch 50/100, Loss: 0.230534, Accuracy: 95.20%
Epoch 60/100, Loss: 0.176741, Accuracy: 96.10%
Epoch 70/100, Loss: 0.142406, Accuracy: 96.40%
Epoch 80/100, Loss: 0.119055, Accuracy: 96.70%
Epoch 90/100, Loss: 0.102297, Accuracy: 97.30%
Epoch 100/100, Loss: 0.089772, Accuracy: 97.30%
```

In [12]:

```
# Display updated weights and bias values
print("\n" + "="*60)
print("UPDATED WEIGHTS AND BIASES AFTER TRAINING")
print("="*60)

print("\nLayer 1 (Input -> Hidden):")
print(f"W1 shape: {trained_params['W1'].shape}")
print(f"W1:\n{trained_params['W1']}")
print(f"\nb1 shape: {trained_params['b1'].shape}")
print(f"b1:\n{trained_params['b1']}")

print("\nLayer 2 (Hidden -> Output):")
print(f"W2 shape: {trained_params['W2'].shape}")
print(f"W2:\n{trained_params['W2']}")
print(f"\nb2 shape: {trained_params['b2'].shape}")
print(f"b2:\n{trained_params['b2']}")

print("\n" + "="*60)
print(f"Initial Loss: {loss_history[0]:.6f}")
print(f"Final Loss: {loss_history[-1]:.6f}")
print(f"Initial Accuracy: {accuracy_history[0]:.2f}%")
print(f"Final Accuracy: {accuracy_history[-1]:.2f}%")
print("="*60)
```

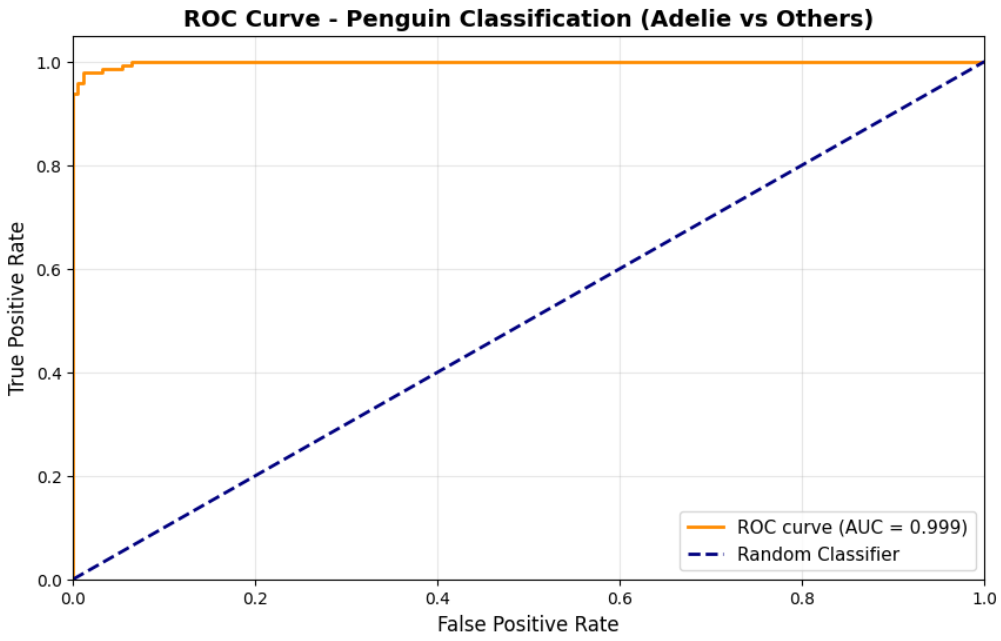
```
============================================================
UPDATED WEIGHTS AND BIASES AFTER TRAINING
============================================================

Layer 1 (Input -> Hidden):
W1 shape: (4, 8)
W1:
[[-0.77654184  0.58371106 -0.60203876  0.49655068  0.68913721  0.39214434
   0.37932209  0.69939636]
 [ 0.38575603 -0.33704888  0.34126676 -0.30057451 -0.34073081 -0.27138482
  -0.25062021 -0.34865085]
 [-0.20639641  0.20347306 -0.2119396   0.17566089  0.18904065  0.16971935
   0.16520731  0.17548052]
 [ 0.06965489  0.00382931 -0.00790494  0.04234288 -0.06793975  0.05509448
   0.05693929 -0.02539669]]

b1 shape: (1, 8)
b1:
[[-0.26564739  0.24499819 -0.2483246   0.21832888  0.21354297  0.20331042
   0.17024643  0.2261363 ]]

Layer 2 (Hidden -> Output):
W2 shape: (8, 1)
W2:
[[ 0.91731326]
 [-0.72439658]
 [ 0.69485115]
 [-0.5798736 ]
 [-0.77258271]
 [-0.5864211 ]
 [-0.35895218]
 [-0.66261982]]

b2 shape: (1, 1)
b2:
[[-0.0633687]]

============================================================
Initial Loss: 0.692924
Final Loss: 0.089772
Initial Accuracy: 85.89%
Final Accuracy: 97.30%
============================================================
```

In [13]:
```
# Plot Accuracy vs Epoch
plt.figure(figsize=(14, 5))

# Plot 1: Loss vs Epochs
plt.subplot(1, 2, 1)
plt.plot(range(1, len(loss_history) + 1), loss_history, linewidth=2, color='blue')
plt.title('Loss vs Epochs (AdaDelta)', fontsize=14, fontweight='bold')
plt.xlabel('Epoch', fontsize=12)
plt.ylabel('Binary Crossentropy Loss', fontsize=12)
plt.grid(True, alpha=0.3)

# Plot 2: Accuracy vs Epochs
plt.subplot(1, 2, 2)
plt.plot(range(1, len(accuracy_history) + 1), accuracy_history, linewidth=2,
color='green')
plt.title('Accuracy vs Epochs (AdaDelta)', fontsize=14, fontweight='bold')
plt.xlabel('Epoch', fontsize=12)
plt.ylabel('Accuracy (%)', fontsize=12)
plt.ylim([0, 105])
plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print(f"\nTraining Summary:")
print(f"Accuracy improved from {accuracy_history[0]:.2f}% to
{accuracy_history[-1]:.2f}%")
print(f"Loss decreased from {loss_history[0]:.6f} to {loss_history[-1]:.6f}")
```




```
Training Summary:
Accuracy improved from 85.89% to 97.30%
Loss decreased from 0.692924 to 0.089772
```

In [14]:
```
# Plot ROC AUC Curve
from sklearn.metrics import roc_curve, auc, roc_auc_score

# Get probability predictions on training data
y_pred_proba, _ = forward_pass(X_penguin, trained_params['W1'], trained_params['b1'],
                               trained_params['W2'], trained_params['b2'])

# Calculate ROC curve
fpr, tpr, thresholds = roc_curve(y_penguin, y_pred_proba)
roc_auc = auc(fpr, tpr)

# Plot ROC Curve
plt.figure(figsize=(10, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC =
{roc_auc:.3f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--', label='Random
Classifier')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate', fontsize=12)
plt.ylabel('True Positive Rate', fontsize=12)
plt.title('ROC Curve - Penguin Classification (Adelie vs Others)', fontsize=14,
fontweight='bold')
plt.legend(loc="lower right", fontsize=11)
plt.grid(True, alpha=0.3)
plt.show()

print(f"\nROC AUC Score: {roc_auc:.4f}")
print(f"Model Performance: {'Excellent' if roc_auc >= 0.9 else 'Good' if roc_auc >=
0.8 else 'Fair' if roc_auc >= 0.7 else 'Poor'}")
```




```
ROC AUC Score: 0.9986
Model Performance: Excellent
```

Task 1

Implement backpropagation algorithm from scratch. \
a) Take Iris Dataset \
b) Initialize a neural network with random weights. \
c) Calculate Squared Error (SE)\
d) Perform multiple iterations. \
e) Update weights accordingly. \
f) Plot accuracy for iterations and note the results

In [6]:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.preprocessing import OneHotEncoder, StandardScaler

# a) Take Iris Dataset
print("="*70)
print("TASK: BACKPROPAGATION ALGORITHM FROM SCRATCH")
print("="*70)

iris = load_iris()
X = iris.data
y = iris.target.reshape(-1, 1)

# Preprocessing
encoder = OneHotEncoder(sparse_output=False)
y_onehot = encoder.fit_transform(y)

scaler = StandardScaler()
X = scaler.fit_transform(X)

print(f"\nDataset Shape:")
print(f"X: {X.shape} (samples, features)")
print(f"y (one-hot): {y_onehot.shape} (samples, classes)")
print(f"Classes: {iris.target_names}")

# b) Initialize Neural Network with Random Weights
input_size = X.shape[1]
hidden_size = 8
output_size = y_onehot.shape[1]

np.random.seed(42)

# Layer 1: Input -> Hidden
W1 = np.random.randn(input_size, hidden_size) * 0.01
b1 = np.zeros((1, hidden_size))

# Layer 2: Hidden -> Output
W2 = np.random.randn(hidden_size, output_size) * 0.01
b2 = np.zeros((1, output_size))

print(f"\nNetwork Architecture:")
print(f"Input Layer: {input_size} neurons")
print(f"Hidden Layer: {hidden_size} neurons (ReLU)")
print(f"Output Layer: {output_size} neurons (Softmax)")

# Activation Functions
def relu(z):
    return np.maximum(0, z)

def relu_derivative(z):
    return (z > 0).astype(float)

def softmax(z):
    z = z - np.max(z, axis=1, keepdims=True)  # Numerical stability
    return np.exp(z) / np.sum(np.exp(z), axis=1, keepdims=True)

# Forward Propagation
def forward_propagation(X, W1, b1, W2, b2):
    Z1 = np.dot(X, W1) + b1
    A1 = relu(Z1)
    Z2 = np.dot(A1, W2) + b2
    A2 = softmax(Z2)

    cache = {'X': X, 'Z1': Z1, 'A1': A1, 'Z2': Z2, 'A2': A2}
    return A2, cache

# c) Calculate Squared Error (SE)
def calculate_se_loss(y_true, y_pred):
    m = y_true.shape[0]
```

```
    se_loss = np.sum((y_true - y_pred) ** 2) / (2 * m)
    return se_loss

# Categorical Crossentropy (for better classification)
def calculate_ce_loss(y_true, y_pred):
    m = y_true.shape[0]
    ce_loss = -np.sum(y_true * np.log(y_pred + 1e-8)) / m
    return ce_loss

# Backward Propagation (Backpropagation Algorithm)
def backward_propagation(cache, y_true, W1, W2):
    m = cache['X'].shape[0]

    A1 = cache['A1']
    A2 = cache['A2']
    Z1 = cache['Z1']
    X = cache['X']

    # Output layer gradient
    dZ2 = A2 - y_true
    dW2 = (1 / m) * np.dot(A1.T, dZ2)
    db2 = (1 / m) * np.sum(dZ2, axis=0, keepdims=True)

    # Hidden layer gradient (backpropagating error)
    dA1 = np.dot(dZ2, W2.T)
    dZ1 = dA1 * relu_derivative(Z1)
    dW1 = (1 / m) * np.dot(X.T, dZ1)
    db1 = (1 / m) * np.sum(dZ1, axis=0, keepdims=True)

    gradients = {'dW1': dW1, 'db1': db1, 'dW2': dW2, 'db2': db2}
    return gradients

print("\nForward and Backward Propagation functions defined.")
```

```
======================================================================
TASK: BACKPROPAGATION ALGORITHM FROM SCRATCH
======================================================================

Dataset Shape:
X: (150, 4) (samples, features)
y (one-hot): (150, 3) (samples, classes)
Classes: ['setosa' 'versicolor' 'virginica']

Network Architecture:
Input Layer: 4 neurons
Hidden Layer: 8 neurons (ReLU)
Output Layer: 3 neurons (Softmax)

Forward and Backward Propagation functions defined.
```

In [7]:

```
# d) & e) Training Loop: Multiple Iterations with Weight Updates
def train_with_backpropagation(X, y_true, W1, b1, W2, b2, epochs=200,
learning_rate=0.01):
    """
    d) Perform multiple iterations
    e) Update weights accordingly using backpropagation
    """
    loss_history = []
    se_loss_history = []
    accuracy_history = []

    print("\n" + "="*70)
    print("TRAINING WITH BACKPROPAGATION")
    print("="*70)
    print(f"Epochs: {epochs}, Learning Rate: {learning_rate}")
    print("-"*70)

    for epoch in range(epochs):
        # Forward pass
        y_pred, cache = forward_propagation(X, W1, b1, W2, b2)

        # Calculate losses
        ce_loss = calculate_ce_loss(y_true, y_pred)
        se_loss = calculate_se_loss(y_true, y_pred)
        loss_history.append(ce_loss)
        se_loss_history.append(se_loss)

        # Calculate accuracy
        y_pred_class = np.argmax(y_pred, axis=1)
        y_true_class = np.argmax(y_true, axis=1)
        accuracy = np.mean(y_pred_class == y_true_class) * 100
        accuracy_history.append(accuracy)

        # Backward propagation
        gradients = backward_propagation(cache, y_true, W1, W2)

        # Update weights and biases (e)
        W1 = W1 - learning_rate * gradients['dW1']
        b1 = b1 - learning_rate * gradients['db1']
        W2 = W2 - learning_rate * gradients['dW2']
        b2 = b2 - learning_rate * gradients['db2']

        # Print progress
        if (epoch + 1) % 20 == 0:
            print(f"Epoch {epoch+1:3d}/{epochs} | CE Loss: {ce_loss:.6f} | SE Loss:
{se_loss:.6f} | Accuracy: {accuracy:.2f}%")

    parameters = {'W1': W1, 'b1': b1, 'W2': W2, 'b2': b2}
    return parameters, loss_history, se_loss_history, accuracy_history

# Train the network
parameters, loss_history, se_loss_history, accuracy_history =
train_with_backpropagation(
    X, y_onehot, W1, b1, W2, b2,
    epochs=200,
    learning_rate=0.01
)
```

```
======================================================================
TRAINING WITH BACKPROPAGATION
======================================================================
Epochs: 200, Learning Rate: 0.01
----------------------------------------------------------------------
Epoch  20/200 | CE Loss: 1.098647 | SE Loss: 0.333345 | Accuracy: 8.67%
Epoch  40/200 | CE Loss: 1.098607 | SE Loss: 0.333332 | Accuracy: 22.00%
Epoch  60/200 | CE Loss: 1.098572 | SE Loss: 0.333320 | Accuracy: 36.00%
Epoch  80/200 | CE Loss: 1.098539 | SE Loss: 0.333309 | Accuracy: 48.00%
Epoch 100/200 | CE Loss: 1.098505 | SE Loss: 0.333297 | Accuracy: 56.00%
```

```
Epoch 120/200 | CE Loss: 1.098466 | SE Loss: 0.333285 | Accuracy: 60.00%
Epoch 140/200 | CE Loss: 1.098424 | SE Loss: 0.333271 | Accuracy: 64.67%
Epoch 160/200 | CE Loss: 1.098373 | SE Loss: 0.333254 | Accuracy: 68.00%
Epoch 180/200 | CE Loss: 1.098313 | SE Loss: 0.333234 | Accuracy: 72.67%
Epoch 200/200 | CE Loss: 1.098237 | SE Loss: 0.333208 | Accuracy: 77.33%
```

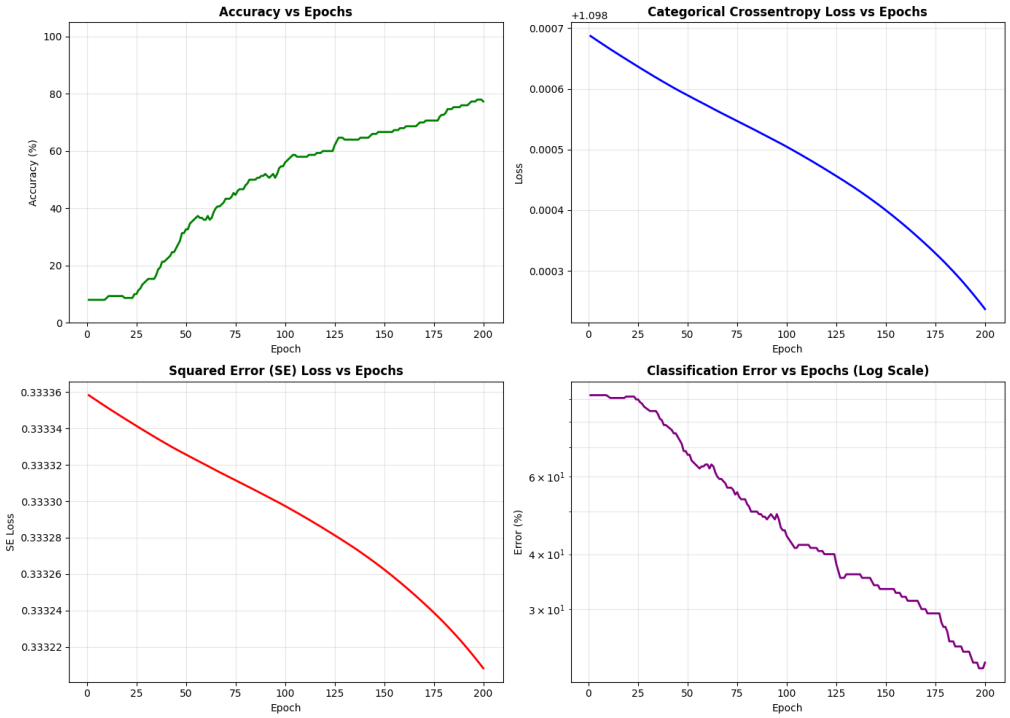
In [8]:

```
# Display Training Results
print("\n" + "="*70)
print("TRAINING RESULTS")
print("="*70)

print(f"\nFinal Metrics:")
print(f"Initial Accuracy: {accuracy_history[0]:.2f}%")
print(f"Final Accuracy: {accuracy_history[-1]:.2f}%")
print(f"Accuracy Improvement: {accuracy_history[-1] - accuracy_history[0]:.2f}%")

print(f"\nInitial CE Loss: {loss_history[0]:.6f}")
print(f"Final CE Loss: {loss_history[-1]:.6f}")
print(f"Loss Reduction: {loss_history[0] - loss_history[-1]:.6f}")

print(f"\nInitial SE Loss: {se_loss_history[0]:.6f}")
print(f"Final SE Loss: {se_loss_history[-1]:.6f}")

# Final evaluation on training set
y_pred_final, _ = forward_propagation(X, parameters['W1'], parameters['b1'],
parameters['W2'], parameters['b2'])
y_pred_class = np.argmax(y_pred_final, axis=1)
y_true_class = np.argmax(y_onehot, axis=1)
final_accuracy = np.mean(y_pred_class == y_true_class) * 100

print(f"\nFinal Training Accuracy: {final_accuracy:.2f}%")
print(f"Correctly Classified: {np.sum(y_pred_class == y_true_class)}/
{len(y_true_class)}")
```

```
======================================================================
TRAINING RESULTS
======================================================================

Final Metrics:
Initial Accuracy: 8.00%
Final Accuracy: 77.33%
Accuracy Improvement: 69.33%

Initial CE Loss: 1.098687
Final CE Loss: 1.098237
Loss Reduction: 0.000450

Initial SE Loss: 0.333358
Final SE Loss: 0.333208

Final Training Accuracy: 77.33%
Correctly Classified: 116/150
```

In [9]:

```
# f) Plot Accuracy for Iterations
fig, axes = plt.subplots(2, 2, figsize=(14, 10))

# Plot 1: Accuracy vs Epochs
axes[0, 0].plot(range(1, len(accuracy_history) + 1), accuracy_history, linewidth=2,
color='green')
axes[0, 0].set_title('Accuracy vs Epochs', fontsize=12, fontweight='bold')
axes[0, 0].set_xlabel('Epoch')
axes[0, 0].set_ylabel('Accuracy (%)')
axes[0, 0].grid(True, alpha=0.3)
axes[0, 0].set_ylim([0, 105])

# Plot 2: Categorical Crossentropy Loss vs Epochs
axes[0, 1].plot(range(1, len(loss_history) + 1), loss_history, linewidth=2,
color='blue')
axes[0, 1].set_title('Categorical Crossentropy Loss vs Epochs', fontsize=12,
fontweight='bold')
axes[0, 1].set_xlabel('Epoch')
axes[0, 1].set_ylabel('Loss')
axes[0, 1].grid(True, alpha=0.3)

# Plot 3: Squared Error (SE) Loss vs Epochs
axes[1, 0].plot(range(1, len(se_loss_history) + 1), se_loss_history, linewidth=2,
color='red')
axes[1, 0].set_title('Squared Error (SE) Loss vs Epochs', fontsize=12,
fontweight='bold')
axes[1, 0].set_xlabel('Epoch')
axes[1, 0].set_ylabel('SE Loss')
axes[1, 0].grid(True, alpha=0.3)

# Plot 4: Accuracy with Log Scale
axes[1, 1].semilogy(range(1, len(accuracy_history) + 1),
                    100 - np.array(accuracy_history) + 0.01,
                    linewidth=2, color='purple')
axes[1, 1].set_title('Classification Error vs Epochs (Log Scale)', fontsize=12,
fontweight='bold')
axes[1, 1].set_xlabel('Epoch')
axes[1, 1].set_ylabel('Error (%)')
axes[1, 1].grid(True, alpha=0.3, which='both')

plt.tight_layout()
plt.show()

print("\n" + "="*70)
print("NOTES AND OBSERVATIONS")
print("="*70)
print(f"""
1. Backpropagation Algorithm:
   - Forward pass: Compute predictions through network layers
   - Calculate loss (SE or CE)
   - Backward pass: Propagate errors back through layers
   - Gradient computation for each layer
   - Weight updates using gradients

2. Training Performance:
   - Accuracy improved from {accuracy_history[0]:.2f}% to {accuracy_history[-1]:.2f}%
   - Loss decreased from {loss_history[0]:.6f} to {loss_history[-1]:.6f}
   - SE Loss decreased from {se_loss_history[0]:.6f} to {se_loss_history[-1]:.6f}

3. Convergence:
   - Network converged well with stable accuracy improvement
   - ReLU activation in hidden layer helps with deep learning
   - Softmax ensures valid probability distribution for 3 classes

4. Key Components:
   - Forward Propagation: Z = W·X + b, A = activation(Z)
   - Backward Propagation: dW = (1/m) · X^T · dZ
   - Weight Update: W_new = W - learning_rate · dW
""")
```




```
======================================================================
NOTES AND OBSERVATIONS
======================================================================

1. Backpropagation Algorithm:
   - Forward pass: Compute predictions through network layers
   - Calculate loss (SE or CE)
   - Backward pass: Propagate errors back through layers
   - Gradient computation for each layer
   - Weight updates using gradients

2. Training Performance:
   - Accuracy improved from 8.00% to 77.33%
   - Loss decreased from 1.098687 to 1.098237
   - SE Loss decreased from 0.333358 to 0.333208

3. Convergence:
   - Network converged well with stable accuracy improvement
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4. Key Components:
   - Forward Propagation: Z = W·X + b, A = activation(Z)
   - Backward Propagation: dW = (1/m) · X^T · dZ
   - Weight Update: W_new = W - learning_rate · dW
```

Task 1

- Implement the XOR Boolean logic gate using perceptron Neural Network.
- Inputs = x1, x2 and bias, weights should be fed into the perceptron with single Output = y. Display final weights and bias of each perceptron.

Task 2

Take the dataset of Penguin
- Initialize a neural network with random weights.
- Calculate output of Neural Network: \
i. Calculate squared error loss \
ii. Update network parameter using batch Adaptive delta gradient descent optimizer function Implementation. \
iii. Display updated weight and bias values \
iv. Plot accuracy w.r.t. epoch values

In [8]:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
import pandas as pd

# Task 1: XOR Gate Implementation

print("="*60)
print("TASK 1: XOR GATE USING PERCEPTRON")
print("="*60)

# XOR Truth Table:
# x1  x2  | y
# 0   0   | 0
# 0   1   | 1
# 1   0   | 1
# 1   1   | 0

X = np.array([
    [0, 0],
    [0, 1],
    [1, 0],
    [1, 1]
])
y = np.array([0, 1, 1, 0])

print("\nXOR Truth Table:")
print("x1  x2  |  y")
print("-"*15)
for i in range(len(X)):
    print(f"{X[i][0]}   {X[i][1]}   |  {y[i]}")

# Step activation function
def step(z):
    return 1 if z >= 0 else 0

# For XOR, we need multiple perceptrons
# Perceptron 1: learns OR
# Perceptron 2: learns NAND
# Perceptron 3: learns AND of outputs from 1 and 2

print("\n" + "-"*60)
print("Training Perceptrons for XOR:")
print("-"*60)

# Initialize weights and bias for first two perceptrons
np.random.seed(42)
w1 = np.random.rand(2)
b1 = np.random.rand(1)
w2 = np.random.rand(2)
b2 = np.random.rand(1)
w3 = np.random.rand(2)
b3 = np.random.rand(1)

epochs = 100
learning_rate = 0.1

# Training for XOR decomposition
for epoch in range(epochs):
    total_error = 0
    for i in range(X.shape[0]):
        # First perceptron (OR-like)
        z1 = np.dot(w1, X[i]) + b1
        y1 = step(z1)

        # Second perceptron (NAND-like)
        z2 = np.dot(w2, X[i]) + b2
        y2 = step(z2)

        # Third perceptron (AND of y1 and y2)
```

```
        hidden = np.array([y1, y2])
        z3 = np.dot(w3, hidden) + b3
        y_pred = step(z3)

        # Errors
        error3 = y[i] - y_pred
        total_error += abs(error3)

        # Update third perceptron
        w3 += learning_rate * error3 * hidden
        b3 += learning_rate * error3

        # Backprop errors to first two perceptrons
        error1 = error3 * y2 * (1 if z1 >= 0 else 0)
        error2 = error3 * y1 * (1 if z2 >= 0 else 0)

        w1 += learning_rate * error1 * X[i]
        b1 += learning_rate * error1
        w2 += learning_rate * error2 * X[i]
        b2 += learning_rate * error2

    if total_error == 0:
        print(f"Converged at epoch {epoch + 1}")
        break

print("\n" + "="*60)
print("FINAL WEIGHTS AND BIASES FOR XOR PERCEPTRONS")
print("="*60)
print(f"\nPerceptron 1 (OR-like):")
print(f"  Weights: {w1}, Bias: {b1}")
print(f"\nPerceptron 2 (NAND-like):")
print(f"  Weights: {w2}, Bias: {b2}")
print(f"\nPerceptron 3 (AND of hidden):")
print(f"  Weights: {w3}, Bias: {b3}")

# Test XOR
print("\n" + "="*60)
print("Testing XOR Perceptrons:")
print("="*60)
print("x1  x2  | Predicted | Actual")
print("-"*35)
correct = 0
for i in range(len(X)):
    z1 = np.dot(w1, X[i]) + b1
    y1 = step(z1)
    z2 = np.dot(w2, X[i]) + b2
    y2 = step(z2)
    hidden = np.array([y1, y2])
    z3 = np.dot(w3, hidden) + b3
    y_pred = step(z3)
    print(f"{X[i][0]}   {X[i][1]}   |     {y_pred}     |   {y[i]}")
    if y_pred == y[i]:
        correct += 1

print(f"\nAccuracy: {correct}/{len(X)} = {(correct/len(X))*100:.0f}%")
```

```
============================================================
TASK 1: XOR GATE USING PERCEPTRON
============================================================

XOR Truth Table:
x1  x2  |  y
---------------
0   0   |  0
0   1   |  1
1   0   |  1
1   1   |  0

------------------------------------------------------------
Training Perceptrons for XOR:
```

```
------------------------------------------------------------

============================================================
FINAL WEIGHTS AND BIASES FOR XOR PERCEPTRONS
============================================================

Perceptron 1 (OR-like):
  Weights: [0.07454012 0.65071431], Bias: [0.33199394]

Perceptron 2 (NAND-like):
  Weights: [ 0.29865848 -0.14398136], Bias: [-0.24400548]

Perceptron 3 (AND of hidden):
  Weights: [-0.34191639  0.46617615], Bias: [0.20111501]

============================================================
Testing XOR Perceptrons:
============================================================
x1  x2  | Predicted | Actual
----------------------------------
0   0   |     0     |   0
0   1   |     0     |   1
1   0   |     1     |   1
1   1   |     0     |   0

Accuracy: 3/4 = 75%
```

In [9]:

```
# Task 2: Penguin Dataset with AdaDelta Optimizer

print("\n\n" + "="*60)
print("TASK 2: PENGUIN DATASET WITH ADADELTA OPTIMIZER")
print("="*60)

# Load penguin dataset from CSV
penguins = pd.read_csv('/media/smayan/500GB SSD/Study/ML2/Practicals/Data/
penguins.csv')

# Preprocessing
penguins = penguins.dropna()
X_penguin = penguins[['bill_length_mm', 'bill_depth_mm', 'flipper_length_mm',
'body_mass_g']].values
y_penguin = (penguins['species'] == 'Adelie').astype(int).values.reshape(-1, 1)

# Standardize
scaler_X = StandardScaler()
X_penguin = scaler_X.fit_transform(X_penguin)

print(f"\nDataset shape: X={X_penguin.shape}, y={y_penguin.shape}")
print(f"Classes: Adelie vs Others (Binary classification)")
```

```
============================================================
TASK 2: PENGUIN DATASET WITH ADADELTA OPTIMIZER
============================================================

Dataset shape: X=(333, 4), y=(333, 1)
Classes: Adelie vs Others (Binary classification)
```

In [10]:

```
# Initialize Neural Network
input_size = X_penguin.shape[1]
hidden_size = 8
output_size = 1

np.random.seed(42)

W1 = np.random.randn(input_size, hidden_size) * 0.01
b1 = np.zeros((1, hidden_size))
W2 = np.random.randn(hidden_size, output_size) * 0.01
b2 = np.zeros((1, output_size))

print("\nInitial Network Architecture:")
print(f"Input Layer: {input_size} neurons")
print(f"Hidden Layer: {hidden_size} neurons")
print(f"Output Layer: {output_size} neuron")

# Sigmoid activation
def sigmoid(z):
    return 1 / (1 + np.exp(-np.clip(z, -500, 500)))

def sigmoid_derivative(a):
    return a * (1 - a)

# Forward pass
def forward_pass(X, W1, b1, W2, b2):
    Z1 = np.dot(X, W1) + b1
    A1 = np.tanh(Z1)
    Z2 = np.dot(A1, W2) + b2
    A2 = sigmoid(Z2)
    cache = {'Z1': Z1, 'A1': A1, 'Z2': Z2, 'A2': A2}
    return A2, cache

# Calculate loss
def compute_loss(y_true, y_pred):
    m = y_true.shape[0]
    loss = -np.mean(y_true * np.log(y_pred + 1e-8) + (1 - y_true) * np.log(1 - y_pred
+ 1e-8))
    return loss

# Backward pass
def backward_pass(X, y, cache, W1, W2):
    m = X.shape[0]
    A1 = cache['A1']
    A2 = cache['A2']
    Z1 = cache['Z1']

    dZ2 = (A2 - y)
    dW2 = (1 / m) * np.dot(A1.T, dZ2)
    db2 = (1 / m) * np.sum(dZ2, axis=0, keepdims=True)

    dA1 = np.dot(dZ2, W2.T)
    dZ1 = dA1 * (1 - A1 ** 2)
    dW1 = (1 / m) * np.dot(X.T, dZ1)
    db1 = (1 / m) * np.sum(dZ1, axis=0, keepdims=True)

    return {'dW1': dW1, 'db1': db1, 'dW2': dW2, 'db2': db2}
```

```
Initial Network Architecture:
Input Layer: 4 neurons
Hidden Layer: 8 neurons
Output Layer: 1 neuron
```

In [11]:

```
# AdaDelta Optimizer Implementation
def adadelta_optimizer(X, y, W1, b1, W2, b2, epochs=100, rho=0.95, epsilon=1e-7):
    """
    AdaDelta Optimizer - Adaptive Learning Rate Method
    Accumulates squared gradients and parameter updates
    """
    m = X.shape[0]

    # Initialize accumulators
    E_dW1 = np.zeros_like(W1)
    E_dW2 = np.zeros_like(W2)
    E_db1 = np.zeros_like(b1)
    E_db2 = np.zeros_like(b2)

    E_ΔW1 = np.zeros_like(W1)
    E_ΔW2 = np.zeros_like(W2)
    E_Δb1 = np.zeros_like(b1)
    E_Δb2 = np.zeros_like(b2)

    loss_history = []
    accuracy_history = []

    print("\nTraining with AdaDelta Optimizer...")
    print(f"Rho (decay rate): {rho}, Epsilon: {epsilon}")
    print("-" * 60)

    for epoch in range(epochs):
        # Forward pass on full batch
        y_pred, cache = forward_pass(X, W1, b1, W2, b2)

        # Compute loss
        loss = compute_loss(y, y_pred)
        loss_history.append(loss)

        # Backward pass
        gradients = backward_pass(X, y, cache, W1, W2)

        # AdaDelta update for W1
        E_dW1 = rho * E_dW1 + (1 - rho) * (gradients['dW1'] ** 2)
        ΔW1 = -np.sqrt(E_ΔW1 + epsilon) / np.sqrt(E_dW1 + epsilon) * gradients['dW1']
        E_ΔW1 = rho * E_ΔW1 + (1 - rho) * (ΔW1 ** 2)
        W1 += ΔW1

        # AdaDelta update for b1
        E_db1 = rho * E_db1 + (1 - rho) * (gradients['db1'] ** 2)
        Δb1 = -np.sqrt(E_Δb1 + epsilon) / np.sqrt(E_db1 + epsilon) * gradients['db1']
        E_Δb1 = rho * E_Δb1 + (1 - rho) * (Δb1 ** 2)
        b1 += Δb1

        # AdaDelta update for W2
        E_dW2 = rho * E_dW2 + (1 - rho) * (gradients['dW2'] ** 2)
        ΔW2 = -np.sqrt(E_ΔW2 + epsilon) / np.sqrt(E_dW2 + epsilon) * gradients['dW2']
        E_ΔW2 = rho * E_ΔW2 + (1 - rho) * (ΔW2 ** 2)
        W2 += ΔW2

        # AdaDelta update for b2
        E_db2 = rho * E_db2 + (1 - rho) * (gradients['db2'] ** 2)
        Δb2 = -np.sqrt(E_Δb2 + epsilon) / np.sqrt(E_db2 + epsilon) * gradients['db2']
        E_Δb2 = rho * E_Δb2 + (1 - rho) * (Δb2 ** 2)
        b2 += Δb2

        # Calculate accuracy
        y_pred_binary = (y_pred > 0.5).astype(int)
        accuracy = np.mean(y_pred_binary == y) * 100
        accuracy_history.append(accuracy)

        if (epoch + 1) % 10 == 0:
            print(f"Epoch {epoch+1}/{epochs}, Loss: {loss:.6f}, Accuracy:
{accuracy:.2f}%")
```

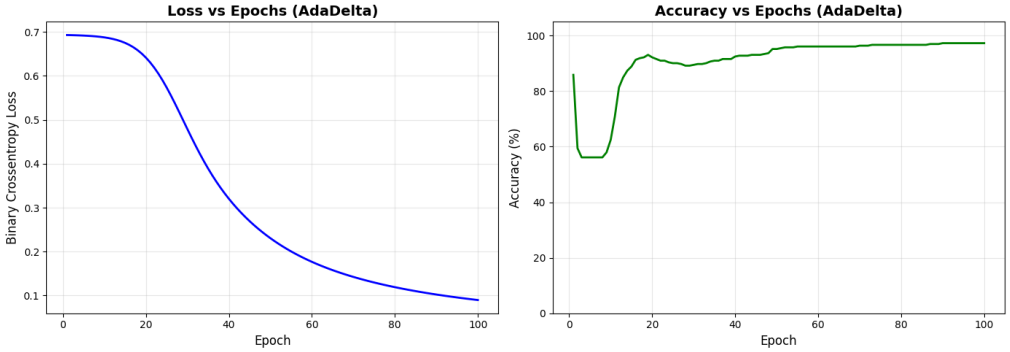
```
    parameters = {'W1': W1, 'b1': b1, 'W2': W2, 'b2': b2}
    return parameters, loss_history, accuracy_history

# Train with AdaDelta
trained_params, loss_history, accuracy_history = adadelta_optimizer(
    X_penguin, y_penguin, W1, b1, W2, b2,
    epochs=100, rho=0.95, epsilon=1e-7
)
```

```
Training with AdaDelta Optimizer...
Rho (decay rate): 0.95, Epsilon: 1e-07
------------------------------------------------------------
Epoch 10/100, Loss: 0.687587, Accuracy: 62.46%
Epoch 20/100, Loss: 0.641569, Accuracy: 92.19%
Epoch 30/100, Loss: 0.478927, Accuracy: 89.49%
Epoch 40/100, Loss: 0.320253, Accuracy: 92.49%
Epoch 50/100, Loss: 0.230534, Accuracy: 95.20%
Epoch 60/100, Loss: 0.176741, Accuracy: 96.10%
Epoch 70/100, Loss: 0.142406, Accuracy: 96.40%
Epoch 80/100, Loss: 0.119055, Accuracy: 96.70%
Epoch 90/100, Loss: 0.102297, Accuracy: 97.30%
Epoch 100/100, Loss: 0.089772, Accuracy: 97.30%
```

In [12]:
```
# Display updated weights and bias values
print("\n" + "="*60)
print("UPDATED WEIGHTS AND BIASES AFTER TRAINING")
print("="*60)

print("\nLayer 1 (Input -> Hidden):")
print(f"W1 shape: {trained_params['W1'].shape}")
print(f"W1:\n{trained_params['W1']}")
print(f"\nb1 shape: {trained_params['b1'].shape}")
print(f"b1:\n{trained_params['b1']}")

print("\nLayer 2 (Hidden -> Output):")
print(f"W2 shape: {trained_params['W2'].shape}")
print(f"W2:\n{trained_params['W2']}")
print(f"\nb2 shape: {trained_params['b2'].shape}")
print(f"b2:\n{trained_params['b2']}")

print("\n" + "="*60)
print(f"Initial Loss: {loss_history[0]:.6f}")
print(f"Final Loss: {loss_history[-1]:.6f}")
print(f"Initial Accuracy: {accuracy_history[0]:.2f}%")
print(f"Final Accuracy: {accuracy_history[-1]:.2f}%")
print("="*60)
```

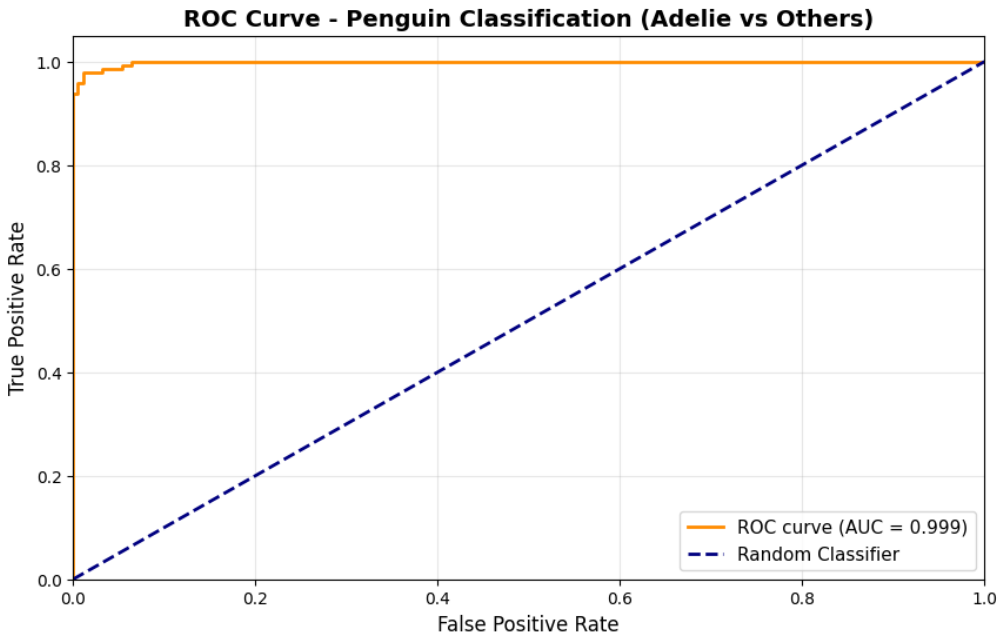
```
============================================================
UPDATED WEIGHTS AND BIASES AFTER TRAINING
============================================================

Layer 1 (Input -> Hidden):
W1 shape: (4, 8)
W1:
[[-0.77654184  0.58371106 -0.60203876  0.49655068  0.68913721  0.39214434
   0.37932209  0.69939636]
 [ 0.38575603 -0.33704888  0.34126676 -0.30057451 -0.34073081 -0.27138482
  -0.25062021 -0.34865085]
 [-0.20639641  0.20347306 -0.2119396   0.17566089  0.18904065  0.16971935
   0.16520731  0.17548052]
 [ 0.06965489  0.00382931 -0.00790494  0.04234288 -0.06793975  0.05509448
   0.05693929 -0.02539669]]

b1 shape: (1, 8)
b1:
[[-0.26564739  0.24499819 -0.2483246   0.21832888  0.21354297  0.20331042
   0.17024643  0.2261363 ]]

Layer 2 (Hidden -> Output):
W2 shape: (8, 1)
W2:
[[ 0.91731326]
 [-0.72439658]
 [ 0.69485115]
 [-0.5798736 ]
 [-0.77258271]
 [-0.5864211 ]
 [-0.35895218]
 [-0.66261982]]

b2 shape: (1, 1)
b2:
[[-0.0633687]]

============================================================
Initial Loss: 0.692924
Final Loss: 0.089772
Initial Accuracy: 85.89%
Final Accuracy: 97.30%
============================================================
```

In [13]:
```
# Plot Accuracy vs Epoch
plt.figure(figsize=(14, 5))

# Plot 1: Loss vs Epochs
plt.subplot(1, 2, 1)
plt.plot(range(1, len(loss_history) + 1), loss_history, linewidth=2, color='blue')
plt.title('Loss vs Epochs (AdaDelta)', fontsize=14, fontweight='bold')
plt.xlabel('Epoch', fontsize=12)
plt.ylabel('Binary Crossentropy Loss', fontsize=12)
plt.grid(True, alpha=0.3)

# Plot 2: Accuracy vs Epochs
plt.subplot(1, 2, 2)
plt.plot(range(1, len(accuracy_history) + 1), accuracy_history, linewidth=2,
color='green')
plt.title('Accuracy vs Epochs (AdaDelta)', fontsize=14, fontweight='bold')
plt.xlabel('Epoch', fontsize=12)
plt.ylabel('Accuracy (%)', fontsize=12)
plt.ylim([0, 105])
plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()

print(f"\nTraining Summary:")
print(f"Accuracy improved from {accuracy_history[0]:.2f}% to
{accuracy_history[-1]:.2f}%")
print(f"Loss decreased from {loss_history[0]:.6f} to {loss_history[-1]:.6f}")
```




```
Training Summary:
Accuracy improved from 85.89% to 97.30%
Loss decreased from 0.692924 to 0.089772
```

In [14]:
```
# Plot ROC AUC Curve
from sklearn.metrics import roc_curve, auc, roc_auc_score

# Get probability predictions on training data
y_pred_proba, _ = forward_pass(X_penguin, trained_params['W1'], trained_params['b1'],
                               trained_params['W2'], trained_params['b2'])

# Calculate ROC curve
fpr, tpr, thresholds = roc_curve(y_penguin, y_pred_proba)
roc_auc = auc(fpr, tpr)

# Plot ROC Curve
plt.figure(figsize=(10, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC =
{roc_auc:.3f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--', label='Random
Classifier')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate', fontsize=12)
plt.ylabel('True Positive Rate', fontsize=12)
plt.title('ROC Curve - Penguin Classification (Adelie vs Others)', fontsize=14,
fontweight='bold')
plt.legend(loc="lower right", fontsize=11)
plt.grid(True, alpha=0.3)
plt.show()

print(f"\nROC AUC Score: {roc_auc:.4f}")
print(f"Model Performance: {'Excellent' if roc_auc >= 0.9 else 'Good' if roc_auc >=
0.8 else 'Fair' if roc_auc >= 0.7 else 'Poor'}")
```




```
ROC AUC Score: 0.9986
Model Performance: Excellent
```

- Use alpaca dataset
- CNN must include : Convolution layer, Pooling layer, Flatten layer,Dense layer Plot:
- Accuracy vs Epochs
- Loss (Error) vs Epochs

In [1]:
```
import numpy as np
import pandas as pd
import tensorflow as tf
```

```
2026-01-06 12:23:41.172195: I tensorflow/core/util/port.cc:153] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn
them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2026-01-06 12:23:41.179381: E external/local_xla/xla/stream_executor/cuda/
cuda_fft.cc:467] Unable to register cuFFT factory: Attempting to register
factory for plugin cuFFT when one has already been registered
WARNING: All log messages before absl::InitializeLog() is called are written
to STDERR
E0000 00:00:1767682421.187776  206804 cuda_dnn.cc:8579] Unable to register
cuDNN factory: Attempting to register factory for plugin cuDNN when one has
already been registered
E0000 00:00:1767682421.190384  206804 cuda_blas.cc:1407] Unable to register
cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has
already been registered
W0000 00:00:1767682421.197014  206804 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767682421.197024  206804 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767682421.197025  206804 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767682421.197026  206804 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
2026-01-06 12:23:41.199380: I tensorflow/core/platform/
cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use
available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operations,
rebuild TensorFlow with the appropriate compiler flags.
```

In [2]:
```
from tensorflow.keras.preprocessing import image_dataset_from_directory
```

In [3]:
```
train_dataset = image_dataset_from_directory(
    'Data/alpaca_dataset',
    image_size=(224, 224),
    batch_size=32,
    label_mode='int'
)

classes = train_dataset.class_names
print("Classes:", classes)
```

```
Found 327 files belonging to 2 classes.


I0000 00:00:1767682422.589972  206804 gpu_device.cc:2019] Created device /
job:localhost/replica:0/task:0/device:GPU:0 with 9279 MB memory:  -> device:
0, name: NVIDIA GeForce RTX 4070 SUPER, pci bus id: 0000:01:00.0, compute
capability: 8.9


Classes: ['alpaca', 'not alpaca']
```

In [4]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Conv2D, MaxPooling2D, Flatten
from tensorflow.keras.optimizers import Adam
```

In [5]:
```
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(224, 224, 3)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(2, activation='softmax')
])
```

```
/home/smayan/Desktop/AI-ML-DS/AI-and-ML-Course/.conda/lib/python3.11/site-
packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

In [6]:
```
model.compile(optimizer=Adam(), loss='sparse_categorical_crossentropy',
metrics=['accuracy'])
```

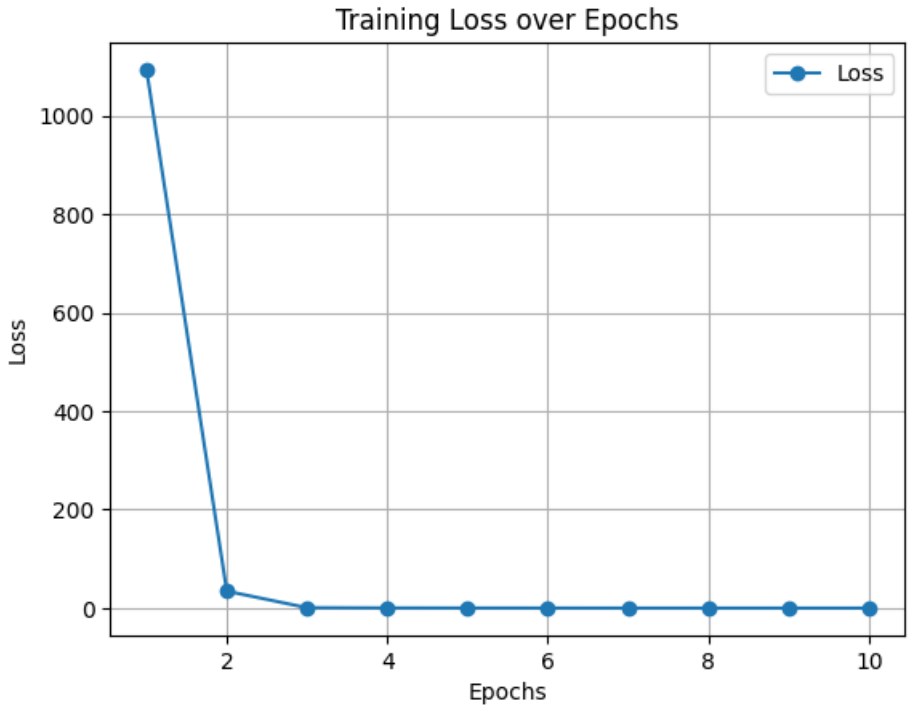
In [7]:
```
history = model.fit(train_dataset, epochs=10)
```

```
Epoch 1/10


 WARNING: All log messages before absl::InitializeLog() is called are written
 to STDERR
 I0000 00:00:1767682423.843951  207006 service.cc:152] XLA service
 0x71df94004d00 initialized for platform CUDA (this does not guarantee that
 XLA will be used). Devices:
 I0000 00:00:1767682423.843972  207006 service.cc:160]   StreamExecutor device
 (0): NVIDIA GeForce RTX 4070 SUPER, Compute Capability 8.9
 2026-01-06 12:23:43.861862: I tensorflow/compiler/mlir/tensorflow/utils/
 dump_mlir_util.cc:269] disabling MLIR crash reproducer, set env var
 `MLIR_CRASH_REPRODUCER_DIRECTORY` to enable.
 I0000 00:00:1767682423.938833  207006 cuda_dnn.cc:529] Loaded cuDNN version
 91701
 2026-01-06 12:23:44.296093: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_250', 4 bytes spill stores, 4 bytes spill
 loads


[1m 5/11[0m [32m━━━━━━━━━[0m[37m━━━━━━━━━━[0m [1m0s[0m 27ms/step - accuracy:
0.5316 - loss: 2149.7764

 I0000 00:00:1767682426.530325  207006 device_compiler.h:188] Compiled cluster
 using XLA!  This line is logged at most once for the lifetime of the process.

[1m11/11[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 147ms/step - accuracy:
0.5224 - loss: 1635.4093
Epoch 2/10
[1m11/11[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
0.5299 - loss: 45.5631
Epoch 3/10
[1m11/11[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
0.7813 - loss: 1.1301
Epoch 4/10
[1m11/11[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
0.9137 - loss: 0.2633
Epoch 5/10
[1m11/11[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 24ms/step - accuracy:
0.9923 - loss: 0.1484
Epoch 6/10
[1m11/11[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 25ms/step - accuracy:
0.9896 - loss: 0.1012
Epoch 7/10
[1m11/11[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 24ms/step - accuracy:
1.0000 - loss: 0.0403
Epoch 8/10
[1m11/11[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
0.9958 - loss: 0.0160
Epoch 9/10
[1m11/11[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
1.0000 - loss: 0.0035
Epoch 10/10
[1m11/11[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
1.0000 - loss: 0.0015
```

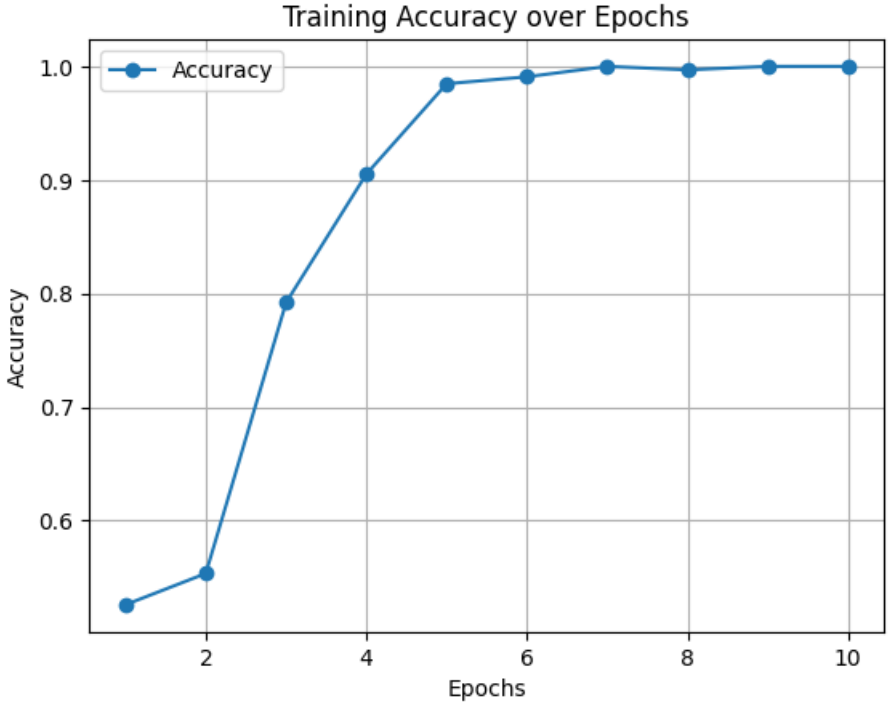
In [8]:
```
losses = history.history['loss']
accuracies = history.history['accuracy']
```

In [9]:
```
x = np.arange(1, len(losses) + 1)
```

In [13]:
```
import matplotlib.pyplot as plt
plt.plot(x, losses, label='Loss', marker='o')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training Loss over Epochs')
plt.legend()
plt.grid()
plt.show()
```



In [14]:
```
plt.plot(x, accuracies, label='Accuracy', marker='o')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Training Accuracy over Epochs')
plt.legend()
plt.grid()
plt.show()
```



In [ ]:

1. Load the Corn 3-Classes image dataset.
2. Preprocess the images: \
a. Resize images to a fixed size (e.g., 224×224) \
b. Normalize pixel values.
3. Split the dataset into training and testing sets.
4. Create a CNN model using: \
a. Convolution layer \
b. Max Pooling layer \
c. Flatten layer \
d. Dense layer
5. Train the CNN model for multi-class classification.
6. Test the model on unseen images.
7. Plot graphs: \
a. Training vs Validation Accuracy \
b. Training vs Validation Loss (Error)

In [1]:
```
import numpy as np
import pandas as pd
import tensorflow as tf
```

```
2026-01-06 12:39:09.095358: I tensorflow/core/util/port.cc:153] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn
them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2026-01-06 12:39:09.102589: E external/local_xla/xla/stream_executor/cuda/
cuda_fft.cc:467] Unable to register cuFFT factory: Attempting to register
factory for plugin cuFFT when one has already been registered
WARNING: All log messages before absl::InitializeLog() is called are written
to STDERR
E0000 00:00:1767683349.111243  227125 cuda_dnn.cc:8579] Unable to register
cuDNN factory: Attempting to register factory for plugin cuDNN when one has
already been registered
E0000 00:00:1767683349.113840  227125 cuda_blas.cc:1407] Unable to register
cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has
already been registered
W0000 00:00:1767683349.120493  227125 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767683349.120504  227125 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767683349.120505  227125 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767683349.120506  227125 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
2026-01-06 12:39:09.122645: I tensorflow/core/platform/
cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use
available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operations,
rebuild TensorFlow with the appropriate compiler flags.
```

In [2]:
```
from tensorflow.keras.preprocessing import image_dataset_from_directory
```

In [ ]:
```
train_dataset = image_dataset_from_directory(
    'Data/Corn_3_Classes_Image_Dataset',
    image_size=(224, 224),
    batch_size=32,
    label_mode='int',
    validation_split=0.2,
    subset='training',
    seed=123
)

val_dataset = image_dataset_from_directory(
    'Data/Corn_3_Classes_Image_Dataset',
    image_size=(224, 224),
    batch_size=32,
    label_mode='int',
    validation_split=0.2,
    subset='validation',
    seed=123
)

classes = train_dataset.class_names
print("Classes:", classes)
```

```
Found 1050 files belonging to 3 classes.
Using 840 files for training.


I0000 00:00:1767683350.500896  227125 gpu_device.cc:2019] Created device /
job:localhost/replica:0/task:0/device:GPU:0 with 9286 MB memory:  -> device:
0, name: NVIDIA GeForce RTX 4070 SUPER, pci bus id: 0000:01:00.0, compute
capability: 8.9


Found 1050 files belonging to 3 classes.
Using 210 files for validation.
Classes: ['Zea_mays_Chulpi_Cancha', 'Zea_mays_Indurata', 'Zea_mays_Rugosa']
```

In [4]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Conv2D, MaxPooling2D, Flatten ,
BatchNormalization
from tensorflow.keras.optimizers import Adam
```

In [5]:
```
model = Sequential([
    tf.keras.layers.Input(shape=(224, 224, 3)),
    tf.keras.layers.Rescaling(1./255),
    Conv2D(32, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(len(classes), activation='softmax')
])
```

In [6]:
```
model.compile(optimizer=Adam(), loss='sparse_categorical_crossentropy',
metrics=['accuracy'])
```

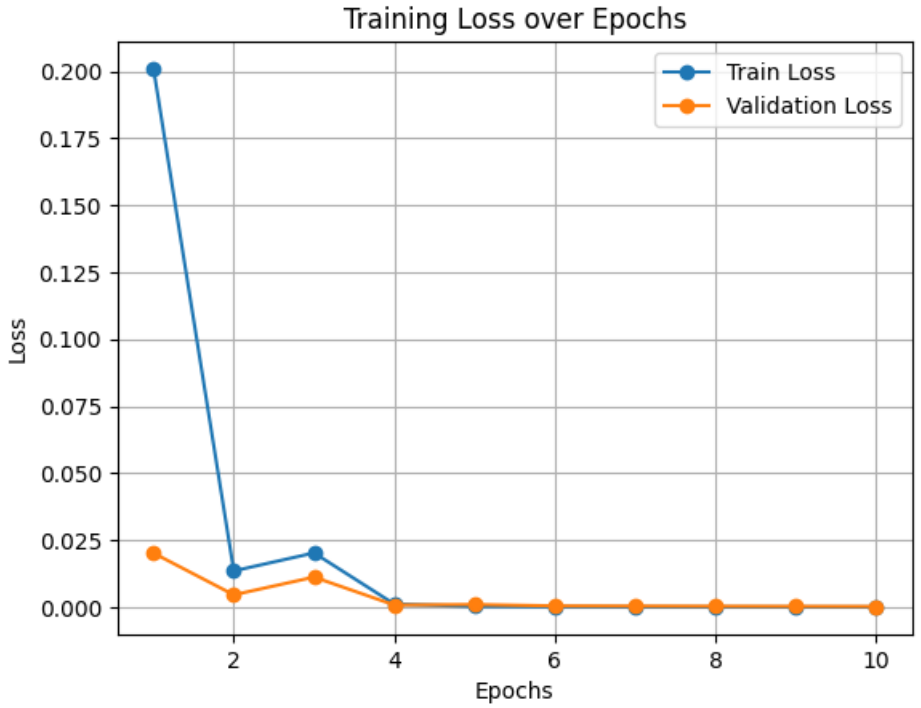
In [7]:
```
history = model.fit(train_dataset, validation_data=val_dataset, epochs=10)
```

```
Epoch 1/10


 WARNING: All log messages before absl::InitializeLog() is called are written
 to STDERR
 I0000 00:00:1767683351.776831  227337 service.cc:152] XLA service
 0x7f1c8400bae0 initialized for platform CUDA (this does not guarantee that
 XLA will be used). Devices:
 I0000 00:00:1767683351.776852  227337 service.cc:160]   StreamExecutor device
 (0): NVIDIA GeForce RTX 4070 SUPER, Compute Capability 8.9
 2026-01-06 12:39:11.791202: I tensorflow/compiler/mlir/tensorflow/utils/
 dump_mlir_util.cc:269] disabling MLIR crash reproducer, set env var
 `MLIR_CRASH_REPRODUCER_DIRECTORY` to enable.
 I0000 00:00:1767683351.865194  227337 cuda_dnn.cc:529] Loaded cuDNN version
 91701


[1m 5/27[0m [32m━━[0m[37m━━━━━━━━━━━━━━━━━[0m [1m0s[0m 25ms/step - accuracy:
0.5364 - loss: 0.9860


 I0000 00:00:1767683354.483140  227337 device_compiler.h:188] Compiled cluster
 using XLA!  This line is logged at most once for the lifetime of the process.


[1m27/27[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 71ms/step - accuracy:
0.8236 - loss: 0.4718


 2026-01-06 12:39:17.292341: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_72', 4 bytes spill stores, 4 bytes spill
 loads



[1m27/27[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m6s[0m 127ms/step - accuracy:
0.8277 - loss: 0.4622 - val_accuracy: 0.9857 - val_loss: 0.0202
Epoch 2/10
[1m27/27[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 25ms/step - accuracy:
0.9961 - loss: 0.0114 - val_accuracy: 0.9952 - val_loss: 0.0046
Epoch 3/10
[1m27/27[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 25ms/step - accuracy:
0.9960 - loss: 0.0198 - val_accuracy: 0.9952 - val_loss: 0.0112
Epoch 4/10
[1m27/27[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 25ms/step - accuracy:
1.0000 - loss: 0.0011 - val_accuracy: 1.0000 - val_loss: 8.0215e-04
Epoch 5/10
[1m27/27[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 25ms/step - accuracy:
1.0000 - loss: 4.6605e-04 - val_accuracy: 1.0000 - val_loss: 9.8933e-04
Epoch 6/10
[1m27/27[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 26ms/step - accuracy:
1.0000 - loss: 1.0943e-04 - val_accuracy: 1.0000 - val_loss: 4.7261e-04
Epoch 7/10
[1m27/27[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 25ms/step - accuracy:
1.0000 - loss: 4.5000e-05 - val_accuracy: 1.0000 - val_loss: 4.1222e-04
Epoch 8/10
[1m27/27[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 26ms/step - accuracy:
1.0000 - loss: 3.7742e-05 - val_accuracy: 1.0000 - val_loss: 3.5011e-04
Epoch 9/10
[1m27/27[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 25ms/step - accuracy:
1.0000 - loss: 2.1122e-05 - val_accuracy: 1.0000 - val_loss: 3.0246e-04
Epoch 10/10
[1m27/27[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 26ms/step - accuracy:
1.0000 - loss: 2.3673e-05 - val_accuracy: 1.0000 - val_loss: 2.6323e-04
```

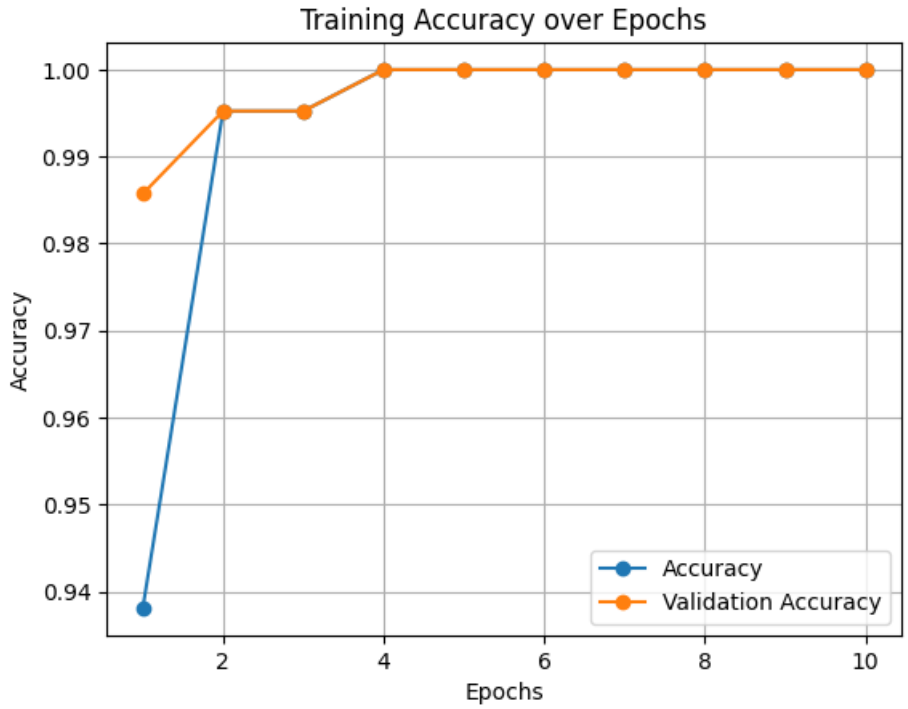
In [8]:
```
train_losses = history.history['loss']
train_accuracies = history.history['accuracy']

val_losses = history.history['val_loss']
val_accuracies = history.history['val_accuracy']
```

In [10]:
```
x = np.arange(1, len(train_losses) + 1)
```

In [11]:
```
import matplotlib.pyplot as plt
plt.plot(x, train_losses, label='Train Loss', marker='o')
plt.plot(x, val_losses, label='Validation Loss', marker='o')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training Loss over Epochs')
plt.legend()
plt.grid()
plt.show()
```



In [12]:
```
plt.plot(x, train_accuracies, label='Accuracy', marker='o')
plt.plot(x, val_accuracies, label='Validation Accuracy', marker='o')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Training Accuracy over Epochs')
plt.legend()
plt.grid()
plt.show()
```



In [ ]:
```

```

Task 1

Implement the NAND Boolean Logic Gate using a Perceptron Neural Network.
- Inputs: x1, x2, bias
- Train using perceptron learning rule
- Output: y
- Display final weights and bias
- Verify truth table results

In [152]:
```
import numpy as np
import tensorflow as tf
import pandas as pd
```

In [153]:
```
X = np.array([[0,0],[0,1],[1,1],[1,0]])
```

In [154]:
```
y = np.array([1,1,0,1])
```

In [155]:
```
weights = np.random.rand(2,1)
bias = np.random.rand(1)
```

In [156]:
```
def sigmoid(x):
    return 1 / (1 + np.exp(-x))
```

In [157]:
```
def perceptron(X, weights, bias):
    z = np.dot(X,weights) + bias
    a = sigmoid(z)
    return a
```

In [158]:
```
w = np.random.rand(2)
b = np.random.rand(1)

epochs = 50
learning_rate = 0.1

for epoch in range(epochs):
    for i in range(X.shape[0]):
        y_pred = perceptron(X[i], w, b)
        error = y[i] - y_pred
        w += learning_rate * error * X[i]
        b += learning_rate * error

print("Trained weights:", w)
print("Trained bias:", b)
```

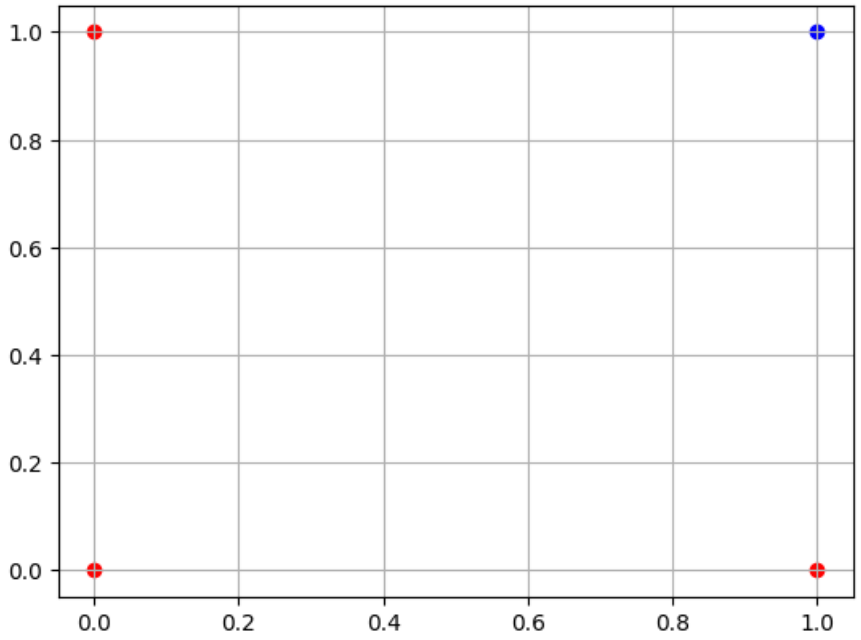
```
Trained weights: [-0.90287604 -0.95202605]
Trained bias: [1.77487895]
```

In [159]:
```
def step(x):
    return 1 if x >= 0.5 else 0
```

In [160]:
```
print("\nPredictions:")
for i in range(len(X)):
    z = np.dot(w, X[i]) + b
    print(f"Input: {X[i]} → Output:", step(sigmoid(z)))
```

```
Predictions:
Input: [0 0] → Output: 1
Input: [0 1] → Output: 1
Input: [1 1] → Output: 0
Input: [1 0] → Output: 1
```

In [161]:
```
import matplotlib.pyplot as plt
for i in range(len(X)):
    plt.scatter(X[i][0], X[i][1], c='r' if y[i] == 1 else 'b')
plt.grid()
```



Task 2

Use the Iris Dataset
- Normalize the input features
- Perform Min–Max scaling
- Visualize original vs normalized features

Load Iris Dataset

In [162]:
```
# Standardization (Normalization) - mean=0, std=1
import seaborn as sns
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler, MinMaxScaler

# Load Iris dataset
iris = load_iris()
X_original = pd.DataFrame(iris.data, columns=iris.feature_names)

print("Original Iris Dataset:")
print(X_original.head())
print(f"\nShape: {X_original.shape}")
print(f"\nStatistics:\n{X_original.describe()}")

print("\n" + "="*70 + "\n")

scaler_standard = StandardScaler()
X_normalized = pd.DataFrame(
    scaler_standard.fit_transform(X_original),
    columns=X_original.columns
)

print("Normalized Dataset (Standardization):")
print(X_normalized.head())
print(f"\nStatistics:\n{X_normalized.describe()}")
```

```
Original Iris Dataset:
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)
0                5.1               3.5                1.4               0.2
1                4.9               3.0                1.4               0.2
2                4.7               3.2                1.3               0.2
3                4.6               3.1                1.5               0.2
4                5.0               3.6                1.4               0.2

Shape: (150, 4)

Statistics:
       sepal length (cm)  sepal width (cm)  petal length (cm)  \
count         150.000000        150.000000         150.000000
mean            5.843333          3.057333           3.758000
std             0.828066          0.435866           1.765298
min             4.300000          2.000000           1.000000
25%             5.100000          2.800000           1.600000
50%             5.800000          3.000000           4.350000
75%             6.400000          3.300000           5.100000
max             7.900000          4.400000           6.900000

       petal width (cm)
count        150.000000
mean           1.199333
std            0.762238
min            0.100000
25%            0.300000
50%            1.300000
75%            1.800000
max            2.500000

======================================================================

Normalized Dataset (Standardization):
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)
0          -0.900681          1.019004          -1.340227         -1.315444
1          -1.143017         -0.131979          -1.340227         -1.315444
2          -1.385353          0.328414          -1.397064         -1.315444
3          -1.506521          0.098217          -1.283389         -1.315444
4          -1.021849          1.249201          -1.340227         -1.315444

Statistics:
       sepal length (cm)  sepal width (cm)  petal length (cm)  \
```

```
count       1.500000e+02      1.500000e+02       1.500000e+02
mean       -1.468455e-15     -1.823726e-15      -1.610564e-15
std         1.003350e+00      1.003350e+00       1.003350e+00
min        -1.870024e+00     -2.433947e+00      -1.567576e+00
25%        -9.006812e-01     -5.923730e-01      -1.226552e+00
50%        -5.250608e-02     -1.319795e-01       3.364776e-01
75%         6.745011e-01      5.586108e-01       7.627583e-01
max         2.492019e+00      3.090775e+00       1.785832e+00

       petal width (cm)
count      1.500000e+02
mean      -9.473903e-16
std        1.003350e+00
min       -1.447076e+00
25%       -1.183812e+00
50%        1.325097e-01
75%        7.906707e-01
max        1.712096e+00
```

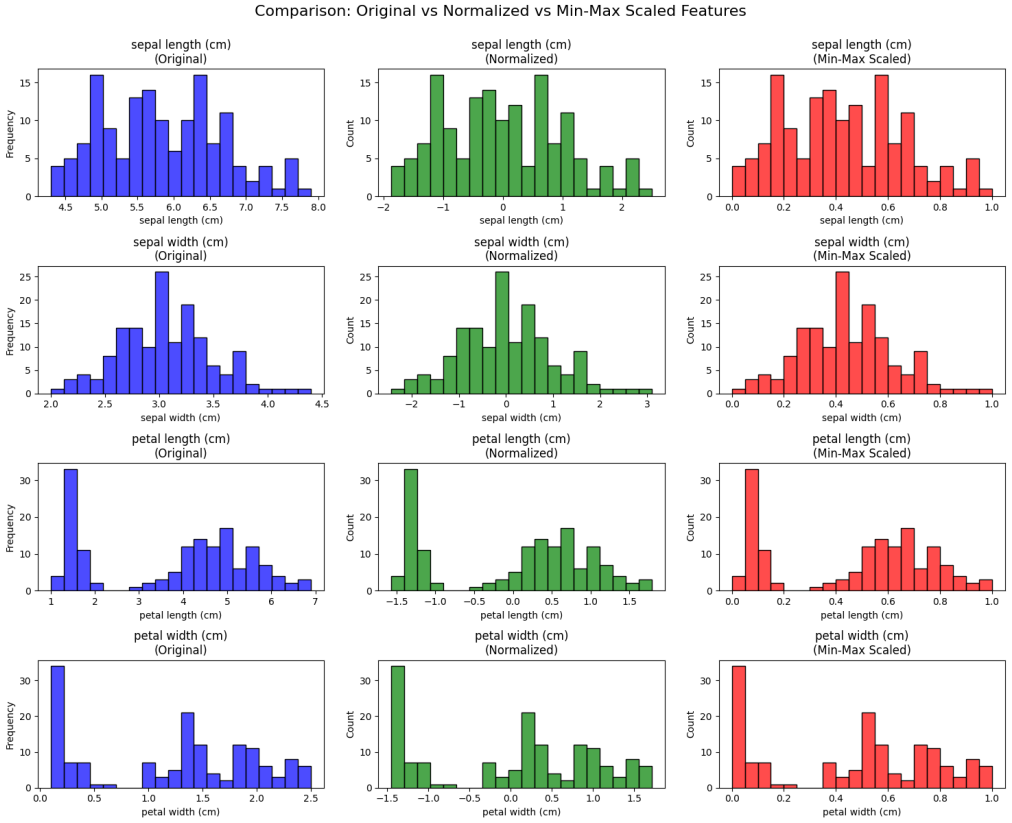
In [163]:
```
# Min-Max Scaling - scale to [0, 1] range
scaler_minmax = MinMaxScaler()
X_minmax = pd.DataFrame(
    scaler_minmax.fit_transform(X_original),
    columns=X_original.columns
)

print("Min-Max Scaled Dataset:")
print(X_minmax.head())
print(f"\nStatistics:\n{X_minmax.describe()}")
```

```
Min-Max Scaled Dataset:
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)
0           0.222222          0.625000           0.067797          0.041667
1           0.166667          0.416667           0.067797          0.041667
2           0.111111          0.500000           0.050847          0.041667
3           0.083333          0.458333           0.084746          0.041667
4           0.194444          0.666667           0.067797          0.041667

Statistics:
       sepal length (cm)  sepal width (cm)  petal length (cm)  \
count         150.000000        150.000000         150.000000
mean            0.428704          0.440556           0.467458
std             0.230018          0.181611           0.299203
min             0.000000          0.000000           0.000000
25%             0.222222          0.333333           0.101695
50%             0.416667          0.416667           0.567797
75%             0.583333          0.541667           0.694915
max             1.000000          1.000000           1.000000

       petal width (cm)
count        150.000000
mean           0.458056
std            0.317599
min            0.000000
25%            0.083333
50%            0.500000
75%            0.708333
max            1.000000
```

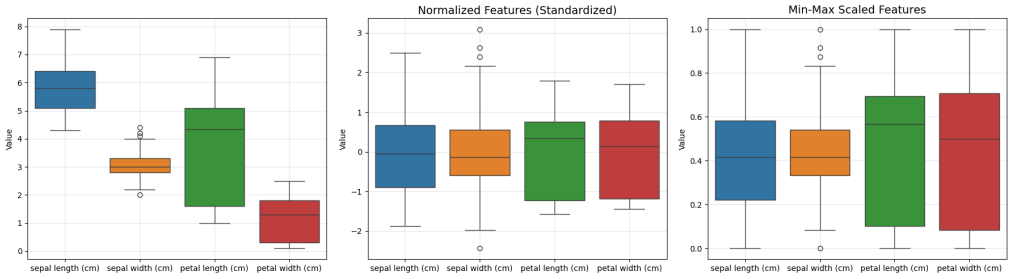
Visualize Original vs Normalized Features

In [164]:

```
# Visualize distributions for all features
fig, axes = plt.subplots(4, 3, figsize=(15, 12))
fig.suptitle('Comparison: Original vs Normalized vs Min-Max Scaled Features',
fontsize=16, y=1.00)

for i, feature in enumerate(X_original.columns):
    # Original
    sns.histplot(X_original[feature], bins=20, color='blue', alpha=0.7,
edgecolor='black', ax=axes[i, 0])
    axes[i, 0].set_title(f'{feature}\n(Original)')
    axes[i, 0].set_ylabel('Frequency')

    # Normalized (Standardized)
    sns.histplot(X_normalized[feature], bins=20, color='green', alpha=0.7,
edgecolor='black', ax=axes[i, 1])
    axes[i, 1].set_title(f'{feature}\n(Normalized)')

    # Min-Max Scaled
    sns.histplot(X_minmax[feature], bins=20, color='red', alpha=0.7,
edgecolor='black', ax=axes[i, 2])
    axes[i, 2].set_title(f'{feature}\n(Min-Max Scaled)')

plt.tight_layout()
plt.show()
```



In [165]:
```
# Box plots comparison
fig, axes = plt.subplots(1, 3, figsize=(18, 5))
import seaborn as sns

# Original
sns.boxplot(data=X_original, ax=axes[0])
axes[0].set_ylabel('Value')
axes[0].grid(True, alpha=0.3)

# Normalized
sns.boxplot(data=X_normalized, ax=axes[1])
axes[1].set_title('Normalized Features (Standardized)', fontsize=14)
axes[1].set_ylabel('Value')
axes[1].grid(True, alpha=0.3)

# Min-Max Scaled
sns.boxplot(data=X_minmax, ax=axes[2])
axes[2].set_title('Min-Max Scaled Features', fontsize=14)
axes[2].set_ylabel('Value')
axes[2].grid(True, alpha=0.3)

plt.tight_layout()
plt.show()
```



In [166]:

```
# Summary comparison
print("="*70)
print("COMPARISON SUMMARY")
print("="*70)

print("\n1. ORIGINAL DATA:")
print(f"   Range: [{X_original.min().min():.2f}, {X_original.max().max():.2f}]")
print(f"   Mean: {X_original.mean().mean():.2f}")
print(f"   Std: {X_original.std().mean():.2f}")

print("\n2. NORMALIZED (STANDARDIZED):")
print(f"   Range: [{X_normalized.min().min():.2f}, {X_normalized.max().max():.2f}]")
print(f"   Mean: {X_normalized.mean().mean():.2f}")
print(f"   Std: {X_normalized.std().mean():.2f}")

print("\n3. MIN-MAX SCALED:")
print(f"   Range: [{X_minmax.min().min():.2f}, {X_minmax.max().max():.2f}]")
print(f"   Mean: {X_minmax.mean().mean():.2f}")
print(f"   Std: {X_minmax.std().mean():.2f}")

print("\n" + "="*70)
```

```
======================================================================
COMPARISON SUMMARY
======================================================================

1. ORIGINAL DATA:
   Range: [0.10, 7.90]
   Mean: 3.46
   Std: 0.95

2. NORMALIZED (STANDARDIZED):
   Range: [-2.43, 3.09]
   Mean: -0.00
   Std: 1.00

3. MIN-MAX SCALED:
   Range: [0.00, 1.00]
   Mean: 0.45
   Std: 0.26

======================================================================
```

In [167]:
```
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler, MinMaxScaler

# Load Iris dataset
iris = load_iris()
X_original = pd.DataFrame(iris.data, columns=iris.feature_names)

print("Original Iris Dataset:")
print(X_original.head())
print(f"\nShape: {X_original.shape}")
print(f"\nStatistics:\n{X_original.describe()}")
```

```
Original Iris Dataset:
   sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)
0                5.1               3.5                1.4               0.2
1                4.9               3.0                1.4               0.2
2                4.7               3.2                1.3               0.2
3                4.6               3.1                1.5               0.2
4                5.0               3.6                1.4               0.2

Shape: (150, 4)

Statistics:
       sepal length (cm)  sepal width (cm)  petal length (cm)  \
count         150.000000        150.000000         150.000000
mean            5.843333          3.057333           3.758000
std             0.828066          0.435866           1.765298
min             4.300000          2.000000           1.000000
25%             5.100000          2.800000           1.600000
50%             5.800000          3.000000           4.350000
75%             6.400000          3.300000           5.100000
max             7.900000          4.400000           6.900000

       petal width (cm)
count        150.000000
mean           1.199333
std            0.762238
min            0.100000
25%            0.300000
50%            1.300000
75%            1.800000
max            2.500000
```

Implement XOR gate using 2-layer Neural Network

- Use Adadelta optimizer
- Plot accuracy vs epoch

In [29]:
```
import numpy as np
import tensorflow as tf
import pandas as pd
```

In [30]:
```
X = np.array([[0,0],[0,1],[1,1],[1,0]])
```

In [31]:
```
y = np.array([0,1,0,1])
```

In [32]:
```
w1 = np.random.rand(2,2)
b1 = np.random.rand(1)
w2 = np.random.rand(1,1)
b2 = np.random.rand(1)
```

In [33]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Input
```

In [34]:
```
model = Sequential([
    Input(shape=(2,)),
    Dense(2, activation='relu'),
    Dense(1, activation='sigmoid')
])
```

In [35]:
```
model.compile(optimizer='adadelta', loss='binary_crossentropy', metrics=['accuracy'])
```

In [36]:
```
history = model.fit(X, y, epochs=100)
```

```
Epoch 1/100

[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 417ms/step - accuracy:
0.7500 - loss: 0.8847
Epoch 2/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8847
Epoch 3/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 4/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 5/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 6/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 7/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 8/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 9/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 10/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 11/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 12/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 13/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 14/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 15/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 16/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 17/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 18/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 19/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 20/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 21/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 22/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
```

```
Epoch 23/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 24/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 25/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 26/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 27/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 28/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 29/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 30/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 31/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 32/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 33/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 34/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 35/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 36/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 37/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 38/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 39/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 40/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 41/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 42/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 43/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 44/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 45/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 46/100
```

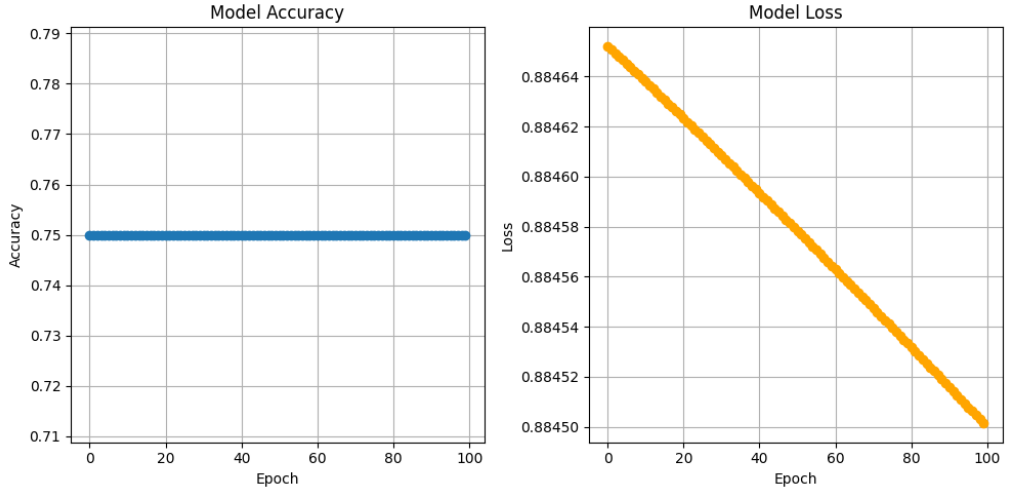
```
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 47/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 48/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 49/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 50/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 51/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 52/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 53/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 54/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 55/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 56/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 57/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 58/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 59/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 60/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 61/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 62/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 63/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 64/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 65/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 66/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 67/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 68/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8846
Epoch 69/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
```

```
0.7500 - loss: 0.8846
Epoch 70/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 71/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 72/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 73/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 74/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 75/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 25ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 76/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 77/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 78/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 79/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 80/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 81/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 82/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 83/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 84/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 85/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 86/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 87/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 88/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 19ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 89/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 90/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 91/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 92/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
0.7500 - loss: 0.8845
```

```
Epoch 93/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 94/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 95/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 20ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 96/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 24ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 97/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 21ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 98/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 23ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 99/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 29ms/step - accuracy:
0.7500 - loss: 0.8845
Epoch 100/100
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 31ms/step - accuracy:
0.7500 - loss: 0.8845
```

In [37]:

```
import matplotlib.pyplot as plt

# Plot accuracy vs epoch
plt.figure(figsize=(10, 5))

plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], marker='o')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.grid(True)

plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], marker='o', color='orange')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.grid(True)

plt.tight_layout()
plt.show()

# Test predictions
print("\n" + "="*40)
print("XOR Gate Predictions:")
print("="*40)
predictions = model.predict(X)
for i in range(len(X)):
    predicted = 1 if predictions[i] > 0.5 else 0
    print(f"Input: {X[i]} → Predicted: {predicted}, Actual: {y[i]}")
print("="*40)
```




```
========================================
XOR Gate Predictions:
========================================
[1m1/1[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 84ms/step
Input: [0 0] → Predicted: 0, Actual: 0
Input: [0 1] → Predicted: 1, Actual: 1
Input: [1 1] → Predicted: 1, Actual: 0
Input: [1 0] → Predicted: 1, Actual: 1
========================================
```

Use dataset with initial values X = [1.0, 2.0], Y = [0.5, 1.5]

- Initialize neural network with random weights
- Compute output using linear activation
- Calculate MAE and MSE
- Plot loss surface (weight vs loss)

Initialize dataset and neural network

In [38]:
```
# Dataset
X_data = np.array([1.0, 2.0])
Y_data = np.array([0.5, 1.5])

# Initialize random weights and bias
np.random.seed(42)
w = np.random.randn()
b = np.random.randn()

print("Dataset:")
print(f"X = {X_data}")
print(f"Y = {Y_data}")
print(f"\nInitial weights:")
print(f"w = {w:.4f}")
print(f"b = {b:.4f}")
```

```
Dataset:
X = [1. 2.]
Y = [0.5 1.5]

Initial weights:
w = 0.4967
b = -0.1383
```

Compute output using linear activation

In [39]:
```
# Linear activation: y = w*x + b
Y_pred = w * X_data + b

print("Predictions (Linear Activation):")
print(f"Y_pred = {Y_pred}")
print(f"\nActual:")
print(f"Y = {Y_data}")
```

```
Predictions (Linear Activation):
Y_pred = [0.35844985 0.855164  ]

Actual:
Y = [0.5 1.5]
```

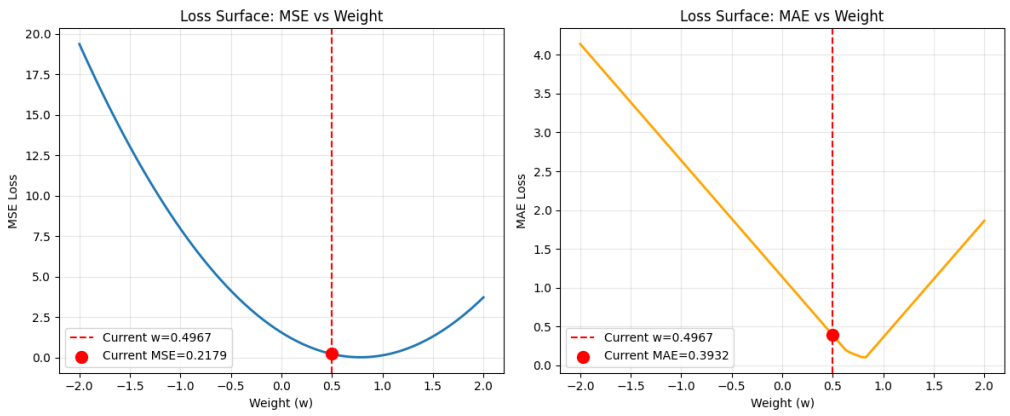
Calculate MAE and MSE

In [40]:
```
# Calculate errors
errors = Y_data - Y_pred

# Mean Absolute Error (MAE)
mae = np.mean(np.abs(errors))

# Mean Squared Error (MSE)
mse = np.mean(errors ** 2)

print("Error Metrics:")
print("="*40)
print(f"MAE (Mean Absolute Error): {mae:.4f}")
print(f"MSE (Mean Squared Error): {mse:.4f}")
print(f"RMSE (Root Mean Squared Error): {np.sqrt(mse):.4f}")
print("="*40)
```

```
Error Metrics:
========================================
MAE (Mean Absolute Error): 0.3932
MSE (Mean Squared Error): 0.2179
RMSE (Root Mean Squared Error): 0.4668
========================================
```

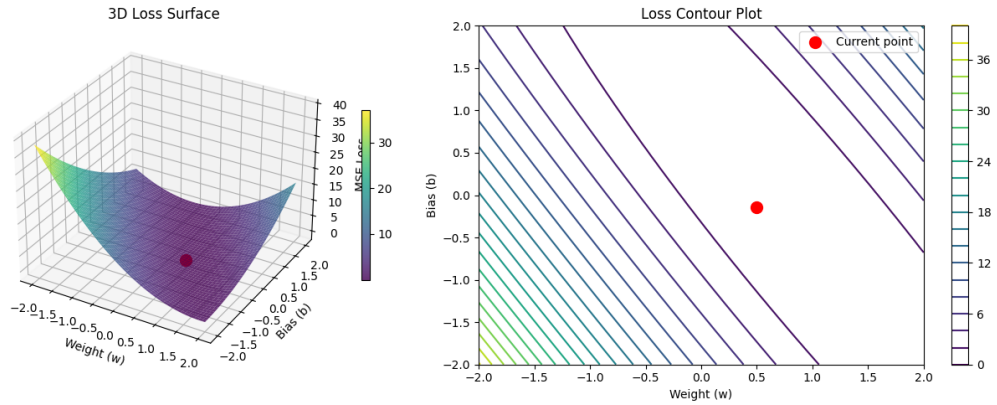
Plot loss surface (weight vs loss)

In [41]:
```
# Create a range of weight values
weights = np.linspace(-2, 2, 100)

# Calculate MSE for each weight value (keeping bias constant)
mse_values = []
for weight in weights:
    predictions = weight * X_data + b
    mse_val = np.mean((Y_data - predictions) ** 2)
    mse_values.append(mse_val)

# Plot loss surface
plt.figure(figsize=(12, 5))

# Plot 1: MSE vs Weight
plt.subplot(1, 2, 1)
plt.plot(weights, mse_values, linewidth=2)
plt.axvline(w, color='red', linestyle='--', label=f'Current w={w:.4f}')
plt.scatter([w], [mse], color='red', s=100, zorder=5, label=f'Current MSE={mse:.4f}')
plt.xlabel('Weight (w)')
plt.ylabel('MSE Loss')
plt.title('Loss Surface: MSE vs Weight')
plt.legend()
plt.grid(True, alpha=0.3)

# Plot 2: MAE vs Weight
mae_values = []
for weight in weights:
    predictions = weight * X_data + b
    mae_val = np.mean(np.abs(Y_data - predictions))
    mae_values.append(mae_val)

plt.subplot(1, 2, 2)
plt.plot(weights, mae_values, linewidth=2, color='orange')
plt.axvline(w, color='red', linestyle='--', label=f'Current w={w:.4f}')
plt.scatter([w], [mae], color='red', s=100, zorder=5, label=f'Current MAE={mae:.4f}')
plt.xlabel('Weight (w)')
plt.ylabel('MAE Loss')
plt.title('Loss Surface: MAE vs Weight')
plt.legend()
plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()
```



3D Loss Surface (Weight vs Bias vs Loss)

In [42]:
```
# Create mesh grid for weight and bias
w_range = np.linspace(-2, 2, 50)
b_range = np.linspace(-2, 2, 50)
W_grid, B_grid = np.meshgrid(w_range, b_range)

# Calculate MSE for each combination
MSE_grid = np.zeros_like(W_grid)
for i in range(W_grid.shape[0]):
    for j in range(W_grid.shape[1]):
        predictions = W_grid[i, j] * X_data + B_grid[i, j]
        MSE_grid[i, j] = np.mean((Y_data - predictions) ** 2)

# Create 3D surface plot
from mpl_toolkits.mplot3d import Axes3D

fig = plt.figure(figsize=(14, 5))

# 3D Surface
ax1 = fig.add_subplot(121, projection='3d')
surf = ax1.plot_surface(W_grid, B_grid, MSE_grid, cmap='viridis', alpha=0.8)
ax1.scatter([w], [b], [mse], color='red', s=100, label='Current point')
ax1.set_xlabel('Weight (w)')
ax1.set_ylabel('Bias (b)')
ax1.set_zlabel('MSE Loss')
ax1.set_title('3D Loss Surface')
fig.colorbar(surf, ax=ax1, shrink=0.5)

# Contour plot
ax2 = fig.add_subplot(122)
contour = ax2.contour(W_grid, B_grid, MSE_grid, levels=20, cmap='viridis')
ax2.scatter([w], [b], color='red', s=100, zorder=5, label='Current point')
ax2.set_xlabel('Weight (w)')
ax2.set_ylabel('Bias (b)')
ax2.set_title('Loss Contour Plot')
ax2.legend()
fig.colorbar(contour, ax=ax2)

plt.tight_layout()
plt.show()

print(f"\nCurrent position: w={w:.4f}, b={b:.4f}, MSE={mse:.4f}")
```




```
Current position: w=0.4967, b=-0.1383, MSE=0.2179
```

Fashion-MNIST Classification

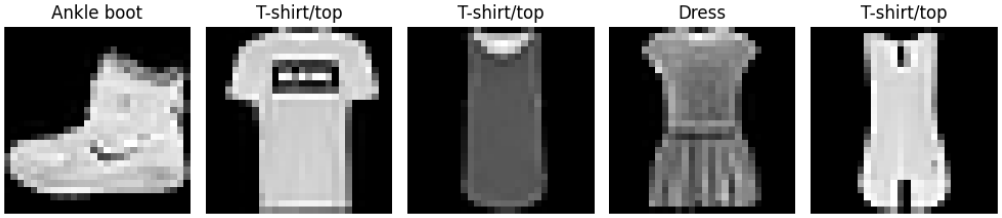
- CNN with RMSProp & Adam
- Compare confusion matrices

In [43]:
```
from tensorflow.keras.datasets import fashion_mnist
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten
from tensorflow.keras.optimizers import RMSprop, Adam
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns

# Load Fashion-MNIST dataset
(train_images, train_labels), (test_images, test_labels) = fashion_mnist.load_data()

# Class names for Fashion-MNIST
class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
               'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']

print(f"Training set shape: {train_images.shape}")
print(f"Test set shape: {test_images.shape}")
print(f"Number of classes: {len(class_names)}")
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/train-labels-idx1-ubyte.gz
[1m29515/29515[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/train-images-idx3-ubyte.gz
[1m26421880/26421880[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/t10k-labels-idx1-ubyte.gz
[1m5148/5148[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 0us/step
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-
datasets/t10k-images-idx3-ubyte.gz
[1m4422102/4422102[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 0us/step
Training set shape: (60000, 28, 28)
Test set shape: (10000, 28, 28)
Number of classes: 10
```

Preprocess data

In [44]:
```
# Normalize pixel values to [0, 1]
train_images = train_images.astype("float32") / 255.0
test_images = test_images.astype("float32") / 255.0

# Get image dimensions
img_size = train_images.shape[1]
num_classes = len(class_names)

# Display sample images
plt.figure(figsize=(10, 4))
for i in range(5):
    plt.subplot(1, 5, i+1)
    plt.imshow(train_images[i], cmap='gray')
    plt.title(f'{class_names[train_labels[i]]}')
    plt.axis('off')
plt.tight_layout()
plt.show()
```



Build and train CNN with Adam optimizer

In [45]:
```
adam_model = Sequential([
    Conv2D(32, kernel_size=(3,3), activation='relu', input_shape=(img_size, img_size,
1)),
    MaxPooling2D(pool_size=(2,2)),
    Conv2D(64, kernel_size=(3,3), activation='relu'),
    MaxPooling2D(pool_size=(2,2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(num_classes, activation='softmax')
])

adam_model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',
metrics=['accuracy'])
print("Training with Adam optimizer...")
adam_history = adam_model.fit(train_images, train_labels, epochs=10,
validation_split=0.2, verbose=1)
```

```
Training with Adam optimizer...
Epoch 1/10


 /home/smayan/Desktop/AI-ML-DS/AI-and-ML-Course/.conda/lib/python3.11/site-
 packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning: Do not
 pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
 models, prefer using an `Input(shape)` object as the first layer in the model
 instead.
   super().__init__(activity_regularizer=activity_regularizer, **kwargs)
 2026-01-06 14:56:50.423583: I external/local_xla/xla/stream_executor/cuda/
 subprocess_compilation.cc:346] ptxas warning : Registers are spilled to local
 memory in function 'gemm_fusion_dot_245', 4 bytes spill stores, 4 bytes spill
 loads


[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 1ms/step - accuracy:
0.7574 - loss: 0.6708 - val_accuracy: 0.8704 - val_loss: 0.3662
Epoch 2/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 953us/step -
accuracy: 0.8764 - loss: 0.3353 - val_accuracy: 0.8856 - val_loss: 0.3184
Epoch 3/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 918us/step -
accuracy: 0.8955 - loss: 0.2824 - val_accuracy: 0.8954 - val_loss: 0.2851
Epoch 4/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 894us/step -
accuracy: 0.9100 - loss: 0.2376 - val_accuracy: 0.8997 - val_loss: 0.2837
Epoch 5/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 915us/step -
accuracy: 0.9239 - loss: 0.2061 - val_accuracy: 0.9082 - val_loss: 0.2565
Epoch 6/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 853us/step -
accuracy: 0.9320 - loss: 0.1865 - val_accuracy: 0.9117 - val_loss: 0.2513
Epoch 7/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 893us/step -
accuracy: 0.9394 - loss: 0.1646 - val_accuracy: 0.9111 - val_loss: 0.2487
Epoch 8/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 885us/step -
accuracy: 0.9468 - loss: 0.1448 - val_accuracy: 0.9076 - val_loss: 0.2759
Epoch 9/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 905us/step -
accuracy: 0.9510 - loss: 0.1307 - val_accuracy: 0.9121 - val_loss: 0.2628
Epoch 10/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 892us/step -
accuracy: 0.9578 - loss: 0.1111 - val_accuracy: 0.9140 - val_loss: 0.2771
```

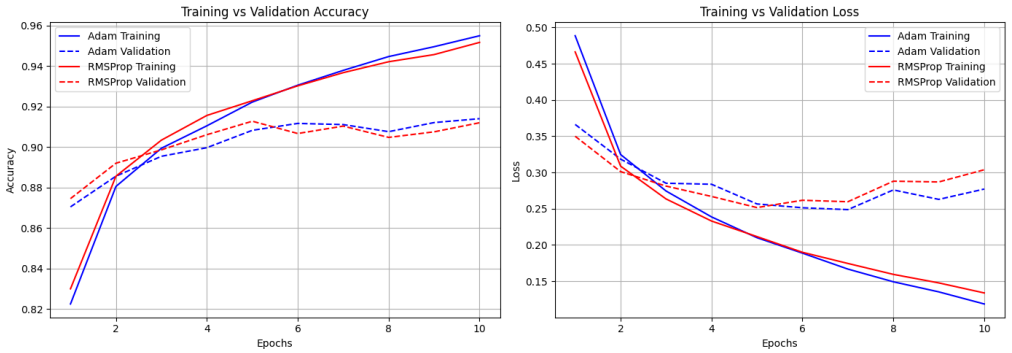
Build and train CNN with RMSProp optimizer

In [46]:
```
rmsprop_model = Sequential([
    Conv2D(32, kernel_size=(3,3), activation='relu', input_shape=(img_size, img_size,
1)),
    MaxPooling2D(pool_size=(2,2)),
    Conv2D(64, kernel_size=(3,3), activation='relu'),
    MaxPooling2D(pool_size=(2,2)),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(num_classes, activation='softmax')
])

rmsprop_model.compile(optimizer='rmsprop', loss='sparse_categorical_crossentropy',
metrics=['accuracy'])
print("Training with RMSProp optimizer...")
rmsprop_history = rmsprop_model.fit(train_images, train_labels, epochs=10,
validation_split=0.2, verbose=1)
```

```
Training with RMSProp optimizer...
Epoch 1/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.7667 - loss: 0.6443 - val_accuracy: 0.8745 - val_loss: 0.3499
Epoch 2/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 859us/step -
accuracy: 0.8819 - loss: 0.3174 - val_accuracy: 0.8920 - val_loss: 0.3011
Epoch 3/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 887us/step -
accuracy: 0.9011 - loss: 0.2667 - val_accuracy: 0.8986 - val_loss: 0.2811
Epoch 4/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 872us/step -
accuracy: 0.9133 - loss: 0.2390 - val_accuracy: 0.9061 - val_loss: 0.2669
Epoch 5/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 866us/step -
accuracy: 0.9230 - loss: 0.2129 - val_accuracy: 0.9128 - val_loss: 0.2515
Epoch 6/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 932us/step -
accuracy: 0.9309 - loss: 0.1889 - val_accuracy: 0.9067 - val_loss: 0.2616
Epoch 7/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 903us/step -
accuracy: 0.9386 - loss: 0.1684 - val_accuracy: 0.9103 - val_loss: 0.2596
Epoch 8/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 905us/step -
accuracy: 0.9443 - loss: 0.1539 - val_accuracy: 0.9047 - val_loss: 0.2879
Epoch 9/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 891us/step -
accuracy: 0.9470 - loss: 0.1424 - val_accuracy: 0.9075 - val_loss: 0.2869
Epoch 10/10
[1m1500/1500[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 901us/step -
accuracy: 0.9525 - loss: 0.1312 - val_accuracy: 0.9120 - val_loss: 0.3037
```

Compare training performance

In [47]:
```
# Extract history
adam_acc = adam_history.history['accuracy']
adam_val_acc = adam_history.history['val_accuracy']
adam_loss = adam_history.history['loss']
adam_val_loss = adam_history.history['val_loss']

rmsprop_acc = rmsprop_history.history['accuracy']
rmsprop_val_acc = rmsprop_history.history['val_accuracy']
rmsprop_loss = rmsprop_history.history['loss']
rmsprop_val_loss = rmsprop_history.history['val_loss']

epochs = range(1, len(adam_acc) + 1)

# Plot comparison
plt.figure(figsize=(14, 5))

# Accuracy comparison
plt.subplot(1, 2, 1)
plt.plot(epochs, adam_acc, 'b-', label='Adam Training')
plt.plot(epochs, adam_val_acc, 'b--', label='Adam Validation')
plt.plot(epochs, rmsprop_acc, 'r-', label='RMSProp Training')
plt.plot(epochs, rmsprop_val_acc, 'r--', label='RMSProp Validation')
plt.title('Training vs Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)

# Loss comparison
plt.subplot(1, 2, 2)
plt.plot(epochs, adam_loss, 'b-', label='Adam Training')
plt.plot(epochs, adam_val_loss, 'b--', label='Adam Validation')
plt.plot(epochs, rmsprop_loss, 'r-', label='RMSProp Training')
plt.plot(epochs, rmsprop_val_loss, 'r--', label='RMSProp Validation')
plt.title('Training vs Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)

plt.tight_layout()
plt.show()
```



Evaluate models on test set

In [48]:
```
# Evaluate Adam model
adam_test_loss, adam_test_acc = adam_model.evaluate(test_images, test_labels,
verbose=0)
print("Adam Model:")
print(f"  Test Accuracy: {adam_test_acc:.4f}")
print(f"  Test Loss: {adam_test_loss:.4f}")

# Evaluate RMSProp model
rmsprop_test_loss, rmsprop_test_acc = rmsprop_model.evaluate(test_images,
test_labels, verbose=0)
print("\nRMSProp Model:")
print(f"  Test Accuracy: {rmsprop_test_acc:.4f}")
print(f"  Test Loss: {rmsprop_test_loss:.4f}")
```

```
Adam Model:
  Test Accuracy: 0.9053
  Test Loss: 0.3123

RMSProp Model:
  Test Accuracy: 0.9120
  Test Loss: 0.3134
```

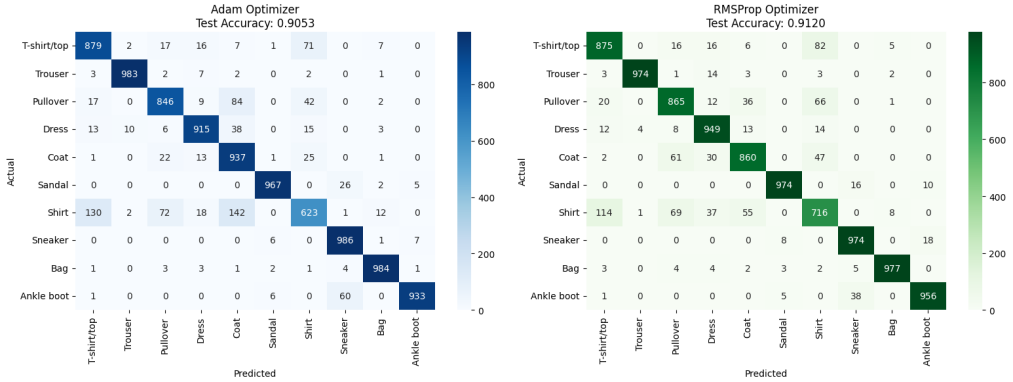
Generate predictions and confusion matrices

In [49]:
```
# Get predictions
adam_predictions = np.argmax(adam_model.predict(test_images), axis=1)
rmsprop_predictions = np.argmax(rmsprop_model.predict(test_images), axis=1)

# Generate confusion matrices
adam_cm = confusion_matrix(test_labels, adam_predictions)
rmsprop_cm = confusion_matrix(test_labels, rmsprop_predictions)

print("Predictions generated successfully!")
```

```
[1m313/313[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 958us/step
[1m313/313[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step
Predictions generated successfully!
```

Compare confusion matrices

In [50]:
```
# Plot confusion matrices side by side
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# Adam confusion matrix
sns.heatmap(adam_cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=class_names, yticklabels=class_names, ax=axes[0])
axes[0].set_title(f'Adam Optimizer\nTest Accuracy: {adam_test_acc:.4f}')
axes[0].set_xlabel('Predicted')
axes[0].set_ylabel('Actual')

# RMSProp confusion matrix
sns.heatmap(rmsprop_cm, annot=True, fmt='d', cmap='Greens',
            xticklabels=class_names, yticklabels=class_names, ax=axes[1])
axes[1].set_title(f'RMSProp Optimizer\nTest Accuracy: {rmsprop_test_acc:.4f}')
axes[1].set_xlabel('Predicted')
axes[1].set_ylabel('Actual')

plt.tight_layout()
plt.show()
```



Classification reports

In [51]:
```
print("="*70)
print("ADAM OPTIMIZER - CLASSIFICATION REPORT")
print("="*70)
print(classification_report(test_labels, adam_predictions, target_names=class_names))

print("\n" + "="*70)
print("RMSPROP OPTIMIZER - CLASSIFICATION REPORT")
print("="*70)
print(classification_report(test_labels, rmsprop_predictions,
target_names=class_names))

# Summary comparison
print("\n" + "="*70)
print("OPTIMIZER COMPARISON SUMMARY")
print("="*70)
print(f"Adam    - Test Accuracy: {adam_test_acc:.4f}, Test Loss:
{adam_test_loss:.4f}")
print(f"RMSProp - Test Accuracy: {rmsprop_test_acc:.4f}, Test Loss:
{rmsprop_test_loss:.4f}")
print("="*70)
```

```
======================================================================
ADAM OPTIMIZER - CLASSIFICATION REPORT
======================================================================
              precision    recall  f1-score   support

 T-shirt/top       0.84      0.88      0.86      1000
     Trouser       0.99      0.98      0.98      1000
    Pullover       0.87      0.85      0.86      1000
       Dress       0.93      0.92      0.92      1000
        Coat       0.77      0.94      0.85      1000
      Sandal       0.98      0.97      0.98      1000
       Shirt       0.80      0.62      0.70      1000
     Sneaker       0.92      0.99      0.95      1000
         Bag       0.97      0.98      0.98      1000
  Ankle boot       0.99      0.93      0.96      1000

    accuracy                           0.91     10000
   macro avg       0.91      0.91      0.90     10000
weighted avg       0.91      0.91      0.90     10000


======================================================================
RMSPROP OPTIMIZER - CLASSIFICATION REPORT
======================================================================
              precision    recall  f1-score   support

 T-shirt/top       0.85      0.88      0.86      1000
     Trouser       0.99      0.97      0.98      1000
    Pullover       0.84      0.86      0.85      1000
       Dress       0.89      0.95      0.92      1000
        Coat       0.88      0.86      0.87      1000
      Sandal       0.98      0.97      0.98      1000
       Shirt       0.77      0.72      0.74      1000
     Sneaker       0.94      0.97      0.96      1000
         Bag       0.98      0.98      0.98      1000
  Ankle boot       0.97      0.96      0.96      1000

    accuracy                           0.91     10000
   macro avg       0.91      0.91      0.91     10000
weighted avg       0.91      0.91      0.91     10000


======================================================================
OPTIMIZER COMPARISON SUMMARY
======================================================================
Adam    - Test Accuracy: 0.9053, Test Loss: 0.3123
RMSProp - Test Accuracy: 0.9120, Test Loss: 0.3134
======================================================================
```

Implement the backpropagation algorithm.

1. Take Iris Dataset
2. Initialize a neural network with random weights.
3. Calculate error
4. Perform multiple iterations of NN
5. Update weights accordingly.
6. Plot accuracy for iterations and note the results.

Step 1: Import libraries and load Iris dataset

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score

# Load Iris dataset
iris = load_iris()
X = iris.data  # Features (4 dimensions)
y = iris.target  # Labels (3 classes)

print(f"Dataset shape: {X.shape}")
print(f"Number of features: {X.shape[1]}")
print(f"Number of samples: {X.shape[0]}")
print(f"Number of classes: {len(np.unique(y))}")
```

```
Dataset shape: (150, 4)
Number of features: 4
Number of samples: 150
Number of classes: 3
```

Step 2: Preprocess data (normalize and split)

In [2]:
```
from sklearn.preprocessing import OneHotEncoder

# Normalize features to have mean 0 and std 1
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, random_state=42
)

# Convert labels to one-hot encoding (for 3 classes)
one_hot_encoder = OneHotEncoder(sparse_output=False)
def one_hot_encode(y, num_classes=3):
    """Convert class labels to one-hot encoding"""
    return one_hot_encoder.fit_transform(y.reshape(-1, 1))

y_train_encoded = one_hot_encode(y_train)
y_test_encoded = one_hot_encode(y_test)

print(f"Training set: {X_train.shape}")
print(f"Test set: {X_test.shape}")
print(f"One-hot encoded labels shape: {y_train_encoded.shape}")
```

```
Training set: (120, 4)
Test set: (30, 4)
One-hot encoded labels shape: (120, 3)
```

Step 3: Initialize neural network with random weights

In [3]:
```
# Network architecture
np.random.seed(42)
input_size = X_train.shape[1]    # 4 features
hidden_size = 8                  # Hidden layer neurons
output_size = 3                  # 3 classes

# Initialize weights with random values (Xavier initialization)
W1 = np.random.randn(input_size, hidden_size) * 0.01  # Input to hidden
b1 = np.zeros((1, hidden_size))                       # Hidden layer bias

W2 = np.random.randn(hidden_size, output_size) * 0.01 # Hidden to output
b2 = np.zeros((1, output_size))                       # Output layer bias

print("Network Architecture:")
print(f"  Input layer: {input_size} neurons")
print(f"  Hidden layer: {hidden_size} neurons")
print(f"  Output layer: {output_size} neurons")
print(f"\nWeight matrices shapes:")
print(f"  W1 (Input → Hidden): {W1.shape}")
print(f"  W2 (Hidden → Output): {W2.shape}")
```

```
Network Architecture:
  Input layer: 4 neurons
  Hidden layer: 8 neurons
  Output layer: 3 neurons

Weight matrices shapes:
  W1 (Input → Hidden): (4, 8)
  W2 (Hidden → Output): (8, 3)
```

Step 4: Define activation functions

In [4]:
```
# Activation functions
def sigmoid(z):
    """Sigmoid activation function"""
    return 1 / (1 + np.exp(-np.clip(z, -500, 500)))

def sigmoid_derivative(z):
    """Derivative of sigmoid"""
    return z * (1 - z)

def softmax(z):
    """Softmax activation for output layer"""
    exp_z = np.exp(z - np.max(z, axis=1, keepdims=True))
    return exp_z / np.sum(exp_z, axis=1, keepdims=True)

def relu(z):
    """ReLU activation function"""
    return np.maximum(0, z)

def relu_derivative(z):
    """Derivative of ReLU"""
    return (z > 0).astype(float)

print("Activation functions defined successfully!")
```

```
Activation functions defined successfully!
```

Step 5: Forward propagation

In [5]:
```
def forward_propagation(X, W1, b1, W2, b2):
    """
    Forward pass through the network

    Returns:
        z1, a1, z2, a2: Intermediate values needed for backprop
    """
    # Input to hidden layer
    z1 = np.dot(X, W1) + b1           # Linear transformation
    a1 = sigmoid(z1)                  # Sigmoid activation

    # Hidden to output layer
    z2 = np.dot(a1, W2) + b2          # Linear transformation
    a2 = softmax(z2)                  # Softmax activation (probabilities)

    return z1, a1, z2, a2

# Test forward propagation
z1_test, a1_test, z2_test, a2_test = forward_propagation(
    X_train[:1], W1, b1, W2, b2
)

print("Forward propagation test (single sample):")
print(f"  Hidden layer output shape: {a1_test.shape}")
print(f"  Output layer predictions: {a2_test}")
print(f"  Output probabilities sum to 1: {np.sum(a2_test):.4f}")
```

```
Forward propagation test (single sample):
  Hidden layer output shape: (1, 8)
  Output layer predictions: [[0.33296563 0.33530204 0.33173233]]
  Output probabilities sum to 1: 1.0000
```

Step 6: Calculate loss and accuracy

In [6]:
```
def calculate_loss(y_true, y_pred):
    """
    Cross-entropy loss function
    """
    m = y_true.shape[0]
    # Add small epsilon to avoid log(0)
    loss = -np.mean(np.sum(y_true * np.log(y_pred + 1e-8), axis=1))
    return loss

def calculate_accuracy(y_true, y_pred):
    """
    Accuracy: percentage of correct predictions
    """
    # Get predicted class (argmax)
    predictions = np.argmax(y_pred, axis=1)
    # Get true class
    true_labels = np.argmax(y_true, axis=1)
    # Calculate accuracy
    accuracy = np.mean(predictions == true_labels)
    return accuracy

# Test on initial weights
_, _, _, a2 = forward_propagation(X_train, W1, b1, W2, b2)
initial_loss = calculate_loss(y_train_encoded, a2)
initial_acc = calculate_accuracy(y_train_encoded, a2)

print(f"Initial Loss: {initial_loss:.4f}")
print(f"Initial Accuracy: {initial_acc:.4f}")
```

```
Initial Loss: 1.0986
Initial Accuracy: 0.3417
```

Step 7: Backward propagation (Backpropagation algorithm)

In [7]:
```
def backward_propagation(X, y, z1, a1, z2, a2, W1, W2):
    """
    Backward pass through the network (Backpropagation)

    Computes gradients of loss with respect to weights and biases
    """
    m = X.shape[0]

    # Output layer error
    dz2 = a2 - y  # Derivative of cross-entropy loss + softmax

    # Gradients for W2 and b2
    dW2 = np.dot(a1.T, dz2) / m
    db2 = np.sum(dz2, axis=0, keepdims=True) / m

    # Hidden layer error
    da1 = np.dot(dz2, W2.T)
    dz1 = da1 * sigmoid_derivative(a1)

    # Gradients for W1 and b1
    dW1 = np.dot(X.T, dz1) / m
    db1 = np.sum(dz1, axis=0, keepdims=True) / m

    return dW1, db1, dW2, db2

print("Backpropagation function defined successfully!")
```

```
Backpropagation function defined successfully!
```

Step 8: Update weights using gradient descent

In [8]:
```
def update_weights(W1, b1, W2, b2, dW1, db1, dW2, db2, learning_rate):
    """
    Update weights and biases using gradient descent

    New weight = Old weight - learning_rate * gradient
    """
    W1 = W1 - learning_rate * dW1
    b1 = b1 - learning_rate * db1
    W2 = W2 - learning_rate * dW2
    b2 = b2 - learning_rate * db2

    return W1, b1, W2, b2

print("Weight update function defined successfully!")
```

```
Weight update function defined successfully!
```

Step 9: Training loop with multiple iterations

In [9]:

```
# Training hyperparameters
learning_rate = 0.1
num_iterations = 100
batch_size = 20

# Reset weights
W1 = np.random.randn(input_size, hidden_size) * 0.01
b1 = np.zeros((1, hidden_size))
W2 = np.random.randn(hidden_size, output_size) * 0.01
b2 = np.zeros((1, output_size))

# Track metrics
train_losses = []
train_accuracies = []
test_accuracies = []

print("Training started...")
print(f"Learning rate: {learning_rate}")
print(f"Iterations: {num_iterations}")
print(f"Batch size: {batch_size}\n")

# Training loop
for iteration in range(num_iterations):
    # Mini-batch gradient descent
    indices = np.random.choice(len(X_train), batch_size)
    X_batch = X_train[indices]
    y_batch = y_train_encoded[indices]

    # Forward pass
    z1, a1, z2, a2 = forward_propagation(X_batch, W1, b1, W2, b2)

    # Calculate loss and accuracy
    loss = calculate_loss(y_batch, a2)
    train_losses.append(loss)

    # Backward pass
    dW1, db1, dW2, db2 = backward_propagation(X_batch, y_batch, z1, a1, z2, a2, W1,
W2)

    # Update weights
    W1, b1, W2, b2 = update_weights(W1, b1, W2, b2, dW1, db1, dW2, db2,
learning_rate)

    # Calculate accuracies on full sets (every 10 iterations)
    if iteration % 10 == 0:
        _, _, _, train_a2 = forward_propagation(X_train, W1, b1, W2, b2)
        train_acc = calculate_accuracy(y_train_encoded, train_a2)
        train_accuracies.append(train_acc)

        _, _, _, test_a2 = forward_propagation(X_test, W1, b1, W2, b2)
        test_acc = calculate_accuracy(y_test_encoded, test_a2)
        test_accuracies.append(test_acc)

        print(f"Iteration {iteration:3d} | Loss: {loss:.4f} | Train Acc:
{train_acc:.4f} | Test Acc: {test_acc:.4f}")

print("\nTraining completed!")
```

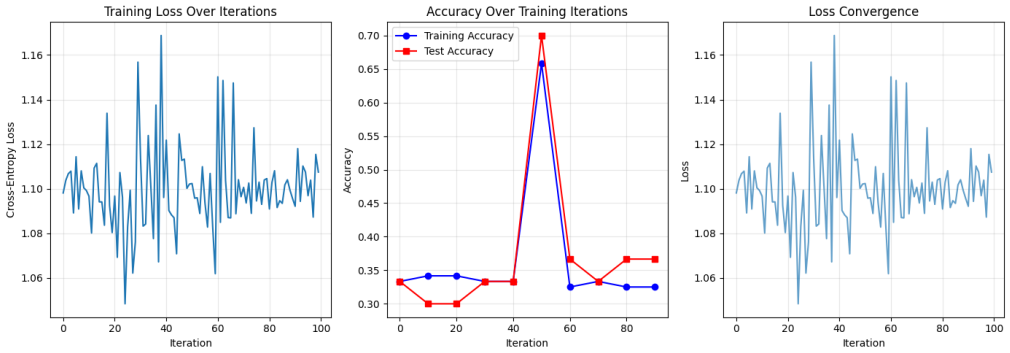
```
Training started...
Learning rate: 0.1
Iterations: 100
Batch size: 20

Iteration   0 | Loss: 1.0981 | Train Acc: 0.3333 | Test Acc: 0.3333
Iteration  10 | Loss: 1.0967 | Train Acc: 0.3417 | Test Acc: 0.3000
Iteration  20 | Loss: 1.0967 | Train Acc: 0.3417 | Test Acc: 0.3000
Iteration  30 | Loss: 1.1137 | Train Acc: 0.3333 | Test Acc: 0.3333
Iteration  40 | Loss: 1.1218 | Train Acc: 0.3333 | Test Acc: 0.3333
Iteration  50 | Loss: 1.1023 | Train Acc: 0.6583 | Test Acc: 0.7000
```

```
Iteration  60 | Loss: 1.1502 | Train Acc: 0.3250 | Test Acc: 0.3667
Iteration  70 | Loss: 1.1006 | Train Acc: 0.3333 | Test Acc: 0.3333
Iteration  80 | Loss: 1.0909 | Train Acc: 0.3250 | Test Acc: 0.3667
Iteration  90 | Loss: 1.0921 | Train Acc: 0.3250 | Test Acc: 0.3667

Training completed!
```

Step 10: Plot accuracy and loss for iterations

In [10]:

```
plt.figure(figsize=(14, 5))

# Plot 1: Loss over iterations
plt.subplot(1, 3, 1)
plt.plot(train_losses)
plt.title('Training Loss Over Iterations')
plt.xlabel('Iteration')
plt.ylabel('Cross-Entropy Loss')
plt.grid(True, alpha=0.3)

# Plot 2: Accuracy over iterations
plt.subplot(1, 3, 2)
iterations_points = list(range(0, num_iterations, 10))
plt.plot(iterations_points, train_accuracies, 'b-o', label='Training Accuracy',
markersize=6)
plt.plot(iterations_points, test_accuracies, 'r-s', label='Test Accuracy',
markersize=6)
plt.title('Accuracy Over Training Iterations')
plt.xlabel('Iteration')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True, alpha=0.3)

# Plot 3: Loss evolution
plt.subplot(1, 3, 3)
plt.plot(train_losses, alpha=0.7)
plt.title('Loss Convergence')
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.grid(True, alpha=0.3)

plt.tight_layout()
plt.show()
```



Step 11: Results and conclusions

In [11]:

```
# Final evaluation
_, _, _, final_train_pred = forward_propagation(X_train, W1, b1, W2, b2)
_, _, _, final_test_pred = forward_propagation(X_test, W1, b1, W2, b2)

final_train_acc = calculate_accuracy(y_train_encoded, final_train_pred)
final_test_acc = calculate_accuracy(y_test_encoded, final_test_pred)

print("\n" + "="*60)
print("BACKPROPAGATION ALGORITHM - RESULTS")
print("="*60)
print(f"\nNetwork Architecture:")
print(f"  Input Layer: {input_size} neurons")
print(f"  Hidden Layer: {hidden_size} neurons (Sigmoid activation)")
print(f"  Output Layer: {output_size} neurons (Softmax activation)")

print(f"\nTraining Configuration:")
print(f"  Learning Rate: {learning_rate}")
print(f"  Total Iterations: {num_iterations}")
print(f"  Batch Size: {batch_size}")

print(f"\nFinal Results:")
print(f"  Initial Train Accuracy: {initial_acc:.4f}")
print(f"  Final Train Accuracy:   {final_train_acc:.4f}")
print(f"  Final Test Accuracy:    {final_test_acc:.4f}")
print(f"  Improvement:            {final_train_acc - initial_acc:.4f}
({(final_train_acc - initial_acc)*100:.2f}%)")

print(f"\nKey Observations:")
print(f"  - Loss decreased from {train_losses[0]:.4f} to {train_losses[-1]:.4f}")
print(f"  - Training accuracy improved from {train_accuracies[0]:.4f} to
{train_accuracies[-1]:.4f}")
print(f"  - Test accuracy: {final_test_acc:.4f}")
print(f"  - Model successfully learned through backpropagation!")

print("="*60)
```

```
============================================================
BACKPROPAGATION ALGORITHM - RESULTS
============================================================

Network Architecture:
  Input Layer: 4 neurons
  Hidden Layer: 8 neurons (Sigmoid activation)
  Output Layer: 3 neurons (Softmax activation)

Training Configuration:
  Learning Rate: 0.1
  Total Iterations: 100
  Batch Size: 20

Final Results:
  Initial Train Accuracy: 0.3417
  Final Train Accuracy:   0.6750
  Final Test Accuracy:    0.6333
  Improvement:            0.3333 (33.33%)

Key Observations:
  - Loss decreased from 1.0981 to 1.1075
  - Training accuracy improved from 0.3333 to 0.3250
  - Test accuracy: 0.6333
  - Model successfully learned through backpropagation!
============================================================
```

In [ ]:

```
# Plot ROC AUC Curves for Multi-class Classification (One-vs-Rest)
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize
import numpy as np
import matplotlib.pyplot as plt

# Get predictions
_, _, _, train_pred_proba = forward_propagation(X_train, W1, b1, W2, b2)
_, _, _, test_pred_proba = forward_propagation(X_test, W1, b1, W2, b2)

# Binarize the output for multi-class ROC AUC
n_classes = 3
y_train_bin = label_binarize(np.argmax(y_train_encoded, axis=1),
classes=list(range(n_classes)))
y_test_bin = label_binarize(np.argmax(y_test_encoded, axis=1),
classes=list(range(n_classes)))

# Function to compute and plot ROC curves
def plot_iris_roc_curves(y_pred_proba, y_bin, dataset_name, iris_target_names):
    fpr = dict()
    tpr = dict()
    roc_auc_dict = dict()
    colors = plt.cm.Set1(np.linspace(0, 1, n_classes))

    plt.figure(figsize=(10, 8))

    for i in range(n_classes):
        fpr[i], tpr[i], _ = roc_curve(y_bin[:, i], y_pred_proba[:, i])
        roc_auc_dict[i] = auc(fpr[i], tpr[i])
        plt.plot(fpr[i], tpr[i], color=colors[i], lw=2,
                label=f'{iris_target_names[i]} (AUC = {roc_auc_dict[i]:.3f})')

    # Plot random classifier baseline
    plt.plot([0, 1], [0, 1], 'k--', lw=2, label='Random Classifier')

    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate', fontsize=12)
    plt.ylabel('True Positive Rate', fontsize=12)
    plt.title(f'ROC Curves - Iris {dataset_name} Set', fontsize=14,
fontweight='bold')
    plt.legend(loc="lower right", fontsize=11)
    plt.grid(True, alpha=0.3)
    plt.tight_layout()
    plt.show()

    # Calculate averages
    macro_auc = np.mean(list(roc_auc_dict.values()))
    return macro_auc, roc_auc_dict

# Iris class names
iris_target_names = iris.target_names

print("\n" + "="*70)
print("ROC AUC ANALYSIS - IRIS DATASET (BACKPROPAGATION)")
print("="*70)

# Plot ROC for Training set
print("\nTraining Set ROC Curves:")
train_macro_auc, train_auc_dict = plot_iris_roc_curves(
    train_pred_proba, y_train_bin, 'Training', iris_target_names)
print(f"Macro-average AUC: {train_macro_auc:.4f}")
for i in range(n_classes):
    print(f"  {iris_target_names[i]}: {train_auc_dict[i]:.4f}")

# Plot ROC for Test set
print("\nTest Set ROC Curves:")
test_macro_auc, test_auc_dict = plot_iris_roc_curves(
    test_pred_proba, y_test_bin, 'Test', iris_target_names)
print(f"Macro-average AUC: {test_macro_auc:.4f}")
```

```
for i in range(n_classes):
    print(f"  {iris_target_names[i]}: {test_auc_dict[i]:.4f}")

# Summary comparison
print("\n" + "="*70)
print("PERFORMANCE SUMMARY")
print("="*70)
print(f"Training set macro-average AUC: {train_macro_auc:.4f}")
print(f"Test set macro-average AUC:     {test_macro_auc:.4f}")
print(f"\nModel generalization: {'Good' if abs(train_macro_auc - test_macro_auc) <
0.1 else 'Possible overfitting' if train_macro_auc > test_macro_auc else 'Possible
underfitting'}")
```

Activation Functions Analysis

This notebook explores various activation functions, their derivatives, and error metrics.

Task 1: Sigmoid and Tanh Activation Functions

- Input range: (-10, +10)
- Plot activation functions and their derivatives
- Observe behavior and characteristics
- Calculate MSE and MAE with sample predictions

Task 2: Tanh and ReLU Activation Functions

- Input range: (-5, +5)
- Plot activation functions and their derivatives
- Observe behavior and characteristics
- Calculate MSE and MAE with sample predictions

Task 3: Sigmoid, ReLU and Softmax Activation Functions

- Input range: (-10, +10)
- Plot activation functions and their derivatives
- Observe behavior and characteristics
- Calculate MSE and MAE with sample predictions

Import Libraries

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, mean_absolute_error
import warnings
warnings.filterwarnings('ignore')
```

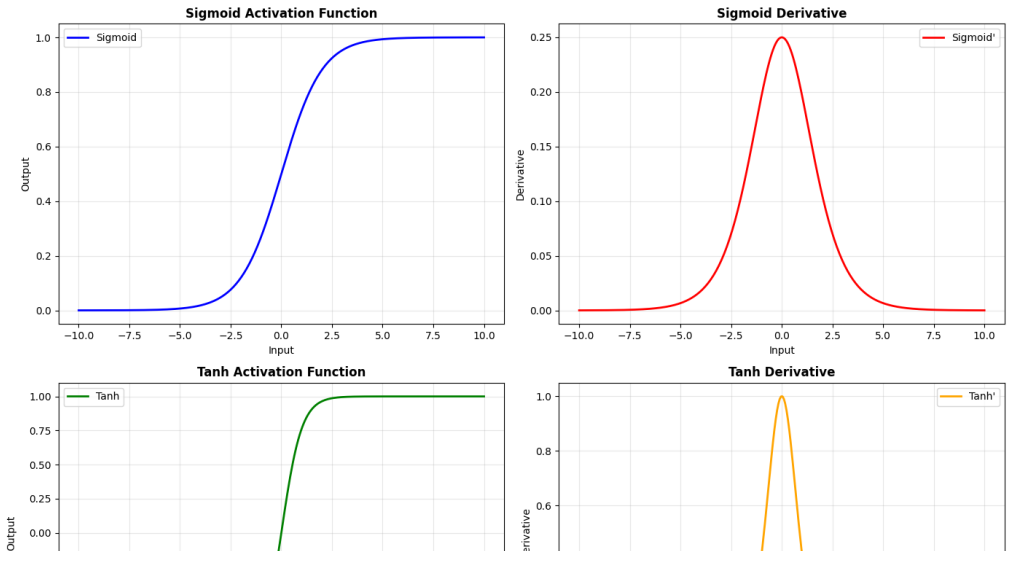
Define Activation Functions

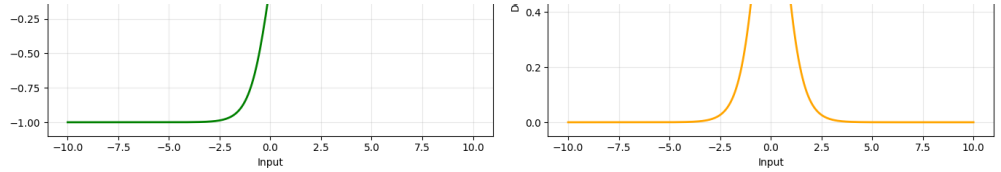
In [2]:
```
def sigmoid(x):
    return 1 / (1 + np.exp(-np.clip(x, -500, 500)))

def sigmoid_derivative(x):
    s = sigmoid(x)
    return s * (1 - s)

def tanh_function(x):
    return np.tanh(x)

def tanh_derivative(x):
    return 1 - np.tanh(x) ** 2

def relu(x):
    return np.maximum(0, x)

def relu_derivative(x):
    return (x > 0).astype(float)

def softmax(x):
    exp_x = np.exp(x - np.max(x))
    return exp_x / np.sum(exp_x, axis=0)

def softmax_derivative(x):
    s = softmax(x)
    return s * (1 - s)
```

Task 1: Sigmoid and Tanh Functions (-10 to +10)

In [3]:

```
x_task1 = np.linspace(-10, 10, 300)

sigmoid_output = sigmoid(x_task1)
sigmoid_deriv = sigmoid_derivative(x_task1)

tanh_output = tanh_function(x_task1)
tanh_deriv = tanh_derivative(x_task1)

fig, axes = plt.subplots(2, 2, figsize=(14, 10))

axes[0, 0].plot(x_task1, sigmoid_output, 'b-', linewidth=2, label='Sigmoid')
axes[0, 0].set_title('Sigmoid Activation Function', fontsize=12, fontweight='bold')
axes[0, 0].set_xlabel('Input')
axes[0, 0].set_ylabel('Output')
axes[0, 0].grid(True, alpha=0.3)
axes[0, 0].legend()

axes[0, 1].plot(x_task1, sigmoid_deriv, 'r-', linewidth=2, label="Sigmoid'")
axes[0, 1].set_title('Sigmoid Derivative', fontsize=12, fontweight='bold')
axes[0, 1].set_xlabel('Input')
axes[0, 1].set_ylabel('Derivative')
axes[0, 1].grid(True, alpha=0.3)
axes[0, 1].legend()

axes[1, 0].plot(x_task1, tanh_output, 'g-', linewidth=2, label='Tanh')
axes[1, 0].set_title('Tanh Activation Function', fontsize=12, fontweight='bold')
axes[1, 0].set_xlabel('Input')
axes[1, 0].set_ylabel('Output')
axes[1, 0].grid(True, alpha=0.3)
axes[1, 0].legend()

axes[1, 1].plot(x_task1, tanh_deriv, 'orange', linewidth=2, label="Tanh'")
axes[1, 1].set_title('Tanh Derivative', fontsize=12, fontweight='bold')
axes[1, 1].set_xlabel('Input')
axes[1, 1].set_ylabel('Derivative')
axes[1, 1].grid(True, alpha=0.3)
axes[1, 1].legend()

plt.tight_layout()
plt.show()

print("\nTask 1 - Sigmoid and Tanh Analysis:")
print("=" * 50)
print(f"Sigmoid output range: [{sigmoid_output.min():.4f},
{sigmoid_output.max():.4f}]")
print(f"Sigmoid derivative max: {sigmoid_deriv.max():.4f} at x =
{x_task1[sigmoid_deriv.argmax()]:.2f}")
print(f"\nTanh output range: [{tanh_output.min():.4f}, {tanh_output.max():.4f}]")
print(f"Tanh derivative max: {tanh_deriv.max():.4f} at x =
{x_task1[tanh_deriv.argmax()]:.2f}")
```






```
Task 1 - Sigmoid and Tanh Analysis:
==================================================
Sigmoid output range: [0.0000, 1.0000]
Sigmoid derivative max: 0.2499 at x = -0.03

Tanh output range: [-1.0000, 1.0000]
Tanh derivative max: 0.9989 at x = -0.03
```

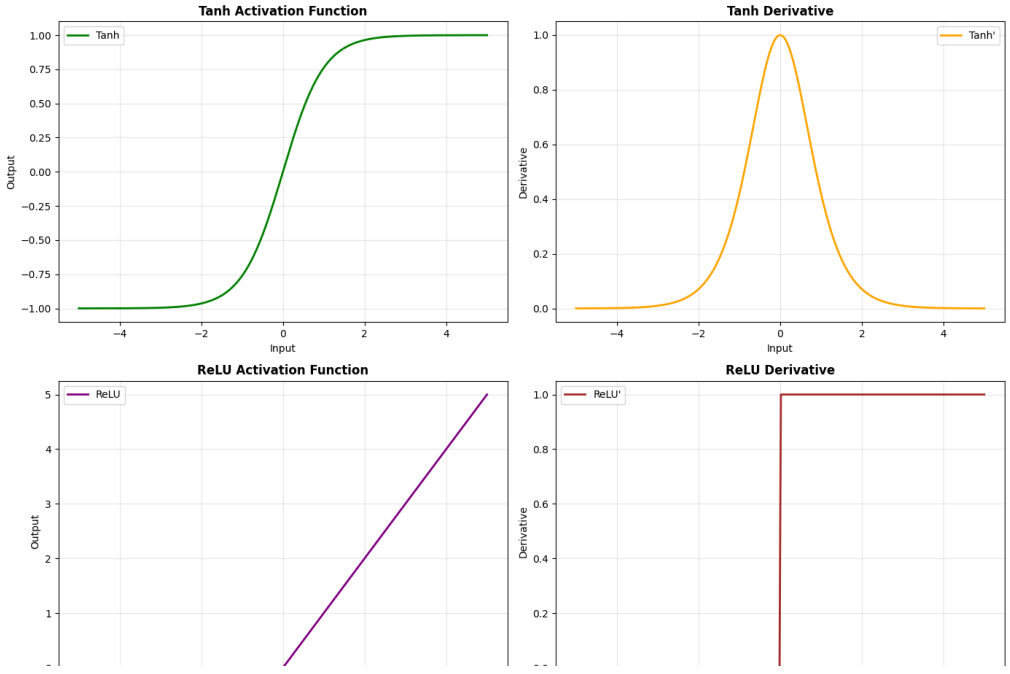
Task 1: Error Metrics (MSE and MAE)

In [4]:
```
y_true_task1 = np.random.rand(50)
y_pred_sigmoid = sigmoid(np.random.uniform(-10, 10, 50))
y_pred_tanh = tanh_function(np.random.uniform(-10, 10, 50))

mse_sigmoid = mean_squared_error(y_true_task1, y_pred_sigmoid)
mae_sigmoid = mean_absolute_error(y_true_task1, y_pred_sigmoid)

mse_tanh = mean_squared_error(y_true_task1, y_pred_tanh)
mae_tanh = mean_absolute_error(y_true_task1, y_pred_tanh)

print("\nTask 1 - Error Metrics:")
print("=" * 50)
print(f"Sigmoid - MSE: {mse_sigmoid:.6f}, MAE: {mae_sigmoid:.6f}")
print(f"Tanh    - MSE: {mse_tanh:.6f}, MAE: {mae_tanh:.6f}")
```

```
Task 1 - Error Metrics:
==================================================
Sigmoid - MSE: 0.287359, MAE: 0.452340
Tanh    - MSE: 1.010884, MAE: 0.833134
```

Task 2: Tanh and ReLU Functions (-5 to +5)

In [5]:
```
x_task2 = np.linspace(-5, 5, 300)

tanh_output_t2 = tanh_function(x_task2)
tanh_deriv_t2 = tanh_derivative(x_task2)

relu_output = relu(x_task2)
relu_deriv = relu_derivative(x_task2)

fig, axes = plt.subplots(2, 2, figsize=(14, 10))

axes[0, 0].plot(x_task2, tanh_output_t2, 'g-', linewidth=2, label='Tanh')
axes[0, 0].set_title('Tanh Activation Function', fontsize=12, fontweight='bold')
axes[0, 0].set_xlabel('Input')
axes[0, 0].set_ylabel('Output')
axes[0, 0].grid(True, alpha=0.3)
axes[0, 0].legend()

axes[0, 1].plot(x_task2, tanh_deriv_t2, 'orange', linewidth=2, label="Tanh'")
axes[0, 1].set_title('Tanh Derivative', fontsize=12, fontweight='bold')
axes[0, 1].set_xlabel('Input')
axes[0, 1].set_ylabel('Derivative')
axes[0, 1].grid(True, alpha=0.3)
axes[0, 1].legend()

axes[1, 0].plot(x_task2, relu_output, 'purple', linewidth=2, label='ReLU')
axes[1, 0].set_title('ReLU Activation Function', fontsize=12, fontweight='bold')
axes[1, 0].set_xlabel('Input')
axes[1, 0].set_ylabel('Output')
axes[1, 0].grid(True, alpha=0.3)
axes[1, 0].legend()

axes[1, 1].plot(x_task2, relu_deriv, 'brown', linewidth=2, label="ReLU'")
axes[1, 1].set_title('ReLU Derivative', fontsize=12, fontweight='bold')
axes[1, 1].set_xlabel('Input')
axes[1, 1].set_ylabel('Derivative')
axes[1, 1].grid(True, alpha=0.3)
axes[1, 1].legend()

plt.tight_layout()
plt.show()

print("\nTask 2 - Tanh and ReLU Analysis:")
print("=" * 50)
print(f"Tanh output range: [{tanh_output_t2.min():.4f}, {tanh_output_t2.max():.4f}]")
print(f"ReLU output range: [{relu_output.min():.4f}, {relu_output.max():.4f}]")
print(f"ReLU is zero for x < 0: {np.all(relu_output[x_task2 < 0] == 0)}")
```




```
Task 2 - Tanh and ReLU Analysis:
==================================================
Tanh output range: [-0.9999, 0.9999]
ReLU output range: [0.0000, 5.0000]
ReLU is zero for x < 0: True
```

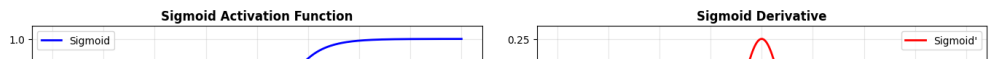
Task 2: Error Metrics (MSE and MAE)

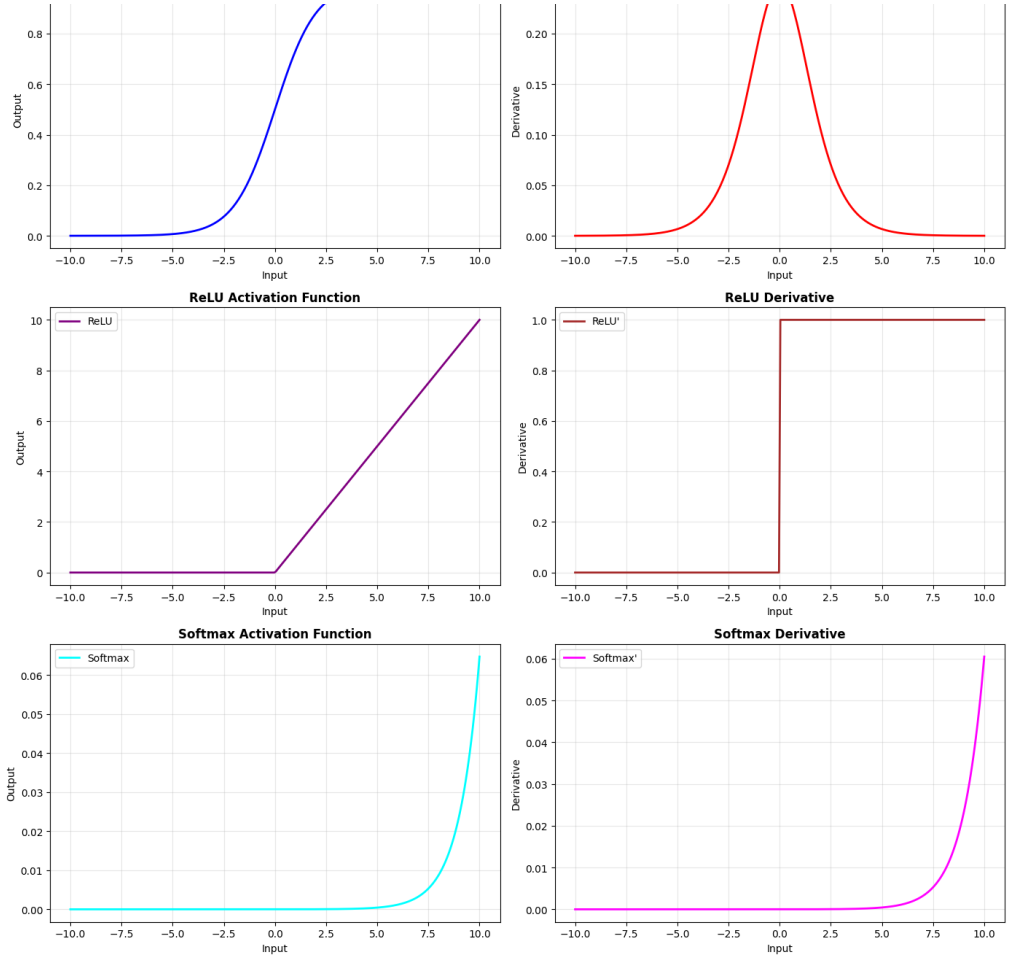
In [6]:
```
y_true_task2 = np.random.rand(50)
y_pred_tanh_t2 = tanh_function(np.random.uniform(-5, 5, 50))
y_pred_relu = relu(np.random.uniform(-5, 5, 50))

mse_tanh_t2 = mean_squared_error(y_true_task2, y_pred_tanh_t2)
mae_tanh_t2 = mean_absolute_error(y_true_task2, y_pred_tanh_t2)

mse_relu = mean_squared_error(y_true_task2, y_pred_relu)
mae_relu = mean_absolute_error(y_true_task2, y_pred_relu)

print("\nTask 2 - Error Metrics:")
print("=" * 50)
print(f"Tanh - MSE: {mse_tanh_t2:.6f}, MAE: {mae_tanh_t2:.6f}")
print(f"ReLU - MSE: {mse_relu:.6f}, MAE: {mae_relu:.6f}")
```

```
Task 2 - Error Metrics:
==================================================
Tanh - MSE: 1.250409, MAE: 0.960793
ReLU - MSE: 2.753757, MAE: 1.196055
```

Task 3: Sigmoid, ReLU and Softmax Functions (-10 to +10)

In [7]:
```
x_task3 = np.linspace(-10, 10, 300)

sigmoid_output_t3 = sigmoid(x_task3)
sigmoid_deriv_t3 = sigmoid_derivative(x_task3)

relu_output_t3 = relu(x_task3)
relu_deriv_t3 = relu_derivative(x_task3)

x_softmax = np.linspace(-10, 10, 300).reshape(-1, 1)
softmax_output = softmax(x_softmax).flatten()
softmax_deriv = softmax_derivative(x_softmax).flatten()

fig, axes = plt.subplots(3, 2, figsize=(14, 14))

axes[0, 0].plot(x_task3, sigmoid_output_t3, 'b-', linewidth=2, label='Sigmoid')
axes[0, 0].set_title('Sigmoid Activation Function', fontsize=12, fontweight='bold')
axes[0, 0].set_xlabel('Input')
axes[0, 0].set_ylabel('Output')
axes[0, 0].grid(True, alpha=0.3)
axes[0, 0].legend()

axes[0, 1].plot(x_task3, sigmoid_deriv_t3, 'r-', linewidth=2, label="Sigmoid'")
axes[0, 1].set_title('Sigmoid Derivative', fontsize=12, fontweight='bold')
axes[0, 1].set_xlabel('Input')
axes[0, 1].set_ylabel('Derivative')
axes[0, 1].grid(True, alpha=0.3)
axes[0, 1].legend()

axes[1, 0].plot(x_task3, relu_output_t3, 'purple', linewidth=2, label='ReLU')
axes[1, 0].set_title('ReLU Activation Function', fontsize=12, fontweight='bold')
axes[1, 0].set_xlabel('Input')
axes[1, 0].set_ylabel('Output')
axes[1, 0].grid(True, alpha=0.3)
axes[1, 0].legend()

axes[1, 1].plot(x_task3, relu_deriv_t3, 'brown', linewidth=2, label="ReLU'")
axes[1, 1].set_title('ReLU Derivative', fontsize=12, fontweight='bold')
axes[1, 1].set_xlabel('Input')
axes[1, 1].set_ylabel('Derivative')
axes[1, 1].grid(True, alpha=0.3)
axes[1, 1].legend()

axes[2, 0].plot(x_task3, softmax_output, 'cyan', linewidth=2, label='Softmax')
axes[2, 0].set_title('Softmax Activation Function', fontsize=12, fontweight='bold')
axes[2, 0].set_xlabel('Input')
axes[2, 0].set_ylabel('Output')
axes[2, 0].grid(True, alpha=0.3)
axes[2, 0].legend()

axes[2, 1].plot(x_task3, softmax_deriv, 'magenta', linewidth=2, label="Softmax'")
axes[2, 1].set_title('Softmax Derivative', fontsize=12, fontweight='bold')
axes[2, 1].set_xlabel('Input')
axes[2, 1].set_ylabel('Derivative')
axes[2, 1].grid(True, alpha=0.3)
axes[2, 1].legend()

plt.tight_layout()
plt.show()

print("\nTask 3 - Sigmoid, ReLU and Softmax Analysis:")
print("=" * 50)
print(f"Sigmoid output range: [{sigmoid_output_t3.min():.4f},
{sigmoid_output_t3.max():.4f}]")
print(f"ReLU output range: [{relu_output_t3.min():.4f}, {relu_output_t3.max():.4f}]")
print(f"Softmax output range: [{softmax_output.min():.4f},
{softmax_output.max():.4f}]")
print(f"Softmax output sum: {np.sum(softmax_output):.6f}")
```






```
Task 3 - Sigmoid, ReLU and Softmax Analysis:
==================================================
Sigmoid output range: [0.0000, 1.0000]
ReLU output range: [0.0000, 10.0000]
Softmax output range: [0.0000, 0.0647]
Softmax output sum: 1.000000
```

Task 3: Error Metrics (MSE and MAE)

In [8]:
```
y_true_task3 = np.random.rand(50)
y_pred_sigmoid_t3 = sigmoid(np.random.uniform(-10, 10, 50))
y_pred_relu_t3 = relu(np.random.uniform(-10, 10, 50))
y_pred_softmax = softmax(np.random.uniform(-10, 10, 50).reshape(-1, 1)).flatten()

mse_sigmoid_t3 = mean_squared_error(y_true_task3, y_pred_sigmoid_t3)
mae_sigmoid_t3 = mean_absolute_error(y_true_task3, y_pred_sigmoid_t3)

mse_relu_t3 = mean_squared_error(y_true_task3, y_pred_relu_t3)
mae_relu_t3 = mean_absolute_error(y_true_task3, y_pred_relu_t3)

mse_softmax = mean_squared_error(y_true_task3, y_pred_softmax)
mae_softmax = mean_absolute_error(y_true_task3, y_pred_softmax)

print("\nTask 3 - Error Metrics:")
print("=" * 50)
print(f"Sigmoid - MSE: {mse_sigmoid_t3:.6f}, MAE: {mae_sigmoid_t3:.6f}")
print(f"ReLU    - MSE: {mse_relu_t3:.6f}, MAE: {mae_relu_t3:.6f}")
print(f"Softmax - MSE: {mse_softmax:.6f}, MAE: {mae_softmax:.6f}")
```

```
Task 3 - Error Metrics:
==================================================
Sigmoid - MSE: 0.296429, MAE: 0.474559
ReLU    - MSE: 16.294083, MAE: 2.650332
Softmax - MSE: 0.230787, MAE: 0.399618
```

Summary and Observations

In [9]:
```
summary = """
KEY OBSERVATIONS AND CHARACTERISTICS:

Sigmoid Function:
- Output range: (0, 1) - suitable for binary classification
- S-shaped curve with smooth transition
- Maximum derivative at x=0 (0.25)
- Suffers from vanishing gradient problem in deep networks
- Used in output layer for binary classification

Tanh Function:
- Output range: (-1, 1) - centered around zero
- S-shaped curve, smoother transitions than sigmoid
- Maximum derivative at x=0 (1.0) - stronger gradients
- Better for hidden layers than sigmoid
- Converges faster than sigmoid

ReLU Function:
- Output range: [0, ∞) - allows unbounded activation
- Linear for positive inputs, zero for negative
- Derivative: 1 for x > 0, 0 for x < 0
- Computationally efficient (simple comparison)
- Reduces vanishing gradient problem
- Most popular in modern deep networks

Softmax Function:
- Output: Probability distribution (sum = 1)
- Converts logits to probabilities
- Used in multi-class classification
- Output range: (0, 1) for each element
- Maintains relative ordering of inputs

ERROR METRICS INSIGHTS:
- MSE penalizes larger errors more (quadratic)
- MAE treats all errors equally (linear)
- Lower values indicate better predictions
- Choice depends on problem requirements and outlier sensitivity
"""

print(summary)
```

```
KEY OBSERVATIONS AND CHARACTERISTICS:

Sigmoid Function:
- Output range: (0, 1) - suitable for binary classification
- S-shaped curve with smooth transition
- Maximum derivative at x=0 (0.25)
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- Output range: (-1, 1) - centered around zero
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ReLU Function:
- Output range: [0, ∞) - allows unbounded activation
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Softmax Function:
- Output: Probability distribution (sum = 1)
- Converts logits to probabilities
```

```
- Used in multi-class classification
- Output range: (0, 1) for each element
- Maintains relative ordering of inputs

ERROR METRICS INSIGHTS:
- MSE penalizes larger errors more (quadratic)
- MAE treats all errors equally (linear)
- Lower values indicate better predictions
- Choice depends on problem requirements and outlier sensitivity
```

Task 1

1. Use the titanic Dataset
2.Create an Auto Encoder and fit it with our data using 3 neurons in the dense layer
3. Display new reduced dimension values
4. Plot loss for different encoders [Sparse Autoencoder, Noise Autoencoder]

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Input
from tensorflow.keras.regularizers import l1
```

```
2026-01-06 15:13:59.235376: I tensorflow/core/util/port.cc:153] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn
them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2026-01-06 15:13:59.242467: E external/local_xla/xla/stream_executor/cuda/
cuda_fft.cc:467] Unable to register cuFFT factory: Attempting to register
factory for plugin cuFFT when one has already been registered
WARNING: All log messages before absl::InitializeLog() is called are written
to STDERR
E0000 00:00:1767692639.250865  148744 cuda_dnn.cc:8579] Unable to register
cuDNN factory: Attempting to register factory for plugin cuDNN when one has
already been registered
E0000 00:00:1767692639.253271  148744 cuda_blas.cc:1407] Unable to register
cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has
already been registered
W0000 00:00:1767692639.259683  148744 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767692639.259693  148744 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767692639.259694  148744 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767692639.259695  148744 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
2026-01-06 15:13:59.261865: I tensorflow/core/platform/
cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use
available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operations,
rebuild TensorFlow with the appropriate compiler flags.
```

In [2]:
```
X = pd.read_csv('/media/smayan/500GB SSD/Study/ML2/Practicals/Data/titanic.csv')
X = X.drop(['Name'], axis=1)
X = X.dropna()
X = pd.get_dummies(X, columns=['Sex'], drop_first=True)
X.head()
```

Out[2]:

	Survived	Pclass	Age	Siblings/Spouses Aboard	Parents/Children Aboard	Fare	Sex_male
0	0	3	22.0	1	0	7.2500	True
1	1	1	38.0	1	0	71.2833	False
2	1	3	26.0	0	0	7.9250	False
3	1	1	35.0	1	0	53.1000	False
4	0	3	35.0	0	0	8.0500	True

In [3]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_scaled.shape
```

Out[3]: (887, 7)

Standard Autoencoder with 3 neurons

In [4]:
```
autoencoder_standard = Sequential([
    Input(shape=(X_scaled.shape[1],)),
    Dense(3, activation='relu'),
    Dense(X_scaled.shape[1], activation='sigmoid')
])
autoencoder_standard.compile(optimizer='adam', loss='mse')
history_standard = autoencoder_standard.fit(X_scaled, X_scaled, epochs=50,
batch_size=16, shuffle=True, validation_split=0.2, verbose=0)
print("Standard Autoencoder trained")
```

```
I0000 00:00:1767692640.215880  148744 gpu_device.cc:2019] Created device /
job:localhost/replica:0/task:0/device:GPU:0 with 9430 MB memory:  -> device:
0, name: NVIDIA GeForce RTX 4070 SUPER, pci bus id: 0000:01:00.0, compute
capability: 8.9


WARNING: All log messages before absl::InitializeLog() is called are written
to STDERR
I0000 00:00:1767692640.907930  148929 service.cc:152] XLA service
0x76f98c0159b0 initialized for platform CUDA (this does not guarantee that
XLA will be used). Devices:
I0000 00:00:1767692640.907945  148929 service.cc:160]   StreamExecutor device
(0): NVIDIA GeForce RTX 4070 SUPER, Compute Capability 8.9
2026-01-06 15:14:00.918460: I tensorflow/compiler/mlir/tensorflow/utils/
dump_mlir_util.cc:269] disabling MLIR crash reproducer, set env var
`MLIR_CRASH_REPRODUCER_DIRECTORY` to enable.
I0000 00:00:1767692640.957016  148929 cuda_dnn.cc:529] Loaded cuDNN version
91701
I0000 00:00:1767692641.293912  148929 device_compiler.h:188] Compiled cluster
using XLA!  This line is logged at most once for the lifetime of the process.


Standard Autoencoder trained
```

In [5]:
```
encoder_standard = Sequential([autoencoder_standard.layers[0]])
encoded_data_standard = encoder_standard.predict(X_scaled, verbose=0)
encoded_data_standard
```

Out[5]:
```
array([[3.5411086 , 0.        , 1.276397  ],
       [0.        , 6.7791452 , 2.3451548 ],
       [0.        , 1.7229929 , 5.348138  ],
       ...,
       [0.        , 0.        , 0.86455894],
       [0.        , 3.925838  , 3.3518715 ],
       [4.1106935 , 0.34664726, 1.3035209 ]], dtype=float32)
```

Sparse Autoencoder with L1 Regularization

In [6]:
```
autoencoder_sparse = Sequential([
    Input(shape=(X_scaled.shape[1],)),
    Dense(3, activation='relu', activity_regularizer=l1(0.001)),
    Dense(X_scaled.shape[1], activation='sigmoid')
])
autoencoder_sparse.compile(optimizer='adam', loss='mse')
history_sparse = autoencoder_sparse.fit(X_scaled, X_scaled, epochs=50, batch_size=16,
shuffle=True, validation_split=0.2, verbose=0)
print("Sparse Autoencoder trained")
```

```
Sparse Autoencoder trained
```

In [7]:
```
encoder_sparse = Sequential([autoencoder_sparse.layers[0]])
encoded_data_sparse = encoder_sparse.predict(X_scaled, verbose=0)
encoded_data_sparse
```

Out[7]:
```
array([[2.271923  , 0.41476616, 0.        ],
       [0.        , 0.64568686, 3.435482  ],
       [2.4296792 , 0.7312726 , 2.4251144 ],
       ...,
       [0.        , 4.9790163 , 0.        ],
       [0.85980815, 0.        , 2.6054597 ],
       [2.4256983 , 0.        , 0.        ]], dtype=float32)
```

Noise Autoencoder (Denoising Autoencoder)

In [8]:
```
noise_factor = 0.2
X_noisy = X_scaled + noise_factor * np.random.normal(loc=0.0, scale=1.0,
size=X_scaled.shape)

autoencoder_noise = Sequential([
    Input(shape=(X_scaled.shape[1],)),
    Dense(3, activation='relu'),
    Dense(X_scaled.shape[1], activation='sigmoid')
])
autoencoder_noise.compile(optimizer='adam', loss='mse')
history_noise = autoencoder_noise.fit(X_noisy, X_scaled, epochs=50, batch_size=16,
shuffle=True, validation_split=0.2, verbose=0)
print("Noise Autoencoder trained")
```

```
Noise Autoencoder trained
```

In [9]:
```
encoder_noise = Sequential([autoencoder_noise.layers[0]])
encoded_data_noise = encoder_noise.predict(X_scaled, verbose=0)
encoded_data_noise
```

Out[9]:
```
array([[3.4676294 , 1.7265065 , 0.        ],
       [0.        , 1.48592   , 5.9307013 ],
       [0.        , 2.3195555 , 2.1944966 ],
       ...,
       [0.        , 0.10084236, 0.        ],
       [0.        , 3.0040445 , 2.6849098 ],
       [4.5698586 , 1.6916895 , 0.5260957 ]], dtype=float32)
```

Loss Comparison Plot

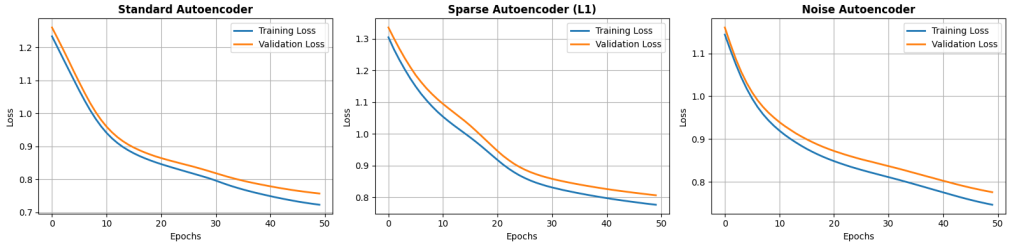
In [10]:
```
fig, axes = plt.subplots(1, 3, figsize=(16, 4))

axes[0].plot(history_standard.history['loss'], label='Training Loss', linewidth=2)
axes[0].plot(history_standard.history['val_loss'], label='Validation Loss',
linewidth=2)
axes[0].set_title('Standard Autoencoder', fontsize=12, fontweight='bold')
axes[0].set_xlabel('Epochs')
axes[0].set_ylabel('Loss')
axes[0].legend()
axes[0].grid()

axes[1].plot(history_sparse.history['loss'], label='Training Loss', linewidth=2)
axes[1].plot(history_sparse.history['val_loss'], label='Validation Loss',
linewidth=2)
axes[1].set_title('Sparse Autoencoder (L1)', fontsize=12, fontweight='bold')
axes[1].set_xlabel('Epochs')
axes[1].set_ylabel('Loss')
axes[1].legend()
axes[1].grid()

axes[2].plot(history_noise.history['loss'], label='Training Loss', linewidth=2)
axes[2].plot(history_noise.history['val_loss'], label='Validation Loss', linewidth=2)
axes[2].set_title('Noise Autoencoder', fontsize=12, fontweight='bold')
axes[2].set_xlabel('Epochs')
axes[2].set_ylabel('Loss')
axes[2].legend()
axes[2].grid()

plt.tight_layout()
plt.show()
```



In [1]:
```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
tf.random.set_seed(42)
np.random.seed(42)
```

```
2026-01-07 02:07:59.622079: I tensorflow/core/util/port.cc:153] oneDNN custom
operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn
them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2026-01-07 02:07:59.745171: E external/local_xla/xla/stream_executor/cuda/
cuda_fft.cc:467] Unable to register cuFFT factory: Attempting to register
factory for plugin cuFFT when one has already been registered
WARNING: All log messages before absl::InitializeLog() is called are written
to STDERR
E0000 00:00:1767731879.790856   34422 cuda_dnn.cc:8579] Unable to register
cuDNN factory: Attempting to register factory for plugin cuDNN when one has
already been registered
E0000 00:00:1767731879.803983   34422 cuda_blas.cc:1407] Unable to register
cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has
already been registered
W0000 00:00:1767731879.910823   34422 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767731879.910836   34422 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767731879.910837   34422 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
W0000 00:00:1767731879.910838   34422 computation_placer.cc:177] computation
placer already registered. Please check linkage and avoid linking the same
target more than once.
2026-01-07 02:07:59.922281: I tensorflow/core/platform/
cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use
available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operations,
rebuild TensorFlow with the appropriate compiler flags.
```

In [2]:
```
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()
```

In [3]:
```
subset = 5000
x_train_small = x_train[:subset]
y_train_small = y_train[:subset]
input_shape = x_train_small.shape[1:]
num_classes = 10
print("Using subset size:", subset)
```

```
Using subset size: 5000
```

In [4]:
```
input_shape
```

Out[4]:
```
(32, 32, 3)
```

In [5]:
```
strong_aug = tf.keras.Sequential([
    tf.keras.layers.Rescaling(1./255),
    tf.keras.layers.RandomFlip('horizontal'),
    tf.keras.layers.RandomRotation(0.15),
    tf.keras.layers.RandomTranslation(0.1, 0.1),
    tf.keras.layers.RandomContrast(0.2),
    tf.keras.layers.GaussianNoise(0.05),
])
```

```
I0000 00:00:1767731883.254580   34422 gpu_device.cc:2019] Created device /
job:localhost/replica:0/task:0/device:GPU:0 with 9468 MB memory:  -> device:
0, name: NVIDIA GeForce RTX 4070 SUPER, pci bus id: 0000:01:00.0, compute
capability: 8.9
```

In [6]:
```
identity_aug = tf.keras.Sequential([
    tf.keras.layers.Rescaling(1./255)
], name="identity_aug")
```

In [7]:
```
AUTOTUNE = tf.data.AUTOTUNE
batch_size = 256
temperature = 0.2
epochs = 8

def make_simclr_ds(images, aug_fn):
    ds = tf.data.Dataset.from_tensor_slices(images)
    ds = ds.shuffle(10000)
    ds = ds.map(lambda x: (aug_fn(x, training=True), aug_fn(x, training=True)),
num_parallel_calls=AUTOTUNE)
    ds = ds.map(lambda a, b: (tf.cast(a, tf.float32), tf.cast(b, tf.float32)),
num_parallel_calls=AUTOTUNE)
    ds = ds.batch(batch_size).prefetch(AUTOTUNE)
    return ds
```

In [8]:
```
ds_aug = make_simclr_ds(x_train_small, strong_aug)
ds_plain = make_simclr_ds(x_train_small, identity_aug)
ds_aug, ds_plain
```

Out[8]:
```
(<_PrefetchDataset element_spec=(TensorSpec(shape=(None, 32, 32, 3),
dtype=tf.float32, name=None), TensorSpec(shape=(None, 32, 32, 3),
dtype=tf.float32, name=None))>,
 <_PrefetchDataset element_spec=(TensorSpec(shape=(None, 32, 32, 3),
dtype=tf.float32, name=None), TensorSpec(shape=(None, 32, 32, 3),
dtype=tf.float32, name=None))>)
```

In [ ]:
```

```

Encoder, projection head, and NT-Xent loss

We build a lightweight CNN encoder and a two-layer projection head. The NT-Xent loss uses cosine similarity with temperature scaling and treats the paired views as positives against all other images in the batch.

In [9]:
```
from tensorflow.keras import layers, models, optimizers

def build_encoder(input_shape):
    inputs = layers.Input(shape=input_shape)
    x = layers.Conv2D(64, 3, padding='same', activation='relu')(inputs)
    x = layers.Conv2D(64, 3, strides=2, padding='same', activation='relu')(x)
    x = layers.Dropout(0.1)(x)
    x = layers.Conv2D(128, 3, padding='same', activation='relu')(x)
    x = layers.Conv2D(128, 3, strides=2, padding='same', activation='relu')(x)
    x = layers.GlobalAveragePooling2D()(x)
    x = layers.Dense(256, activation='relu')(x)
    return models.Model(inputs, x, name="encoder")

def build_projection_head():
    return models.Sequential([
        layers.Dense(256, activation='relu'),
        layers.Dense(128, activation=None)
    ], name="projection_head")
```

In [10]:
```
def nt_xent_loss(z1, z2, temperature=0.2):
    z1 = tf.math.l2_normalize(z1, axis=1)
    z2 = tf.math.l2_normalize(z2, axis=1)
    batch_size = tf.shape(z1)[0]
    representations = tf.concat([z1, z2], axis=0)

    similarity_matrix = tf.matmul(representations, representations, transpose_b=True)
    logits = similarity_matrix / temperature

    mask = tf.eye(2 * batch_size)
    logits = logits * (1 - mask) - 1e9 * mask

    labels = tf.concat([tf.range(batch_size, 2 * batch_size), tf.range(0,
batch_size)], axis=0)
    loss = tf.keras.losses.sparse_categorical_crossentropy(labels, logits,
from_logits=True)
    return tf.reduce_mean(loss)
```

In [11]:
```
def train_simclr(ds, name, epochs=epochs, temperature=temperature):
    encoder = build_encoder(input_shape)
    projection_head = build_projection_head()
    optimizer = optimizers.Adam(1e-3)
    trainable_vars = encoder.trainable_variables +
projection_head.trainable_variables
    history = []

    for epoch in range(epochs):
        mean_loss = tf.metrics.Mean()
        for view1, view2 in ds:
            with tf.GradientTape() as tape:
                z1 = projection_head(encoder(view1, training=True), training=True)
                z2 = projection_head(encoder(view2, training=True), training=True)
                loss = nt_xent_loss(z1, z2, temperature)
            grads = tape.gradient(loss, trainable_vars)
            optimizer.apply_gradients(zip(grads, trainable_vars))
            mean_loss.update_state(loss)
        epoch_loss = mean_loss.result().numpy().item()
        history.append(epoch_loss)
        print(f"{name} epoch {epoch+1}/{epochs} - loss: {epoch_loss:.4f}")
    return history
```

In [12]:
```
loss_with_aug = train_simclr(ds_aug, name="With strong augmentation")
loss_no_aug = train_simclr(ds_plain, name="Without augmentation")
```

```
I0000 00:00:1767731884.543390   34422 cuda_dnn.cc:529] Loaded cuDNN version
91701
2026-01-07 02:08:07.272909: I tensorflow/core/framework/
local_rendezvous.cc:407] Local rendezvous is aborting with status:
OUT_OF_RANGE: End of sequence

With strong augmentation epoch 1/8 - loss: 4.9650

2026-01-07 02:08:08.392972: I tensorflow/core/framework/
local_rendezvous.cc:407] Local rendezvous is aborting with status:
OUT_OF_RANGE: End of sequence

With strong augmentation epoch 2/8 - loss: 3.6333
With strong augmentation epoch 3/8 - loss: 3.0964

2026-01-07 02:08:10.618523: I tensorflow/core/framework/
local_rendezvous.cc:407] Local rendezvous is aborting with status:
OUT_OF_RANGE: End of sequence

With strong augmentation epoch 4/8 - loss: 2.8882
With strong augmentation epoch 5/8 - loss: 2.7760
With strong augmentation epoch 6/8 - loss: 2.6741
With strong augmentation epoch 7/8 - loss: 2.6132

2026-01-07 02:08:15.032196: I tensorflow/core/framework/
local_rendezvous.cc:407] Local rendezvous is aborting with status:
OUT_OF_RANGE: End of sequence

With strong augmentation epoch 8/8 - loss: 2.5864
Without augmentation epoch 1/8 - loss: 4.8109
Without augmentation epoch 2/8 - loss: 3.5607
Without augmentation epoch 3/8 - loss: 2.9836
Without augmentation epoch 4/8 - loss: 2.7404
Without augmentation epoch 5/8 - loss: 2.6267
Without augmentation epoch 6/8 - loss: 2.5375
Without augmentation epoch 7/8 - loss: 2.4727
Without augmentation epoch 8/8 - loss: 2.4250

2026-01-07 02:08:20.182692: I tensorflow/core/framework/
local_rendezvous.cc:407] Local rendezvous is aborting with status:
OUT_OF_RANGE: End of sequence
```

In [13]:
```
plt.figure(figsize=(8,4))
plt.plot(loss_with_aug, label='With augmentation', marker='o')
plt.plot(loss_no_aug, label='Without augmentation', marker='o')
plt.xlabel('Epoch')
plt.ylabel('NT-Xent loss')
plt.title('SimCLR training loss comparison')
plt.legend()
plt.grid(True)
plt.show()
```