Assignment: ANN

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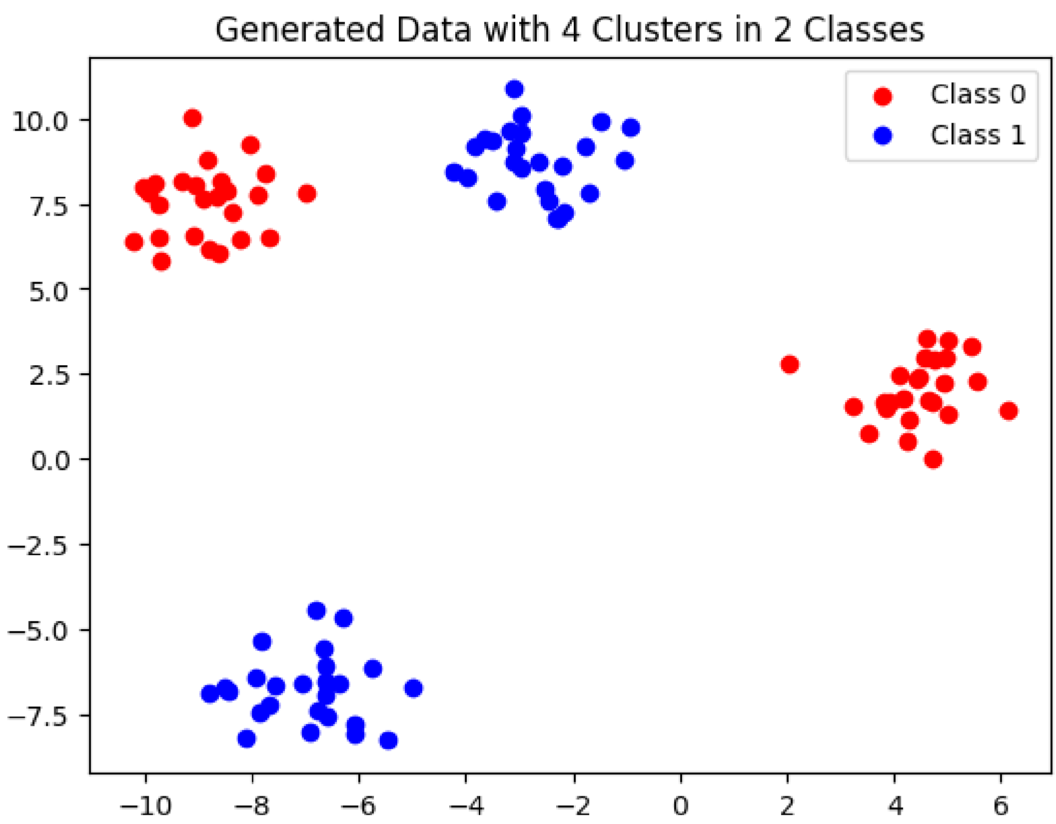
Link 2D Dataset: https://drive.google.com/file/d/1uvxB8O3hXM5Qqr29zAVwtgY0kZU6QyW9/view?usp=sharing

Link Image Dataset: https://drive.google.com/drive/folders/17SWbfn0Egf4NQ6uccWcp6uretlYbY0SU?usp=sharing

2D Data

Generate 2D Data

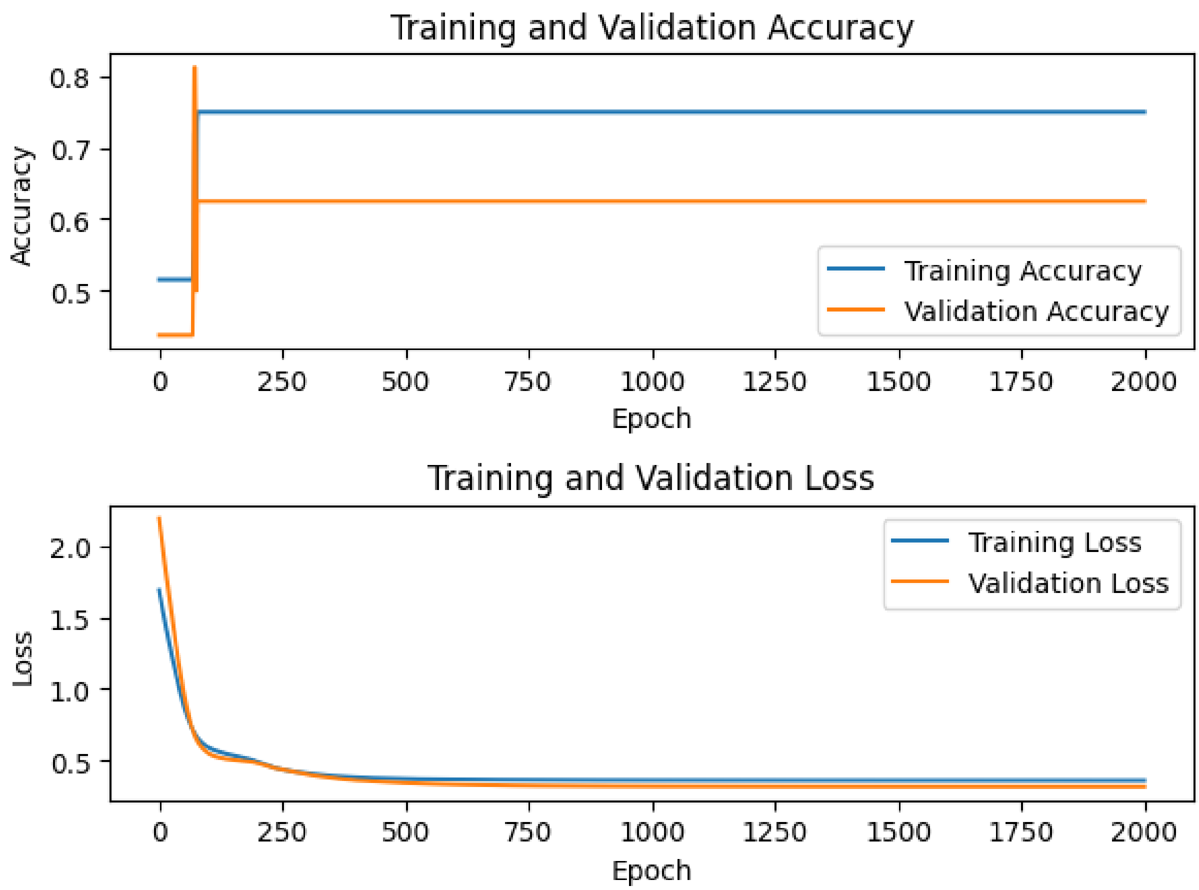
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import make_blobs
from sklearn.model_selection import train_test_split
from tensorflow import keras
from tensorflow.keras import layers

# Generate 2D data with 4 clusters
data ,labels = make_blobs(n_samples = 100, n_features = 2, centers =
4, cluster_std = 1.0, random_state = 42)

labels = (labels % 2 == 0).astype(int) # Convert labels to 2 classes

plt.scatter(data[labels == 0 , 0], data[labels == 0 , 1], c = 'red',
label = 'Class 0')
plt.scatter( data [ labels == 1 , 0], data[ labels == 1 , 1],
c='blue', label = 'Class 1')
plt.title("Generated Data with 4 Clusters in 2 Classes")
plt.legend()
plt.show()
```



Create Model

```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(data, labels,
test_size=0.2, random_state=42)

# Build a simple model using Keras
model = keras.Sequential ([
    layers.Dense(3, activation ='relu', input_shape =(2 ,)),
    layers.Dense(2, activation ='softmax') # = จำนวนคลาส
])

# Compile the model
model.compile(optimizer='adam', loss
='sparse_categorical_crossentropy', metrics =['accuracy'])

# Train the model
history = model.fit(X_train, y_train, epochs=2000,
validation_split=0.2 ,verbose=0)

# Plot training history for accuracy
plt.subplot(2 , 1 , 1)
plt.plot(history.history['accuracy'], label ='Training Accuracy')
plt.plot(history.history['val_accuracy'], label ='Validation
Accuracy')
```

```
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Plot training history for loss
plt.subplot(2 , 1 , 2 )
plt.plot(history.history['loss'], label ='Training Loss')
plt.plot(history.history['val_loss'], label ='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.tight_layout()
plt.show()
```



Testing

```
X_test.shape

(20, 2)
```

```
prob_pred = model.predict(X_test)
prob_pred
```

```
1/1 [==============================] - 0s 80ms/step
```

```
array([[5.1566845e-01, 4.8433149e-01],
       [5.5388646e-04, 9.9944603e-01],
       [9.9973822e-01, 2.6184111e-04],
       [2.5438407e-04, 9.9974573e-01],
       [5.1566845e-01, 4.8433149e-01],
       [9.9986243e-01, 1.3754587e-04],
       [5.1566845e-01, 4.8433149e-01],
       [9.9992245e-01, 7.7519850e-05],
       [5.1566845e-01, 4.8433149e-01],
       [4.6054476e-01, 5.3945518e-01],
       [5.1566845e-01, 4.8433149e-01],
       [2.5751907e-04, 9.9974251e-01],
       [5.1566845e-01, 4.8433149e-01],
       [5.1566845e-01, 4.8433149e-01],
       [9.9987954e-01, 1.2043148e-04],
       [5.1566845e-01, 4.8433149e-01],
       [2.3536349e-04, 9.9976462e-01],
       [5.1566845e-01, 4.8433149e-01],
       [4.5476068e-04, 9.9954516e-01],
       [9.9991965e-01, 8.0391241e-05]], dtype=float32)
```

```
y_pred = np.argmax(model.predict(X_test), axis=1)
y_pred
```

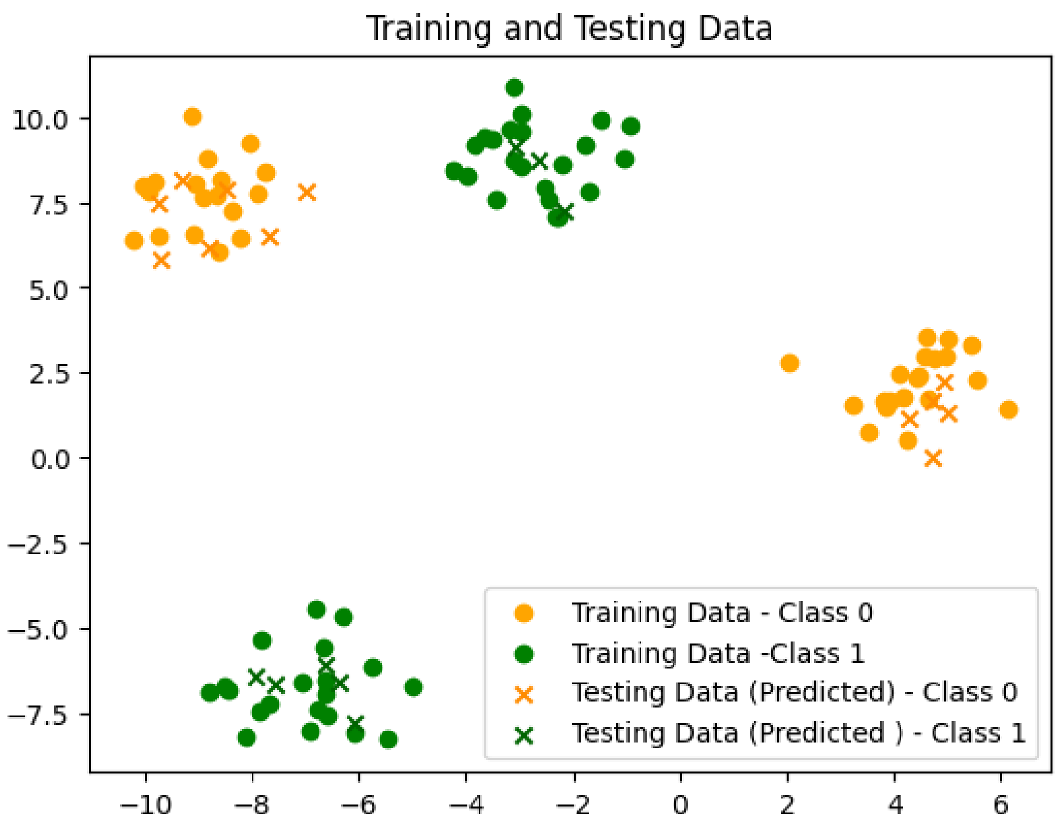
```
1/1 [==============================] - 0s 20ms/step
```

```
array([0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0])
```

Plotting Result

```
# Plot the training data
plt.scatter(X_train[y_train ==0 , 0], X_train [ y_train ==0 , 1],
c='orange', marker ='o', label ='Training Data - Class 0')
plt.scatter(X_train[y_train ==1 , 0], X_train [ y_train ==1 , 1],
c='green', marker ='o', label ='Training Data -Class 1')

# Plot the testing data with predicted labels
plt.scatter(X_test[y_test ==0 , 0], X_test [ y_test ==0 , 1],
c='darkorange', marker ='x', label ='Testing Data (Predicted) - Class
0')
plt.scatter(X_test[y_test ==1 , 0], X_test [ y_test ==1 , 1],
c='darkgreen', marker ='x', label ='Testing Data (Predicted ) - Class
1')
plt.title("Training and Testing Data")
```

```
plt.legend()
plt.show()
```



Model Exploration

```
model.summary()

Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense_2 (Dense)             (None, 3)                 9         
                                                                 
 dense_3 (Dense)             (None, 2)                 8         
                                                                 
=================================================================
Total params: 17 (68.00 Byte)
Trainable params: 17 (68.00 Byte)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________

model.get_weights()
```

```
[array([[-0.23996465,  1.654307  , -0.01125003],
        [-0.43923938,  0.08076783, -0.40816075]], dtype=float32),
 array([ 0.3468808 ,  0.7159669 , -0.21797493], dtype=float32),
 array([[-1.4071357 ,  0.43987364],
        [ 0.97931343, -0.05420568],
        [-0.3781685 , -0.78804487]], dtype=float32),
 array([ 0.03134724, -0.03134722], dtype=float32)]
```

```
model.layers[0].get_config()['activation']
```

```
{"type":"string"}
```

```
model.layers[1].get_config()['activation']
```

```
{"type":"string"}
```

```
x_new = np.array([[0 , 0]])
model.predict(x_new)
```

```
1/1 [==============================] - 0s 56ms/step
```

```
array([[0.54040366, 0.45959634]], dtype=float32)
```

Tabular Table Data

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from keras.models import Sequential
from keras.layers import Dense
```

Read Data

```
df = pd.read_csv('/content/drive/MyDrive/INT421/Dataset/drug200.csv')
df.head()
```

```
   Age Sex      BP Cholesterol  Na_to_K   Drug
0   23   F    HIGH        HIGH   25.355  DrugY
1   47   M     LOW        HIGH   13.093  drugC
2   47   M     LOW        HIGH   10.114  drugC
3   28   F  NORMAL        HIGH    7.798  drugX
4   61   F     LOW        HIGH   18.043  DrugY
```

```
df['Drug'].unique()
```

```
array(['DrugY', 'drugC', 'drugX', 'drugA', 'drugB'], dtype=object)
```

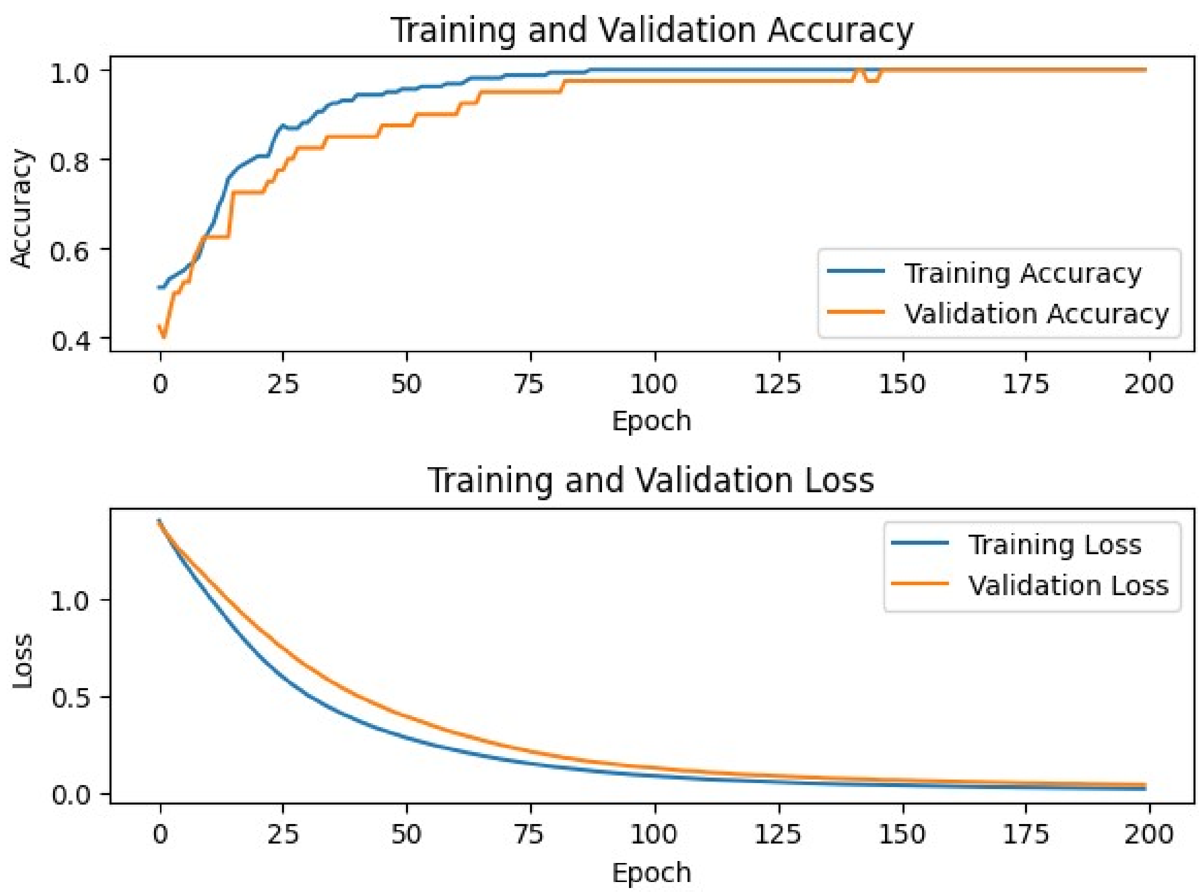
Preprocess Data

```
# Categorical Encoding
le_sex = LabelEncoder().fit(df['Sex'])
le_bp = LabelEncoder().fit(df['BP'])
le_chol = LabelEncoder().fit(df['Cholesterol'])
le_drug = LabelEncoder()
le_drug.classes_ = np.array(['drugA', 'drugB', 'drugC', 'drugX',
'DrugY'])
df['Sex'] = le_sex . transform( df['Sex'])
df['BP'] = le_bp . transform( df['BP'])
df['Cholesterol'] = le_chol.transform ( df['Cholesterol'])
df['Drug'] = le_drug.transform ( df['Drug'])
X = df.drop('Drug', axis =1)
y = df['Drug']

# Split the data 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 )

# Standardize the data
scaler = StandardScaler ()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
```

Model Creation

```
# Build the neural network model
model = Sequential()
model.add(Dense (32 , input_shape =(5,) , activation ='relu') )
model.add(Dense (16 , activation ='relu') )
model.add(Dense (5 , activation ='softmax') )

# Compile the model
model.compile(loss='sparse_categorical_crossentropy', optimizer
='adam', metrics =['accuracy'])

# Train the model
history = model.fit(X_train, y_train, epochs=200 ,
batch_size=32 ,validation_data =(X_test , y_test ) ,verbose =0 )

# Plot training history for accuracy
plt.subplot (2 , 1 , 1 )
plt.plot (history.history ['accuracy'], label ='Training Accuracy')
plt.plot (history.history ['val_accuracy'], label ='Validation
Accuracy')
plt.title ('Training and Validation Accuracy')
plt.xlabel ('Epoch')
plt.ylabel ('Accuracy')
plt.legend ()
```

```
# Plot training history for loss
plt.subplot (2 , 1 , 2 )
plt.plot (history.history ['loss'], label ='Training Loss')
plt.plot (history.history ['val_loss'], label ='Validation Loss')
plt.title ('Training and Validation Loss')
plt.xlabel ('Epoch')
plt.ylabel ('Loss')
plt.legend ()
plt.tight_layout ()
plt.show ()
```



Model Testing and Evaluation

```
y_pred = np . argmax ( model . predict ( X_test ) , axis =1 )
y_pred

2/2 [==============================] - 0s 7ms/step

array([3, 4, 3, 2, 4, 4, 4, 3, 0, 3, 0, 3, 4, 0, 1, 4, 1, 3, 2, 4, 1,
3,
       3, 4, 4, 4, 2, 3, 4, 3, 4, 2, 2, 4, 0, 4, 3, 0, 4, 0])
```

```
y_test.values
```

```
array([3, 4, 3, 2, 4, 4, 4, 3, 0, 3, 0, 3, 4, 0, 1, 4, 1, 3, 2, 4, 1,
3,
       3, 4, 4, 4, 2, 3, 4, 3, 4, 2, 2, 4, 0, 4, 3, 0, 4, 0])
```

```
from sklearn . metrics import confusion_matrix , classification_report
# Confusion Matrix
cm = confusion_matrix ( y_test , y_pred )
print ("Confusion Matrix :")
print ( cm )
# Classification Report
class_report = classification_report ( y_test , y_pred )
print ("Classification Report :")
print ( class_report )
```

```
Confusion Matrix :
[[ 6  0  0  0  0]
 [ 0  3  0  0  0]
 [ 0  0  5  0  0]
 [ 0  0  0 11  0]
 [ 0  0  0  0 15]]
Classification Report :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         6
           1       1.00      1.00      1.00         3
           2       1.00      1.00      1.00         5
           3       1.00      1.00      1.00        11
           4       1.00      1.00      1.00        15

    accuracy                           1.00        40
   macro avg       1.00      1.00      1.00        40
weighted avg       1.00      1.00      1.00        40
```

Image Data

Dataset: https://www.kaggle.com/datasets/pranavraikokte/covid19-image-dataset

Load Image Data

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
train_ds = keras.utils.image_dataset_from_directory (
directory =
'/content/drive/MyDrive/INT421/Dataset/Covid19-dataset/train',
labels = 'inferred',
label_mode ='categorical',
```

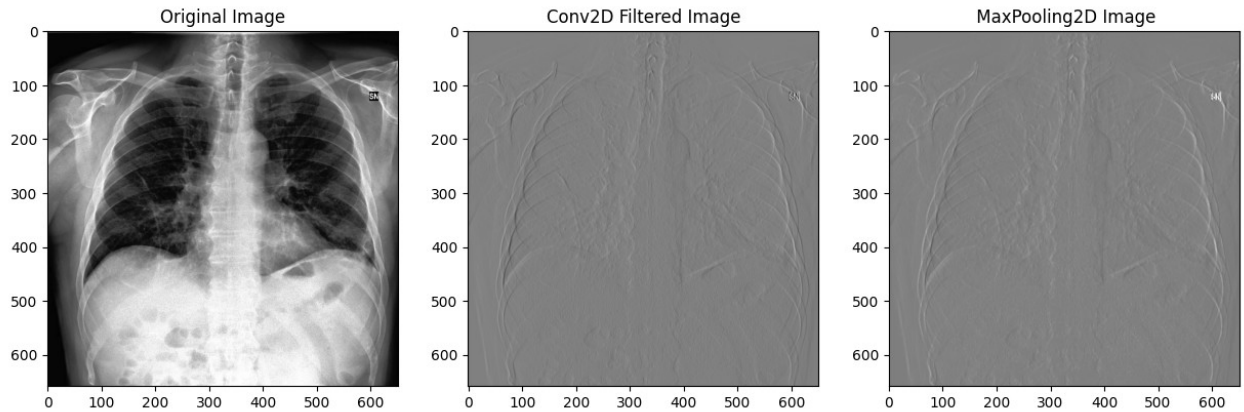
```
batch_size = 32,
image_size = (224, 224))
test_ds = keras.utils.image_dataset_from_directory(
directory =
'/content/drive/MyDrive/INT421/Dataset/Covid19-dataset/test',
labels = 'inferred',
label_mode = 'categorical',
batch_size = 32,
image_size = (224, 224))
```

```
Found 251 files belonging to 3 classes.
Found 66 files belonging to 3 classes.
```

Convu2D and MaxPooling2D Concepts

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.signal import convolve2d
from scipy.ndimage import maximum_filter
from scipy import misc

# Load a sample image
image_path =
'/content/drive/MyDrive/INT421/Dataset/Covid19-dataset/test/Covid/
0100.jpeg' # Replace with your image path
image = plt.imread(image_path)

# Define a simple Conv2D filter
filter_kernel = np.array ([[2 , 0 , -2], [2 , 0 , -2], [2 , 0 , -2]])

# Apply the Conv2D filter to the image
convolved_image = convolve2d (image [:, :, 0], filter_kernel , mode
='same',boundary ='symm')

# Apply MaxPooling2D to the convolved image
pooling_size = 2
pooled_image = maximum_filter ( convolved_image , size =
( pooling_size , pooling_size) )

# Visualize the original , convolved , and pooled images
plt.figure(figsize=( 15 , 5 ))
plt.subplot(1 , 3 , 1 )
plt.imshow(image)
plt.title('Original Image')
plt.subplot(1 , 3 , 2 )
plt.imshow(convolved_image , cmap ='gray')
plt.title('Conv2D Filtered Image')
plt.subplot(1 , 3 , 3 )
plt.imshow(pooled_image , cmap ='gray')
```

```
plt.title(' MaxPooling2D Image')
plt.show()
```



Model Creation

```
model = keras.Sequential([
layers.Conv2D(32,(3, 3 ), activation ='relu', input_shape=(224, 224, 3
)),
layers.MaxPooling2D((2,2)),
layers.Conv2D(64,(3,3),activation='relu'),
layers.MaxPooling2D((2, 2)),
layers.Conv2D(128,(3,3),activation ='relu') ,
layers.MaxPooling2D((2,2)),
layers.Flatten(),
layers.Dense(128, activation='relu') ,
layers.Dense(3, activation='softmax') # have 3 classes
])

model.summary()

Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 222, 222, 32)      896

 max_pooling2d (MaxPooling2  (None, 111, 111, 32)      0
 D)

 conv2d_1 (Conv2D)           (None, 109, 109, 64)      18496

 max_pooling2d_1 (MaxPoolin  (None, 54, 54, 64)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 52, 52, 128)       73856
```

```
 max_pooling2d_2 (MaxPoolin  (None, 26, 26, 128)       0
 g2D)

 flatten (Flatten)           (None, 86528)             0

 dense (Dense)               (None, 128)               11075712

 dense_1 (Dense)             (None, 3)                 387

=================================================================
Total params: 11169347 (42.61 MB)
Trainable params: 11169347 (42.61 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
model.compile(optimizer ='adam', loss ='categorical_crossentropy',
metrics = ['accuracy'])
history = model.fit(train_ds, epochs =50, validation_data = test_ds)
```

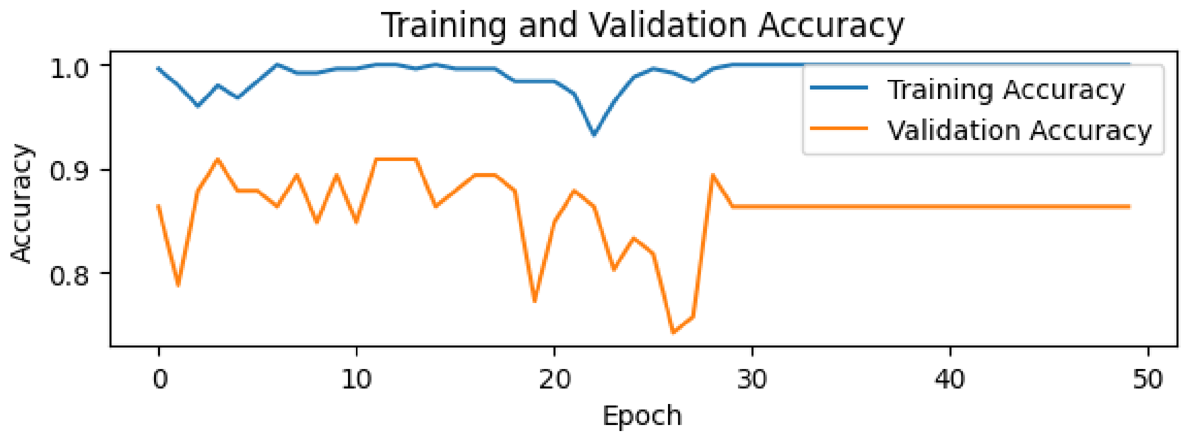
```
Epoch 1/50
8/8 [==============================] - 50s 4s/step - loss: 0.0432 -
accuracy: 0.9960 - val_loss: 3.2238 - val_accuracy: 0.8636
Epoch 2/50
8/8 [==============================] - 36s 4s/step - loss: 0.1027 -
accuracy: 0.9801 - val_loss: 10.1922 - val_accuracy: 0.7879
Epoch 3/50
8/8 [==============================] - 36s 4s/step - loss: 0.7377 -
accuracy: 0.9602 - val_loss: 2.6341 - val_accuracy: 0.8788
Epoch 4/50
8/8 [==============================] - 35s 4s/step - loss: 0.0906 -
accuracy: 0.9801 - val_loss: 2.8157 - val_accuracy: 0.9091
Epoch 5/50
8/8 [==============================] - 42s 5s/step - loss: 0.5827 -
accuracy: 0.9681 - val_loss: 2.5061 - val_accuracy: 0.8788
Epoch 6/50
8/8 [==============================] - 36s 4s/step - loss: 0.1283 -
accuracy: 0.9841 - val_loss: 4.7798 - val_accuracy: 0.8788
Epoch 7/50
8/8 [==============================] - 36s 4s/step - loss: 7.5655e-07
- accuracy: 1.0000 - val_loss: 5.5296 - val_accuracy: 0.8636
Epoch 8/50
8/8 [==============================] - 36s 4s/step - loss: 0.2795 -
accuracy: 0.9920 - val_loss: 3.1340 - val_accuracy: 0.8939
Epoch 9/50
8/8 [==============================] - 38s 4s/step - loss: 0.0765 -
accuracy: 0.9920 - val_loss: 2.3742 - val_accuracy: 0.8485
Epoch 10/50
8/8 [==============================] - 36s 4s/step - loss: 0.0091 -
accuracy: 0.9960 - val_loss: 2.0645 - val_accuracy: 0.8939
Epoch 11/50
```

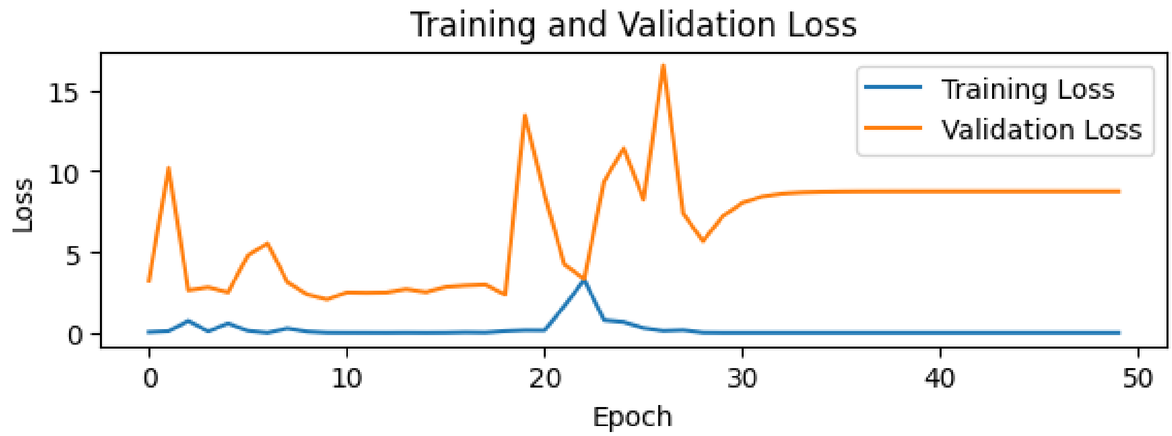
```
8/8 [==============================] - 39s 4s/step - loss: 0.0038 -
accuracy: 0.9960 - val_loss: 2.4933 - val_accuracy: 0.8485
Epoch 12/50
8/8 [==============================] - 36s 4s/step - loss: 0.0029 -
accuracy: 1.0000 - val_loss: 2.4760 - val_accuracy: 0.9091
Epoch 13/50
8/8 [==============================] - 36s 4s/step - loss: 5.8373e-06
- accuracy: 1.0000 - val_loss: 2.4928 - val_accuracy: 0.9091
Epoch 14/50
8/8 [==============================] - 38s 4s/step - loss: 0.0054 -
accuracy: 0.9960 - val_loss: 2.6985 - val_accuracy: 0.9091
Epoch 15/50
8/8 [==============================] - 35s 4s/step - loss: 4.1033e-06
- accuracy: 1.0000 - val_loss: 2.5153 - val_accuracy: 0.8636
Epoch 16/50
8/8 [==============================] - 39s 4s/step - loss: 0.0050 -
accuracy: 0.9960 - val_loss: 2.8374 - val_accuracy: 0.8788
Epoch 17/50
8/8 [==============================] - 35s 4s/step - loss: 0.0286 -
accuracy: 0.9960 - val_loss: 2.9248 - val_accuracy: 0.8939
Epoch 18/50
8/8 [==============================] - 37s 4s/step - loss: 0.0149 -
accuracy: 0.9960 - val_loss: 2.9789 - val_accuracy: 0.8939
Epoch 19/50
8/8 [==============================] - 37s 4s/step - loss: 0.1079 -
accuracy: 0.9841 - val_loss: 2.3607 - val_accuracy: 0.8788
Epoch 20/50
8/8 [==============================] - 35s 4s/step - loss: 0.1603 -
accuracy: 0.9841 - val_loss: 13.4417 - val_accuracy: 0.7727
Epoch 21/50
8/8 [==============================] - 39s 4s/step - loss: 0.1536 -
accuracy: 0.9841 - val_loss: 8.5220 - val_accuracy: 0.8485
Epoch 22/50
8/8 [==============================] - 36s 4s/step - loss: 1.6602 -
accuracy: 0.9721 - val_loss: 4.2172 - val_accuracy: 0.8788
Epoch 23/50
8/8 [==============================] - 35s 4s/step - loss: 3.2808 -
accuracy: 0.9323 - val_loss: 3.3347 - val_accuracy: 0.8636
Epoch 24/50
8/8 [==============================] - 36s 4s/step - loss: 0.7888 -
accuracy: 0.9641 - val_loss: 9.3573 - val_accuracy: 0.8030
Epoch 25/50
8/8 [==============================] - 35s 4s/step - loss: 0.6708 -
accuracy: 0.9880 - val_loss: 11.4137 - val_accuracy: 0.8333
Epoch 26/50
8/8 [==============================] - 36s 4s/step - loss: 0.2972 -
accuracy: 0.9960 - val_loss: 8.2215 - val_accuracy: 0.8182
Epoch 27/50
8/8 [==============================] - 38s 4s/step - loss: 0.1232 -
```

```
accuracy: 0.9920 - val_loss: 16.5339 - val_accuracy: 0.7424
Epoch 28/50
8/8 [==============================] - 34s 4s/step - loss: 0.1677 -
accuracy: 0.9841 - val_loss: 7.3718 - val_accuracy: 0.7576
Epoch 29/50
8/8 [==============================] - 35s 4s/step - loss: 0.0092 -
accuracy: 0.9960 - val_loss: 5.6641 - val_accuracy: 0.8939
Epoch 30/50
8/8 [==============================] - 35s 4s/step - loss: 6.4116e-08
- accuracy: 1.0000 - val_loss: 7.2020 - val_accuracy: 0.8636
Epoch 31/50
8/8 [==============================] - 34s 4s/step - loss: 4.9868e-08
- accuracy: 1.0000 - val_loss: 8.0339 - val_accuracy: 0.8636
Epoch 32/50
8/8 [==============================] - 41s 4s/step - loss: 3.7995e-09
- accuracy: 1.0000 - val_loss: 8.4259 - val_accuracy: 0.8636
Epoch 33/50
8/8 [==============================] - 34s 4s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.6031 - val_accuracy: 0.8636
Epoch 34/50
8/8 [==============================] - 35s 4s/step - loss: 0.0000e+00
- accuracy: 1.0000 - val_loss: 8.6818 - val_accuracy: 0.8636
Epoch 35/50
8/8 [==============================] - 37s 4s/step - loss: 0.0000e+00
- accuracy: 1.0000 - val_loss: 8.7166 - val_accuracy: 0.8636
Epoch 36/50
8/8 [==============================] - 39s 5s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.7319 - val_accuracy: 0.8636
Epoch 37/50
8/8 [==============================] - 36s 4s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.7385 - val_accuracy: 0.8636
Epoch 38/50
8/8 [==============================] - 35s 4s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.7414 - val_accuracy: 0.8636
Epoch 39/50
8/8 [==============================] - 37s 4s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.7426 - val_accuracy: 0.8636
Epoch 40/50
8/8 [==============================] - 35s 4s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.7431 - val_accuracy: 0.8636
Epoch 41/50
8/8 [==============================] - 40s 4s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.7433 - val_accuracy: 0.8636
Epoch 42/50
8/8 [==============================] - 34s 4s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.7433 - val_accuracy: 0.8636
Epoch 43/50
8/8 [==============================] - 35s 4s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.7433 - val_accuracy: 0.8636
```

```
Epoch 44/50
8/8 [==============================] - 35s 4s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.7432 - val_accuracy: 0.8636
Epoch 45/50
8/8 [==============================] - 37s 4s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.7432 - val_accuracy: 0.8636
Epoch 46/50
8/8 [==============================] - 37s 4s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.7431 - val_accuracy: 0.8636
Epoch 47/50
8/8 [==============================] - 39s 4s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.7430 - val_accuracy: 0.8636
Epoch 48/50
8/8 [==============================] - 35s 4s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.7429 - val_accuracy: 0.8636
Epoch 49/50
8/8 [==============================] - 35s 4s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.7429 - val_accuracy: 0.8636
Epoch 50/50
8/8 [==============================] - 35s 4s/step - loss: 4.7494e-10
- accuracy: 1.0000 - val_loss: 8.7428 - val_accuracy: 0.8636
```

```python
import matplotlib.pyplot as plt

# Plot training history for accuracy
plt.subplot(2, 1, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

# Plot training history for loss
plt.subplot(2, 1, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.tight_layout()
plt.show()
```



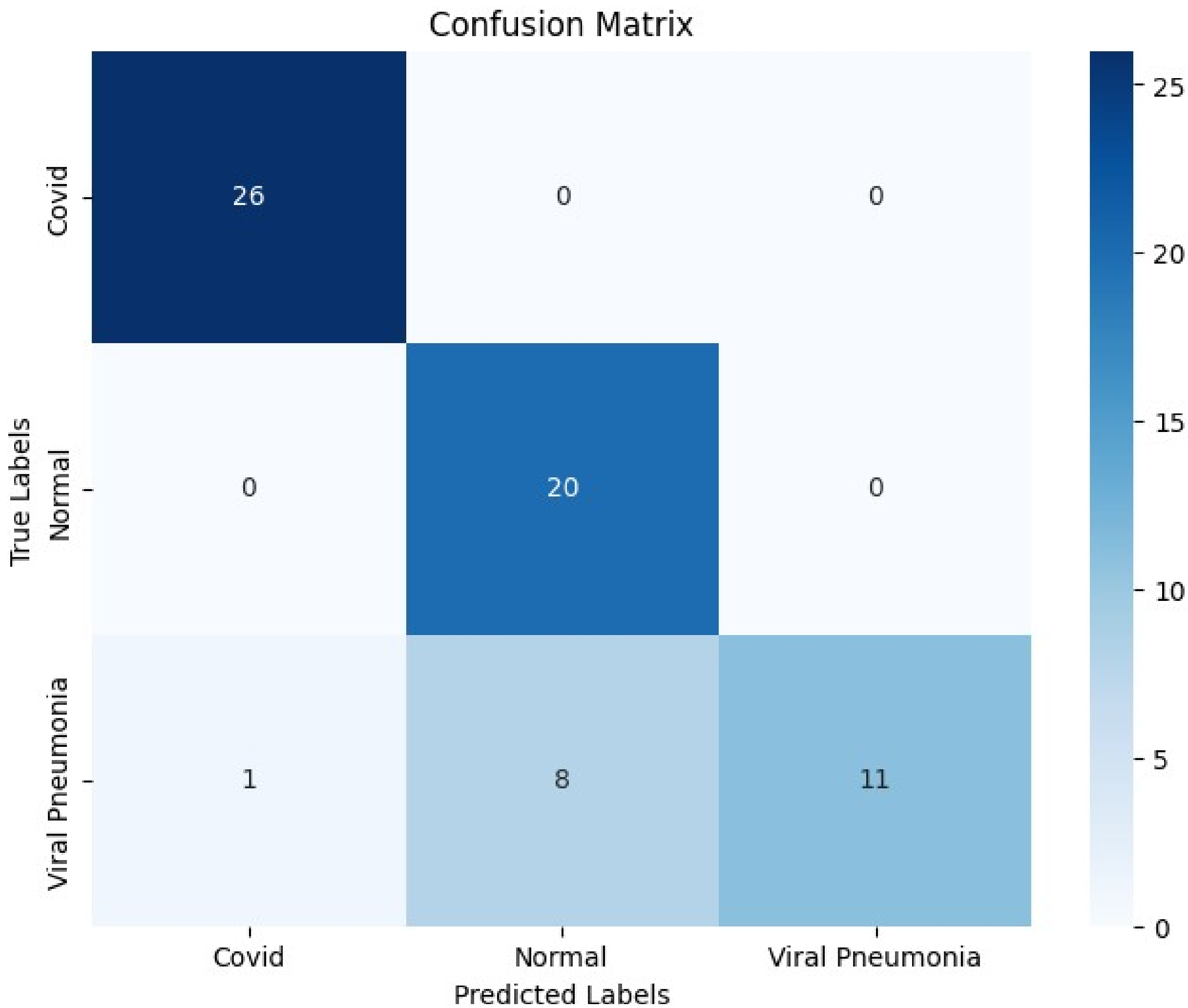


Prediction

```
from sklearn.metrics import confusion_matrix, classification_report,
accuracy_score
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

# Convert the test dataset to numpy arrays
X_test = []
y_true = []
for images, labels in test_ds:
    X_test.append(images.numpy())
    y_true.append(np.argmax(labels.numpy(), axis=1))

X_test = np.vstack(X_test)
y_true = np.concatenate(y_true)

# Make predictions
y_pred_probs = model.predict(X_test)
y_pred = np.argmax(y_pred_probs, axis=1)

# Confusion Matrix
```

```python
conf_matrix = confusion_matrix(y_true, y_pred)
print("Confusion Matrix:")
print(conf_matrix)

# Plot Confusion Matrix as heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=['Covid', 'Normal', 'Viral Pneumonia'],
            yticklabels=['Covid', 'Normal', 'Viral Pneumonia'])
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Confusion Matrix')
plt.show()

# Accuracy
accuracy = accuracy_score(y_true, y_pred)
print("Accuracy:", accuracy)

# Classification Report (Precision, Recall, F1 Score)
class_report = classification_report(y_true, y_pred,
target_names=['Covid', 'Normal', 'Viral Pneumonia'])
print("Classification Report:")
print(class_report)
```

```
3/3 [==============================] - 2s 649ms/step
Confusion Matrix:
[[26  0  0]
 [ 0 20  0]
 [ 1  8 11]]
```




```
Accuracy: 0.8636363636363636
Classification Report:
                 precision    recall  f1-score   support

          Covid       0.96      1.00      0.98        26
         Normal       0.71      1.00      0.83        20
Viral Pneumonia       1.00      0.55      0.71        20

       accuracy                           0.86        66
      macro avg       0.89      0.85      0.84        66
   weighted avg       0.90      0.86      0.85        66
```