In [2]:
```
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# Student Number: 810601044
# Course: Artificial Intelligence
# University of Tehran
# Homework 5 MLP
```

In [3]:
```
# Import the neccessary modules
import numpy as np
import pandas as pd
import keras
import cv2
import random
import matplotlib.pyplot as plt
import tensorflow as tf
import os
from PIL import Image
from keras.layers import Dense, Flatten
from tensorflow.keras.preprocessing import image
from keras.layers import Conv2D, MaxPooling2D, Dense, Flatten, Dropout, Activation,
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error,mean_squared_error, explained_varia
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from tensorflow.keras.utils import to_categorical
from keras.models import Sequential, load_model
from tensorflow.keras.preprocessing.image import ImageDataGenerator, load_img
from keras.models import Sequential
```

In [4]:
```
My_path = r'C:/Users/user/Desktop/German Traffic Sign Recognition Benchmark'

data = []

labels = []

classes = 43

# Configuration of images
for i in range(classes):
    path = os.path.join(My_path,'train',str(i))
    images = os.listdir(path)

    for a in images:
            image = Image.open(path + '\\'+ a)
            image = image.resize((30,30)) # Resize the images
            image = np.array(image)
            data.append([image,i]) # Append the values together
```

In [5]:
```
random.shuffle(data)
print(len(data))
```

```
39209
```

In [6]:
```
x = []
y = []
```

```
for features,label in data:
    x.append(features)
    y.append(label)
```

In [7]:
```
#Converting lists into numpy arrays
x = np.array(x)
y = np.array(y)
```

In [8]:
```
# Splitting the data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(x, y, test_size = 0.1, random_sta

print("Train set shape:", X_train.shape)
print("Validation set shape:", X_val.shape)
```

```
Train set shape: (35288, 30, 30, 3)
Validation set shape: (3921, 30, 30, 3)
```

In [9]:
```
X_train = X_train/255.0
X_val = X_val/255.0

print("Shape of train images is:", X_train.shape)
print("Shape of labels is:", y_train.shape)
```

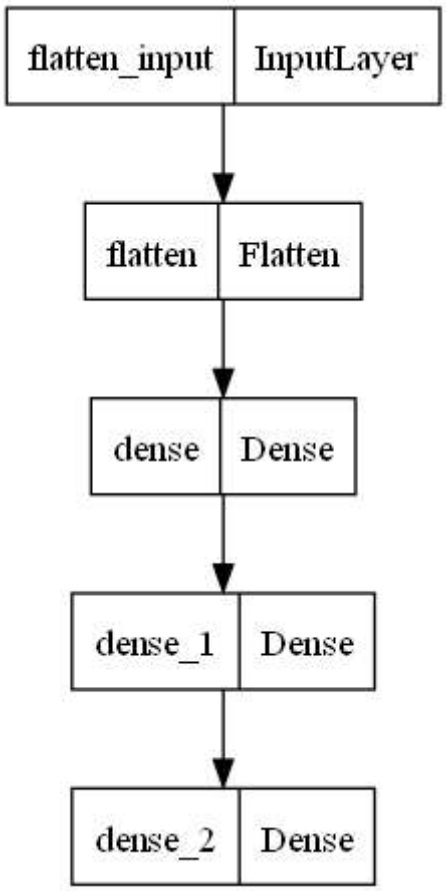
```
Shape of train images is: (35288, 30, 30, 3)
Shape of labels is: (35288,)
```

In [10]:
```
# Define the MLP model
model = Sequential()
model.add(Flatten(input_shape=X_train.shape[1:]))  # Flatten the input shape exclud

# Add hidden layers
model.add(Dense(256, activation='relu'))  # Example hidden layer with 256 neurons
model.add(Dense(128, activation='relu'))  # Another hidden layer with 128 neurons

# Add output layer
model.add(Dense(classes, activation='softmax'))  # Output layer with 'classes' neur

# Compile the model with specified learning rate
learning_rate= 0.001
optimizer = keras.optimizers.Adam(learning_rate = learning_rate, clipvalue = 1.0)
model.compile(optimizer=optimizer, loss='sparse_categorical_crossentropy', metrics=

# Print the model summary
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten (Flatten)           (None, 2700)              0

 dense (Dense)               (None, 256)               691456

 dense_1 (Dense)             (None, 128)               32896

 dense_2 (Dense)             (None, 43)                5547

=================================================================
Total params: 729,899
Trainable params: 729,899
Non-trainable params: 0
_________________________________________________________________
```

In [11]:
```
# The model visualization
keras.utils.plot_model(model)
```

Out[11]:

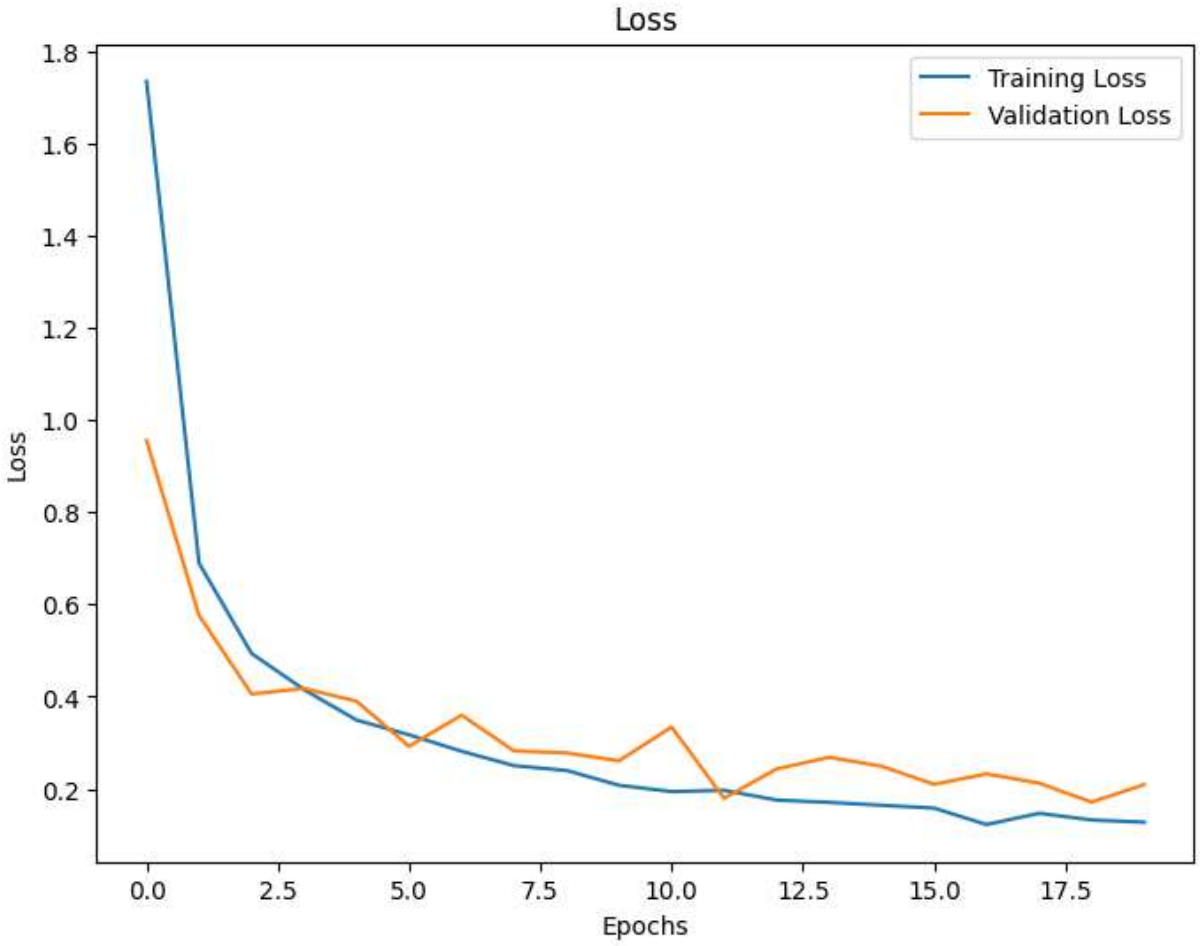


In [36]:
```
# Train the model
batch_size = 32
epochs = 20

history = model.fit(X_train, y_train, batch_size=batch_size, epochs=epochs, validat
```

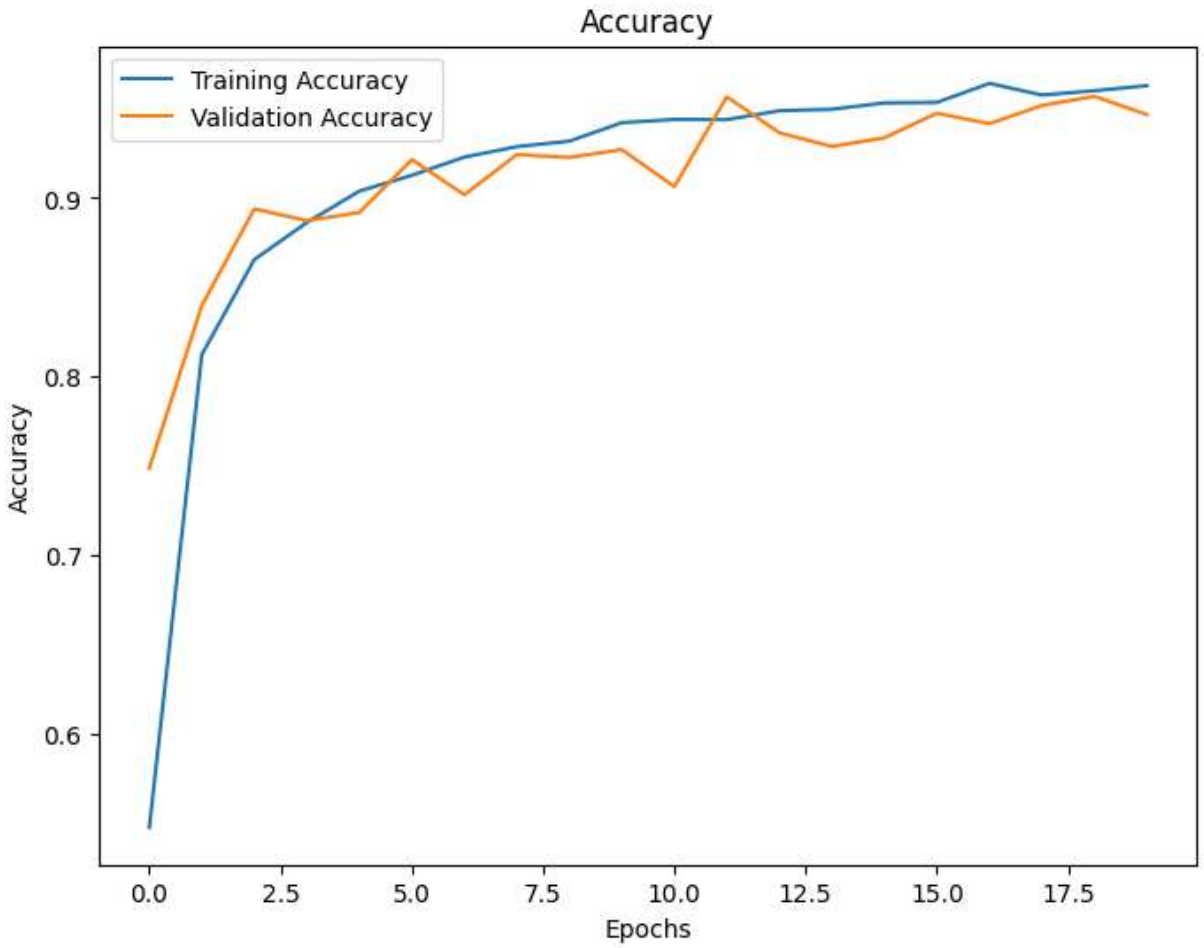
```
Epoch 1/20
1103/1103 [==============================] - 9s 8ms/step - loss: 1.7340 - accuracy:
0.5476 - val_loss: 0.9557 - val_accuracy: 0.7488
Epoch 2/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.6896 - accuracy:
0.8123 - val_loss: 0.5762 - val_accuracy: 0.8398
Epoch 3/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.4937 - accuracy:
0.8655 - val_loss: 0.4059 - val_accuracy: 0.8939
Epoch 4/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.4153 - accuracy:
0.8863 - val_loss: 0.4180 - val_accuracy: 0.8873
Epoch 5/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.3493 - accuracy:
0.9038 - val_loss: 0.3903 - val_accuracy: 0.8919
Epoch 6/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.3174 - accuracy:
0.9127 - val_loss: 0.2925 - val_accuracy: 0.9214
Epoch 7/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.2817 - accuracy:
0.9229 - val_loss: 0.3600 - val_accuracy: 0.9018
Epoch 8/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.2504 - accuracy:
0.9287 - val_loss: 0.2825 - val_accuracy: 0.9243
Epoch 9/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.2401 - accuracy:
0.9318 - val_loss: 0.2780 - val_accuracy: 0.9227
Epoch 10/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.2079 - accuracy:
0.9422 - val_loss: 0.2610 - val_accuracy: 0.9271
Epoch 11/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.1944 - accuracy:
0.9440 - val_loss: 0.3342 - val_accuracy: 0.9064
Epoch 12/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.1970 - accuracy:
0.9439 - val_loss: 0.1796 - val_accuracy: 0.9566
Epoch 13/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.1759 - accuracy:
0.9488 - val_loss: 0.2433 - val_accuracy: 0.9365
Epoch 14/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.1710 - accuracy:
0.9497 - val_loss: 0.2687 - val_accuracy: 0.9288
Epoch 15/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.1647 - accuracy:
0.9532 - val_loss: 0.2492 - val_accuracy: 0.9337
Epoch 16/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.1584 - accuracy:
0.9535 - val_loss: 0.2100 - val_accuracy: 0.9475
Epoch 17/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.1229 - accuracy:
0.9642 - val_loss: 0.2327 - val_accuracy: 0.9416
Epoch 18/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.1472 - accuracy:
0.9576 - val_loss: 0.2126 - val_accuracy: 0.9518
Epoch 19/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.1328 - accuracy:
```

```
0.9600 - val_loss: 0.1715 - val_accuracy: 0.9569
Epoch 20/20
1103/1103 [==============================] - 8s 7ms/step - loss: 0.1280 - accuracy:
0.9629 - val_loss: 0.2094 - val_accuracy: 0.9467
```

In [37]:
```
# Plot the loss
plt.figure(figsize=(8, 6))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



In [38]:
```
# Plot the accuracy
plt.figure(figsize=(8, 6))
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



In [39]:
```
# Load test dataset
y_test = pd.read_csv('C:/Users/user/Desktop/German Traffic Sign Recognition Benchma

# Add path prefix to "Path" column
y_test["Path"] = 'C:/Users/user/Desktop/German Traffic Sign Recognition Benchmark/'

labels = y_test["ClassId"].values
imgs = y_test["Path"].values

data = []

# Load and preprocess images
for img in imgs:
    image = Image.open(img)
    image = image.resize((30, 30))
    data.append(np.array(image) / 255.0)  # Divide each pixel by 255.0

X_test = np.array(data)

# Make predictions for test data
test_pred = np.argmax(model.predict(X_test), axis=-1)

# Get predictions for validation data
val_pred = np.argmax(model.predict(X_val), axis=-1)

# Calculate accuracy for test
```

```
accuracy_test_pred = accuracy_score(labels, test_pred)
print("Accuracy on the test dataset:", accuracy_test_pred)

# Calculate accuracy for validation
accuracy_val_pred = accuracy_score(y_val, val_pred)
print("Accuracy on the validation dataset:", accuracy_val_pred)

# Calculate loss for test
loss_test = model.evaluate(X_test, labels)
print("Loss on the test dataset:", loss_test)

# Calculate loss for validation
loss_val = model.evaluate(X_val, y_val)
print("Loss on the validation dataset:", loss_val)
```

```
395/395 [==============================] - 2s 4ms/step
123/123 [==============================] - 0s 3ms/step
Accuracy on the test dataset: 0.8345209817893904
Accuracy on the validation dataset: 0.9466972711043101
395/395 [==============================] - 2s 4ms/step - loss: 1.1299 - accuracy: 0.
8345
Loss on the test dataset: [1.129865050315857, 0.8345209956169128]
123/123 [==============================] - 1s 4ms/step - loss: 0.2094 - accuracy: 0.
9467
Loss on the validation dataset: [0.20944927632808685, 0.9466972947120667]
```

In [40]:

```
# Create confusion matrix for validation data
val_cm = confusion_matrix(y_val, val_pred)

# Create confusion matrix for test data
test_cm = confusion_matrix(labels, test_pred)

print("Confusion matrix for validation data:")
print(val_cm)
print()

print("Confusion matrix for test data:")
print(test_cm)
```

```
Confusion matrix for validation data:
[[ 13   3   0 ...   0   0   0]
 [  0 203   6 ...   0   0   0]
 [  0   1 213 ...   0   0   0]
 ...
 [  0   0   1 ...  50   0   0]
 [  0   0   0 ...   0  24   0]
 [  0   0   0 ...   0   0  28]]

Confusion matrix for test data:
[[ 21  27   2 ...   0   0   0]
 [  1 560  90 ...   0   0   0]
 [  0  12 688 ...   0   0   0]
 ...
 [  0   0   0 ...  42   0   0]
 [  0   0   0 ...   0  42   0]
 [  0   0   0 ...   0   5  73]]
```