LAB Assignment No. 5

Topic: Artificial Neural Network Model

Question 1

Logic Gates with Neural Network. Implement a feed-forward neural network to learn the AND gate.

- Inputs: (0,0), (0,1), (1,0), (1,1)
- Output: 0, 0, 0, 1

  Tasks:

1. Create dataset using NumPy or pandas.
2. Build a neural network with one hidden layer using TensorFlow/Keras or PyTorch.
3. Train it and show accuracy.
4. Compare model predictions with actual outputs

Code:

```
import numpy as np
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
X = np.array([[0,0], [0,1], [1,0], [1,1]])
y = np.array([[0], [0], [0], [1]])

model = Sequential()
model.add(Dense(4, input_dim=2, activation='relu'))   # Hidden layer with 4 neurons
model.add(Dense(1, activation='sigmoid'))          # Output layer

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
model.fit(X, y, epochs=500, verbose=0)
loss, accuracy = model.evaluate(X, y, verbose=0)print(f"Model Accuracy:
{accuracy*100:.2f}%")
predictions = model.predict(X)
predicted_classes = (predictions > 0.5).astype(int)
```

Output:

```
Model Accuracy: 100.00%
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 102ms/step

Predictions vs Actual:
Input: [0 0]  Predicted: 0  Actual: 0
Input: [0 1]  Predicted: 0  Actual: 0
Input: [1 0]  Predicted: 0  Actual: 0
Input: [1 1]  Predicted: 1  Actual: 1
```

Question 2

Create a dataset $y = x^2$ + noise for x in range [-3,3]. Regression Task with Neural Network

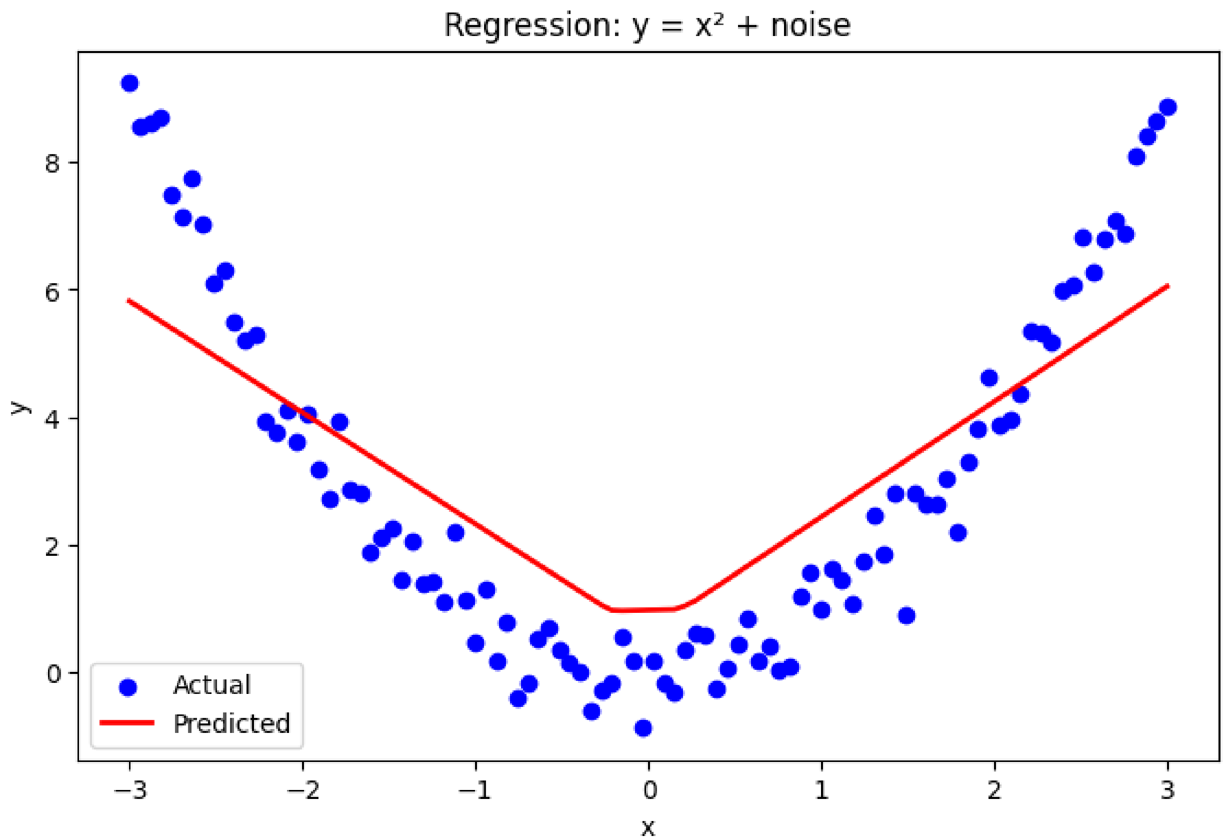
Tasks:

1. Generate 100 samples.
2. Build a neural network to predict y from x.
3. Plot actual vs. predicted results.
4. Discuss how increasing hidden neurons changes results.

Code:

```
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
np.random.seed(42)
X = np.linspace(-3, 3, 100)
y = X**2 + np.random.normal(0, 0.5, X.shape)   # Add Gaussian noise
X = X.reshape(-1, 1)
y = y.reshape(-1, 1)
model = Sequential()
model.add(Dense(10, input_dim=1, activation='relu'))   # Hidden layer (10 neurons)
model.add(Dense(1))                                 # Output layer (regression)

model.compile(optimizer='adam', loss='mse')
model.fit(X, y, epochs=200, verbose=0)

y_pred = model.predict(X)
plt.figure(figsize=(8,5))
plt.scatter(X, y, label='Actual', color='blue')
plt.plot(X, y_pred, label='Predicted', color='red', linewidth=2)
plt.title("Regression: y = x^2 + noise")
plt.xlabel("x")
plt.ylabel("y")
plt.legend()
plt.show()
```

Output:



Question 3:

Use the XOR gate and train networks with different activation functions (sigmoid, tanh, ReLU).

- Compare accuracy, loss, and convergence speed.
- Plot and discuss results.

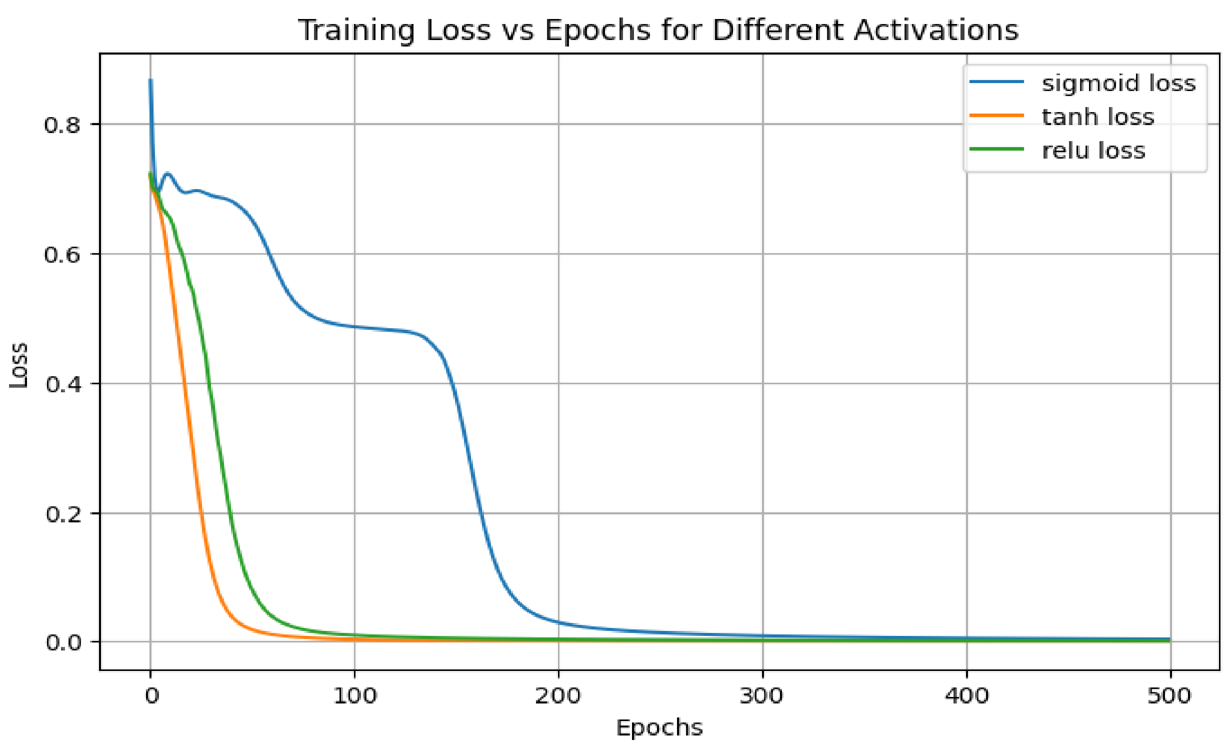
Code:

```
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam
X = np.array([[0,0], [0,1], [1,0], [1,1]])
y = np.array([[0], [1], [1], [0]])
def train_xor_model(activation, epochs=500):
  model = Sequential([
    Dense(4, input_dim=2, activation=activation),
    Dense(1, activation='sigmoid')
  ])
```

```
 model.compile(optimizer=Adam(learning_rate=0.1),
              loss='binary_crossentropy',
              metrics=['accuracy'])
  history = model.fit(X, y, epochs=epochs, verbose=0)
    loss, acc = model.evaluate(X, y, verbose=0)
    return model, history, loss, acc
activations = ['sigmoid', 'tanh', 'relu']
results = {}
for act in activations:
    model, history, loss, acc = train_xor_model(act)
    results[act] = {'loss': loss, 'acc': acc, 'history': history}
    print(f"{act.upper()} → Accuracy: {acc*100:.2f}%, Final Loss: {loss:.4f}")
plt.figure(figsize=(8,5))
for act in activations:
    plt.plot(results[act]['history'].history['loss'], label=f'{act} loss')
plt.title("Training Loss vs Epochs for Different Activations")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.grid(True)
plt.show()
```

Output:

```
SIGMOID → Accuracy: 100.00%, Final Loss: 0.0031
TANH → Accuracy: 100.00%, Final Loss: 0.0002
RELU → Accuracy: 100.00%, Final Loss: 0.0007
```



Question 4

Binary Classification using Neural Network

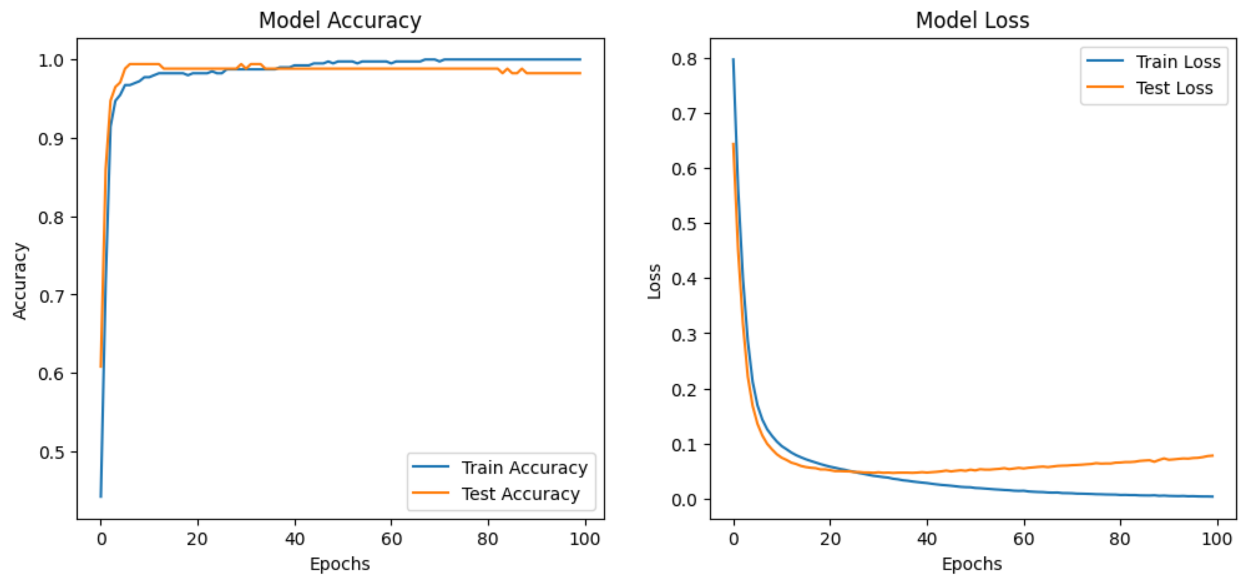
Objective: Build a neural network to classify whether a tumor is malignant or benign using the **Breast Cancer dataset**.

Code:

```
import numpy as np
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
data = load_breast_cancer()
X = data.data
y = data.target  # 0 = malignant, 1 = benign
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
model = Sequential([
   Dense(16, input_dim=X.shape[1], activation='relu'),  # hidden layer 1
   Dense(8, activation='relu'),                  # hidden layer 2
   Dense(1, activation='sigmoid'])
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
history = model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=100, batch_size=16,
verbose=0)
loss, accuracy = model.evaluate(X_test, y_test, verbose=0)
print(f"✅ Test Accuracy: {accuracy*100:.2f}%")
print(f"Loss: {loss:.4f}")
import matplotlib.pyplot as plt
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Test Accuracy')
plt.title("Model Accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.subplot(1,2,2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Test Loss')
plt.title("Model Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
sample = X_test[0].reshape(1, -1)
prediction = model.predict(sample)
print(f"Predicted Class: {'Benign' if prediction[0][0] > 0.5 else 'Malignant'}")
```

Output:

```
✅ Test Accuracy: 98.25%
Loss: 0.0782
```




```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 134ms/step
Predicted Class: Benign
```

Question 5

Multi-Class Classification on Iris Dataset

Objective: Train a neural network to classify flower species (Setosa, Versicolor, Virginica).

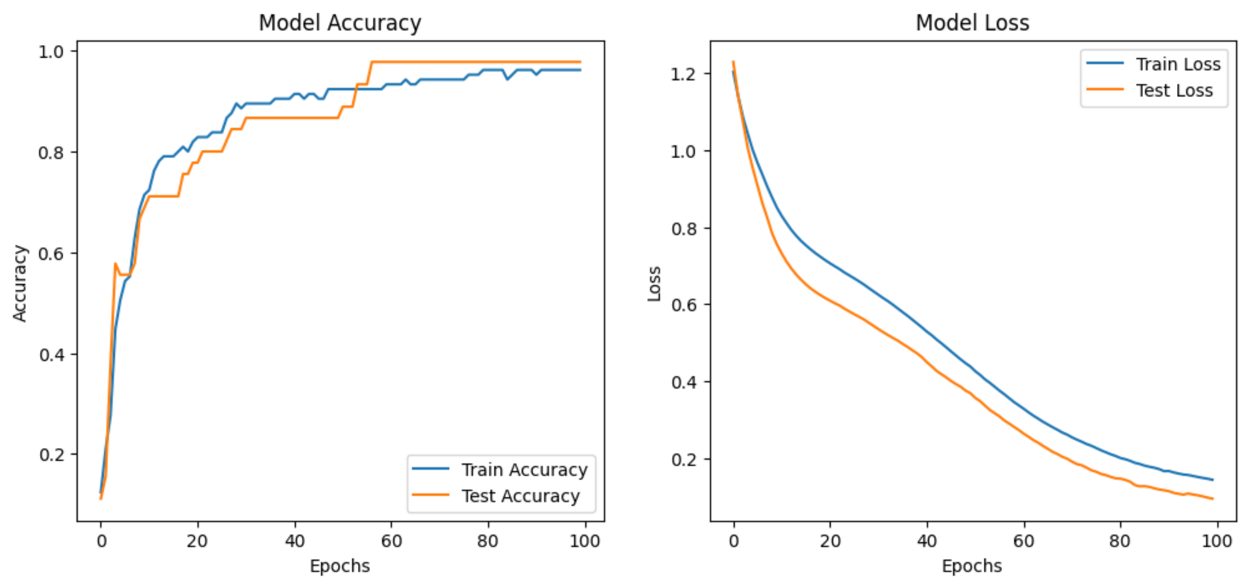
Code:

```
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, LabelEncoder
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.utils import to_categorical
iris = load_iris()
X = iris.data          # Features: sepal/petal length & width
y = iris.target        # Target: 0 = setosa, 1 = versicolor, 2 = virginica
y_encoded = to_categorical(y)
X_train, X_test, y_train, y_test = train_test_split(
   X, y_encoded, test_size=0.3, random_state=42)
```

```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

model = Sequential([
  Dense(8, input_dim=4, activation='relu'),   # hidden layer 1
  Dense(6, activation='relu'),             # hidden layer 2
  Dense(3, activation='softmax')           # output layer (3 neurons = 3 classes)
])
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model.fit(X_train, y_train, validation_data=(X_test, y_test),
              epochs=100, batch_size=8, verbose=0)

loss, accuracy = model.evaluate(X_test, y_test, verbose=0)
print(f"✅ Test Accuracy: {accuracy*100:.2f}%")
print(f"Loss: {loss:.4f}")

plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Test Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.subplot(1,2,2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Test Loss')
plt.title('Model Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

sample = np.array([[5.1, 3.5, 1.4, 0.2]])  # Example: Setosa
sample_scaled = scaler.transform(sample)
prediction = model.predict(sample_scaled)
predicted_class = np.argmax(prediction)
print(f"Predicted Species: {iris.target_names[predicted_class]}")
```

Output:

```
✅ Test Accuracy: 97.78%
Loss: 0.0953
```




```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 107ms/step
Predicted Species: setosa
```

Question 6

Regression Problem (House Price Prediction)

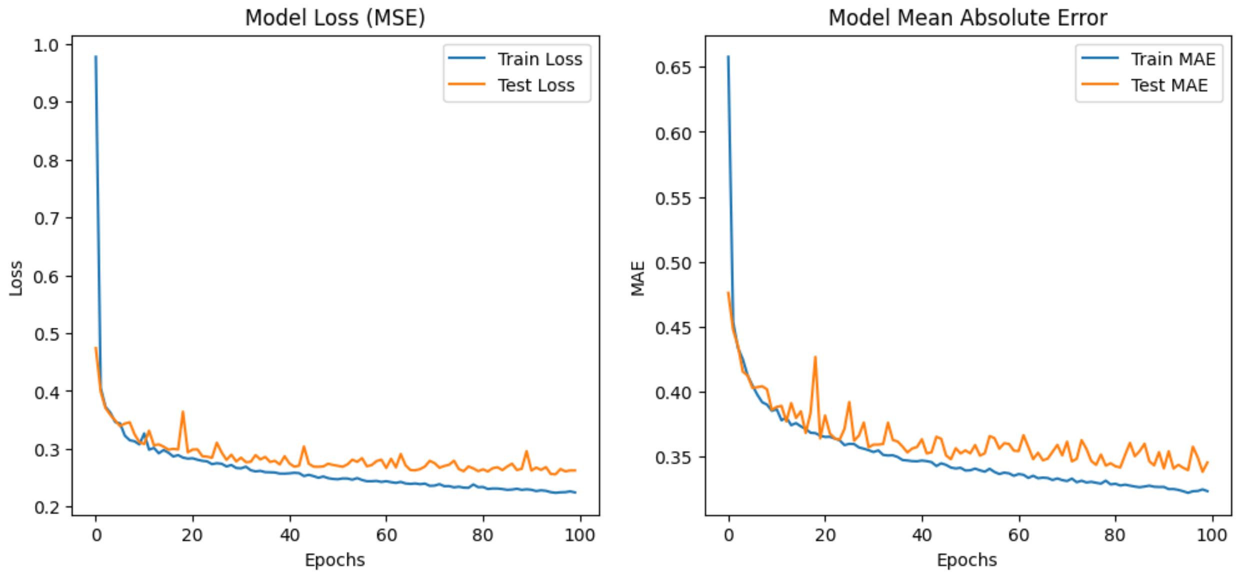
Objective: Predict house prices using the **California Housing dataset**.

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# 1Load the dataset
data = fetch_california_housing()
X = data.data
y = data.target   # Median house value (in 100,000s)

# 2 Split into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
model = Sequential([
   Dense(64, input_dim=X.shape[1], activation='relu'),  # Hidden layer 1
   Dense(32, activation='relu'),                  # Hidden layer 2
   Dense(1)  # Output layer (regression)])

model.compile(optimizer='adam', loss='mse', metrics=['mae'])  # MSE: Mean Squared Error, MAE: Mean Absolute Error

history = model.fit(X_train, y_train, validation_data=(X_test, y_test),
               epochs=100, batch_size=32, verbose=0)
loss, mae = model.evaluate(X_test, y_test, verbose=0)
print(f"✅ Test MAE (Mean Absolute Error): {mae:.3f}")
print(f"Test MSE: {loss:.3f}")

plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Test Loss')
plt.title('Model Loss (MSE)')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.subplot(1,2,2)
plt.plot(history.history['mae'], label='Train MAE')
plt.plot(history.history['val_mae'], label='Test MAE')
plt.title('Model Mean Absolute Error')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.legend()
plt.show()
sample = X_test[0].reshape(1, -1)
predicted_price = model.predict(sample)[0][0]
print(f"Predicted Price: ${predicted_price * 100000:.2f}")
```

Output:

```
✅ Test MAE (Mean Absolute Error): 0.345
Test MSE: 0.262
```




```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 83ms/step
Predicted Price: $50448.07
```

Question 7

Neural Network with Dropout Regularization

Objective: Prevent overfitting using **Dropout** layers on the **MNIST digit dataset**.

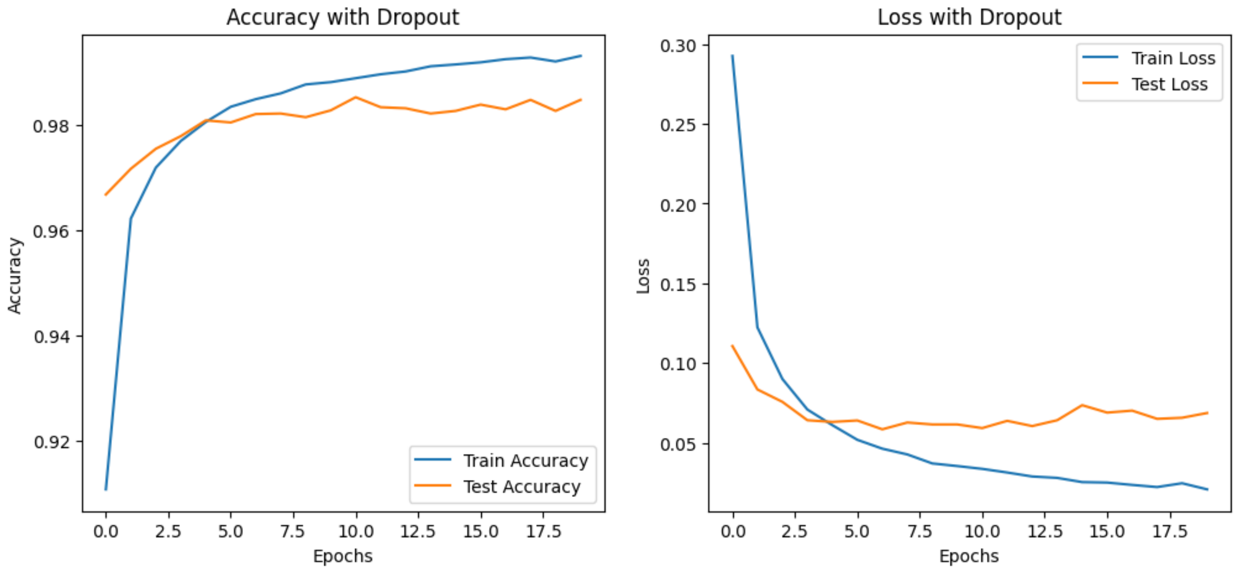
Code:

```
import numpy as np
import matplotlib.pyplot as plt
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Flatten
from tensorflow.keras.utils import to_categorical
(X_train, y_train), (X_test, y_test) = mnist.load_data()
X_train = X_train.astype('float32') / 255.0
X_test = X_test.astype('float32') / 255.0
X_train = X_train.reshape(-1, 28*28)
X_test = X_test.reshape(-1, 28*28)

y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)

model = Sequential([
    Dense(512, input_dim=784, activation='relu'),
    Dropout(0.3),            # 30% of neurons randomly dropped
    Dense(256, activation='relu'),
    Dropout(0.3),            # another Dropout layer
    Dense(10, activation='softmax') # output layer (10 classes)])
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

```
history = model.fit(
   X_train, y_train,
   validation_data=(X_test, y_test),
   epochs=20,
   batch_size=128,
   verbose=1)
loss, accuracy = model.evaluate(X_test, y_test, verbose=0)
print(f"✅ Test Accuracy: {accuracy*100:.2f}%")
print(f"Test Loss: {loss:.4f}")
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Test Accuracy')
plt.title('Accuracy with Dropout')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.subplot(1,2,2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Test Loss')
plt.title('Loss with Dropout')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

Output:

```
11490434/11490434 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
Epoch 1/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 14s 22ms/step - accuracy: 0.8350 - loss: 0.5230 - val_accuracy: 0.9668 - val_loss: 0.1107
Epoch 2/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 9s 19ms/step - accuracy: 0.9608 - loss: 0.1280 - val_accuracy: 0.9717 - val_loss: 0.0834
Epoch 3/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 9s 19ms/step - accuracy: 0.9720 - loss: 0.0910 - val_accuracy: 0.9755 - val_loss: 0.0757
Epoch 4/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 10s 21ms/step - accuracy: 0.9777 - loss: 0.0695 - val_accuracy: 0.9779 - val_loss: 0.0641
Epoch 5/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 10s 20ms/step - accuracy: 0.9820 - loss: 0.0575 - val_accuracy: 0.9809 - val_loss: 0.0631
Epoch 6/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 8s 18ms/step - accuracy: 0.9843 - loss: 0.0492 - val_accuracy: 0.9805 - val_loss: 0.0640
Epoch 7/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 10s 20ms/step - accuracy: 0.9861 - loss: 0.0426 - val_accuracy: 0.9821 - val_loss: 0.0584
Epoch 8/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 10s 21ms/step - accuracy: 0.9866 - loss: 0.0411 - val_accuracy: 0.9822 - val_loss: 0.0627
Epoch 9/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 9s 19ms/step - accuracy: 0.9878 - loss: 0.0372 - val_accuracy: 0.9815 - val_loss: 0.0615
Epoch 10/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 10s 19ms/step - accuracy: 0.9892 - loss: 0.0329 - val_accuracy: 0.9828 - val_loss: 0.0615
Epoch 11/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 11s 21ms/step - accuracy: 0.9901 - loss: 0.0309 - val_accuracy: 0.9853 - val_loss: 0.0592
Epoch 12/20
...
Epoch 20/20
469/469 ━━━━━━━━━━━━━━━━━━━━ 11s 21ms/step - accuracy: 0.9938 - loss: 0.0192 - val_accuracy: 0.9848 - val_loss: 0.0687
✅ Test Accuracy: 98.48%
Test Loss: 0.0687
```



Accuracy with Dropout
Accuracy
Epochs
Train Accuracy
Test Accuracy
0.92
0.94
0.96
0.98
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Loss with Dropout
Loss
Epochs
Train Loss
Test Loss
0.05
0.10
0.15
0.20
0.25
0.30