Singn_Language_Detection_Main_Code

Importing Libraries for Sign Language Detection

This section imports all the necessary libraries required for building, training, and evaluating a sign language detection model. The libraries include:

- **Numpy and Pandas** for data manipulation and analysis.
- **Matplotlib and Seaborn** for data visualization.
- **TensorFlow and Keras** for constructing and training neural network models.
- **Scikit-learn** for model evaluation metrics.
- **OpenCV** for image processing tasks.

```
# Importing necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


# TensorFlow and Keras for building and training the neural network
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Conv2D, MaxPooling2D, Flatten, Dropout, BatchNormalization, Input
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras import regularizers
from tensorflow.keras.utils import to_categorical


# Sklearn for performance metrics and preprocessing
from sklearn.metrics import classification_report, confusion_matrix, f1_score
from sklearn.preprocessing import LabelBinarizer


# OpenCV for image processing
import cv2


# Suppress the specific warning
import warnings
warnings.filterwarnings("ignore", category=UserWarning, module='tensorflow.keras.preprocessing.image')
```

Exploring and Visualizing Sign Language Dataset

This code segment loads and explores the sign language dataset, consisting of both training and test data.

- Loading and Checking Data

- Checking Duplicates
- Visualizing Class Distribution

```
# Loading and Checking Train Data
reference_train_data = pd.read_csv('/content/sign_mnist_train.csv')
print('reference_train_data_shape :', reference_train_data.shape)
print('Null_Values :' ,reference_train_data.isnull().sum().sum()) # To check null values in the data set
reference_train_data.info()
reference_train_data.head()
```

```
reference_train_data_shape : (27455, 785)
Null_Values : 0
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27455 entries, 0 to 27454
Columns: 785 entries, label to pixel784
dtypes: int64(785)
memory usage: 164.4 MB
```

	label	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel775	pixel776	pixel777	pixel778	pi
0	3	107	118	127	134	139	143	146	150	153	...	207	207	207	207	
1	6	155	157	156	156	156	157	156	158	158	...	69	149	128	87	
2	2	187	188	188	187	187	186	187	188	187	...	202	201	200	199	
3	2	211	211	212	212	211	210	211	210	210	...	235	234	233	231	
4	13	164	167	170	172	176	179	180	184	185	...	92	105	105	108	

5 rows × 785 columns

```
# Loading and Checking Test Data
reference_test_data = pd.read_csv('/content/sign_mnist_test.csv')
print('reference_test_data_shape :', reference_test_data.shape)
print('Null_Values :' ,reference_test_data.isnull().sum().sum()) # To check null values in the data set
reference_test_data.info()
reference_test_data.head()
```

```
reference_test_data_shape : (7172, 785)
Null_Values : 0
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7172 entries, 0 to 7171
Columns: 785 entries, label to pixel784
dtypes: int64(785)
memory usage: 43.0 MB
```

	label	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel775	pixel776	pixel777	pixel778	pi
0	6	149	149	150	150	150	151	151	150	151	...	138	148	127	89	
1	5	126	128	131	132	133	134	135	135	136	...	47	104	194	183	
2	10	85	88	92	96	105	123	135	143	147	...	68	166	242	227	
3	0	203	205	207	206	207	209	210	209	210	...	154	248	247	248	
4	3	188	191	193	195	199	201	202	203	203	...	26	40	64	48	

5 rows × 785 columns

```
# Checking Duplicates
print("train_duplicate_values : ", reference_train_data.duplicated().sum()) # To check duplicate values in the train data set
print("test_duplicate_values : ", reference_test_data.duplicated().sum()) # To check duplicate values in the test data set
```

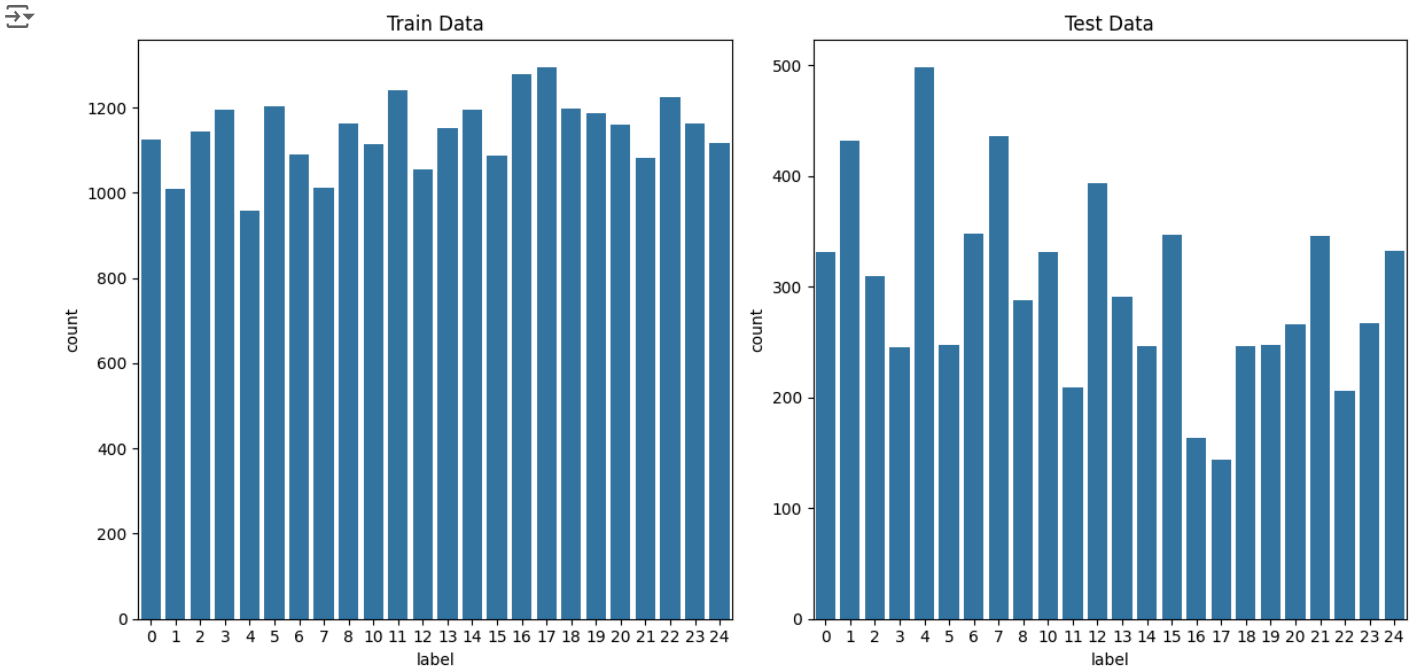
```
train_duplicate_values :  0
test_duplicate_values :  0
```

```
#Visualizing Class Distribution
# Set up the figure with two subplots (1 row, 2 columns)
fig, axs = plt.subplots(1, 2, figsize=(12, 6))

# Plot for training data
sns.countplot(data=reference_train_data, x="label", ax=axs[0])
axs[0].set_title('Train Data')

# Plot for test data
sns.countplot(data=reference_test_data, x="label", ax=axs[1])
axs[1].set_title('Test Data')

# Adjust layout and display the plot
plt.tight_layout()
plt.show()
```



Loading and Preprocessing Sign Language Dataset

This function and subsequent code segment load and preprocess the sign language dataset from CSV files for training and testing purposes.

```
# Function to load data from CSV
def load_data_from_csv(csv_file):
    data = pd.read_csv(csv_file)
    labels = data.iloc[:, 0]  # Extracting the Lables from the data set --> First column of data set
    images = data.iloc[:, 1:].values  # Extracting the Pixels from the data set --> Rest of the columns
    images = images.reshape(-1, 28, 28, 1) # Reshape to 28x28 and add channel dimension and normalization
    return images, labels


# # Function to load data from CSV
# def load_data_from_csv(csv_file):
#     data = pd.read_csv(csv_file)
#     labels = data.iloc[:, 0]  # Extracting the Lables from the data set --> First column of data set
#     images = data.iloc[:, 1:].values  # Extracting the Pixels from the data set --> Rest of the columns
#     return images, labels
```

```
# Load training and testing data
train_images, train_labels = load_data_from_csv('/content/sign_mnist_train.csv')
test_images, test_labels = load_data_from_csv('/content/sign_mnist_test.csv')


# Normalize the images with maximum pixel value 255.0
train_images = train_images / 255.0
test_images = test_images / 255.0

# train_images = train_images.reshape(-1, 28, 28, 1)  # Reshape to 28x28 and add channel dimension
# test_images = test_images.reshape(-1, 28, 28, 1)  # Reshape to 28x28 and add channel dimension

# Label Encoding
label_binarizer = LabelBinarizer()
train_labels = label_binarizer.fit_transform(train_labels)
test_labels = label_binarizer.transform(test_labels)


print("train_image_shape :" ,train_images.shape)
print("train_label_shape :" ,train_labels.shape)
print("test_image_shape :" ,test_images.shape)
print("test_label_shape :" ,test_labels.shape)
```

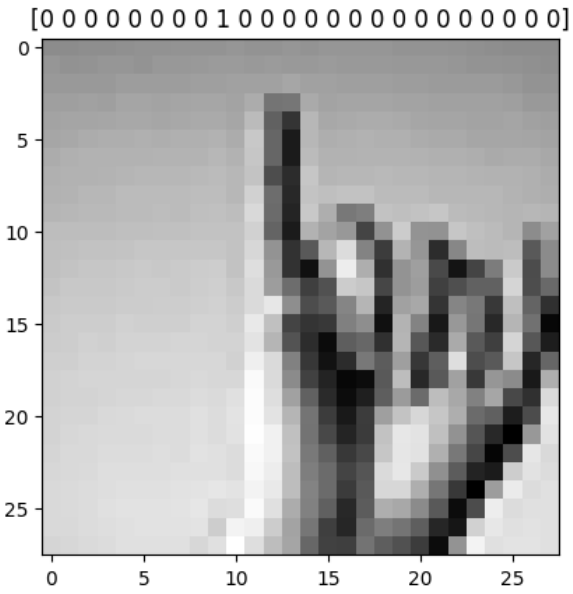
```
train_image_shape : (27455, 28, 28, 1)
train_label_shape : (27455, 24)
test_image_shape : (7172, 28, 28, 1)
test_label_shape : (7172, 24)
```

Verifying Training Dataset Images and Labels

This code segment allows you to verify individual images and their corresponding labels from the training dataset interactively

```
# Verification of train data set image and lable
image_index =int(input()) # Index input
plt.imshow(train_images[image_index],cmap='gray') # Image
plt.title(str(train_labels[image_index]))  # Label
plt.show()
```

```
6
```



Data Augmentation Configuration

This code snippet configures an "ImageDataGenerator" object for data augmentation, which is crucial for increasing the diversity of training examples without collecting additional data.

```
# Data Augmentation
datagen = ImageDataGenerator(
    rotation_range=10,
    width_shift_range=0.1,
    height_shift_range=0.1,
    shear_range=0.1,
    zoom_range=0.1,
    horizontal_flip=False
)
```

Convolutional Neural Network Model Architecture

This code segment defines a Convolutional Neural Network (CNN) model using TensorFlow's Keras API.

Model Architecture:

- Convolutional Layers
- Normalization and Pooling
- Stacking Convolutional Layers
- Flattening and Dense Layers

- Batch Normalization and Dropout
- Output Layer

This CNN architecture is designed for the sign language detection task, incorporating convolutional layers for feature extraction, pooling layers for spatial downsampling, dropout layers for regularization, and fully connected layers for classification. The model aims to learn and classify hand signs represented in the dataset effectively.

```
# Model Building
model = Sequential([
    Input(shape=(28, 28, 1)),
    Conv2D(32, (3, 3), activation='relu', padding='same'),
    BatchNormalization(),
    MaxPooling2D((3, 3)),
    Dropout(0.2),

    Conv2D(64, (3, 3), activation='relu', padding='same'),
    BatchNormalization(),
    MaxPooling2D((2, 2)),
    Dropout(0.2),

    Conv2D(128, (3, 3), activation='relu', padding='same'),
    BatchNormalization(),
    MaxPooling2D((2, 2)),
    Dropout(0.25),

    Flatten(),
    Dense(256, activation='relu', kernel_regularizer=regularizers.l2(0.01)),
    BatchNormalization(),
    Dropout(0.5),

    Dense(24, activation='softmax')
])
```

```
print(train_images.shape, train_images.dtype)
print(train_labels.shape, train_labels.dtype)
print(test_images.shape, test_images.dtype)
print(test_labels.shape, test_labels.dtype)
```

```
(27455, 28, 28, 1) float64
(27455, 24) int64
(7172, 28, 28, 1) float64
(7172, 24) int64
```

Compiling the Convolutional Neural Network Model

This code segment compiles the previously defined Convolutional Neural Network (CNN) model using TensorFlow's Keras API.

Compiling the model configures it for training by specifying the optimizer, loss function, and evaluation metrics. This setup prepares the CNN model to learn from the training data and optimize its performance based on the specified objectives in the sign language detection project.

```
# Compile the model
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='categorical_crossentropy',
              metrics=['accuracy'])


model.summary()
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv2d_15 (Conv2D)	(None, 28, 28, 32)	320
batch_normalization_20 (BatchNormalization)	(None, 28, 28, 32)	128
max_pooling2d_15 (MaxPooling2D)	(None, 9, 9, 32)	0
dropout_20 (Dropout)	(None, 9, 9, 32)	0
conv2d_16 (Conv2D)	(None, 9, 9, 64)	18,496
batch_normalization_21 (BatchNormalization)	(None, 9, 9, 64)	256
max_pooling2d_16 (MaxPooling2D)	(None, 4, 4, 64)	0
dropout_21 (Dropout)	(None, 4, 4, 64)	0
conv2d_17 (Conv2D)	(None, 4, 4, 128)	73,856
batch_normalization_22 (BatchNormalization)	(None, 4, 4, 128)	512
max_pooling2d_17 (MaxPooling2D)	(None, 2, 2, 128)	0
dropout_22 (Dropout)	(None, 2, 2, 128)	0
flatten_5 (Flatten)	(None, 512)	0
dense_10 (Dense)	(None, 256)	131,328
batch_normalization_23 (BatchNormalization)	(None, 256)	1,024
dropout_23 (Dropout)	(None, 256)	0
dense_11 (Dense)	(None, 24)	6,168

Total params: 232,088 (906.59 KB)
Trainable params: 231,128 (902.84 KB)
Non-trainable params: 960 (3.75 KB)

Custom Callback for F1 Score Calculation

The "**F1ScoreCallback**" class is a custom TensorFlow Keras callback designed to compute and print the weighted F1 score at the end of each epoch during model training. This helps assess the model's performance based on precision and recall metrics, providing valuable insights into

its effectiveness for the sign language detection task.

```
# Custom callback to calculate F1 score for each epoch
class F1ScoreCallback(tf.keras.callbacks.Callback):
    def on_epoch_end(self, epoch, logs=None):
        predictions = model.predict(test_images)
        predicted_labels = np.argmax(predictions, axis=1)
        true_labels = np.argmax(test_labels, axis=1)
        f1 = f1_score(true_labels, predicted_labels, average='weighted')
        print(f"Epoch {epoch+1} - F1 Score: {f1:.2f}")
```

Training the Convolutional Neural Network Model

This code trains the CNN model using augmented data batches generated by "**datagen.flow()**", validates the model's performance using the original test dataset, and prints the F1 score after each epoch using a custom callback. It aims to optimize the model's ability to classify sign language images accurately over multiple training iterations.

```
# Model Training
history = model.fit(datagen.flow(train_images, train_labels, batch_size=64),
                    validation_data=(test_images, test_labels),
                    epochs=10,
                    callbacks=[F1ScoreCallback()])
```

```
Epoch 1/10
/usr/local/lib/python3.10/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset` class should call `super().__init__(**kwargs)` in its co
  self._warn_if_super_not_called()
225/225 ━━━━━━━━━━━━━━━━━━━━ 5s 22ms/step
Epoch 1 - F1 Score: 0.54
429/429 ━━━━━━━━━━━━━━━━━━━━ 78s 171ms/step - accuracy: 0.3025 - loss: 5.3327 - val_accuracy: 0.5427 - val_loss: 2.4230
Epoch 2/10
225/225 ━━━━━━━━━━━━━━━━━━━━ 3s 15ms/step
Epoch 2 - F1 Score: 0.94
429/429 ━━━━━━━━━━━━━━━━━━━━ 70s 164ms/step - accuracy: 0.7722 - loss: 1.4333 - val_accuracy: 0.9441 - val_loss: 0.5724
Epoch 3/10
225/225 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step
Epoch 3 - F1 Score: 0.98
429/429 ━━━━━━━━━━━━━━━━━━━━ 75s 149ms/step - accuracy: 0.8721 - loss: 0.7106 - val_accuracy: 0.9760 - val_loss: 0.3429
Epoch 4/10
225/225 ━━━━━━━━━━━━━━━━━━━━ 4s 19ms/step
Epoch 4 - F1 Score: 0.98
429/429 ━━━━━━━━━━━━━━━━━━━━ 84s 153ms/step - accuracy: 0.9067 - loss: 0.5225 - val_accuracy: 0.9756 - val_loss: 0.3110
Epoch 5/10
225/225 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step
Epoch 5 - F1 Score: 0.99
429/429 ━━━━━━━━━━━━━━━━━━━━ 69s 159ms/step - accuracy: 0.9276 - loss: 0.4469 - val_accuracy: 0.9925 - val_loss: 0.2603
Epoch 6/10
225/225 ━━━━━━━━━━━━━━━━━━━━ 3s 15ms/step
Epoch 6 - F1 Score: 0.98
429/429 ━━━━━━━━━━━━━━━━━━━━ 79s 153ms/step - accuracy: 0.9416 - loss: 0.4069 - val_accuracy: 0.9827 - val_loss: 0.2886
Epoch 7/10
225/225 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step
Epoch 7 - F1 Score: 0.97
429/429 ━━━━━━━━━━━━━━━━━━━━ 81s 151ms/step - accuracy: 0.9444 - loss: 0.3917 - val_accuracy: 0.9739 - val_loss: 0.2956
Epoch 8/10
```

```
225/225 ━━━━━━━━━━━━━━━━━━━━ 4s 16ms/step
Epoch 8 - F1 Score: 0.99
429/429 ━━━━━━━━━━━━━━━━━━━━ 83s 154ms/step - accuracy: 0.9468 - loss: 0.3911 - val_accuracy: 0.9900 - val_loss: 0.2804
Epoch 9/10
225/225 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step
Epoch 9 - F1 Score: 1.00
429/429 ━━━━━━━━━━━━━━━━━━━━ 66s 153ms/step - accuracy: 0.9521 - loss: 0.3719 - val_accuracy: 0.9962 - val_loss: 0.2408
Epoch 10/10
225/225 ━━━━━━━━━━━━━━━━━━━━ 3s 14ms/step
Epoch 10 - F1 Score: 0.99
429/429 ━━━━━━━━━━━━━━━━━━━━ 67s 157ms/step - accuracy: 0.9564 - loss: 0.3560 - val_accuracy: 0.9909 - val_loss: 0.2582
```

Evaluating the Trained Convolutional Neural Network Model

This code snippet assesses the CNN model's ability to generalize to unseen data by evaluating its performance on the independent test dataset. It provides a quantitative measure of the model's accuracy in classifying sign language images, indicating how well the model has learned and generalized from the training data.

```
# Model Evaluation
test_loss, test_acc = model.evaluate(test_images, test_labels)
print(f"Test accuracy: {test_acc}")
```

```
225/225 ━━━━━━━━━━━━━━━━━━━━ 3s 15ms/step - accuracy: 0.9901 - loss: 0.2595
Test accuracy: 0.9909369945526123
```

Classification Report and Confusion Matrix for Model Evaluation

- The classification report provides detailed metrics for evaluating the model's performance on each class in the dataset.
- The confusion matrix visually represents the model's predictions compared to the true labels, highlighting any patterns or discrepancies in classification accuracy across different classes.

```
# Classification Report and Confusion Matrix
predictions = model.predict(test_images)
predicted_labels = np.argmax(predictions, axis=1)
true_labels = np.argmax(test_labels, axis=1)
```

```
225/225 ━━━━━━━━━━━━━━━━━━━━ 4s 18ms/step
```

```
# Convert label binarizer classes to list of strings
target_names = [str(class_label) for class_label in label_binarizer.classes_]
```

```
print(classification_report(true_labels, predicted_labels, target_names=target_names))
```

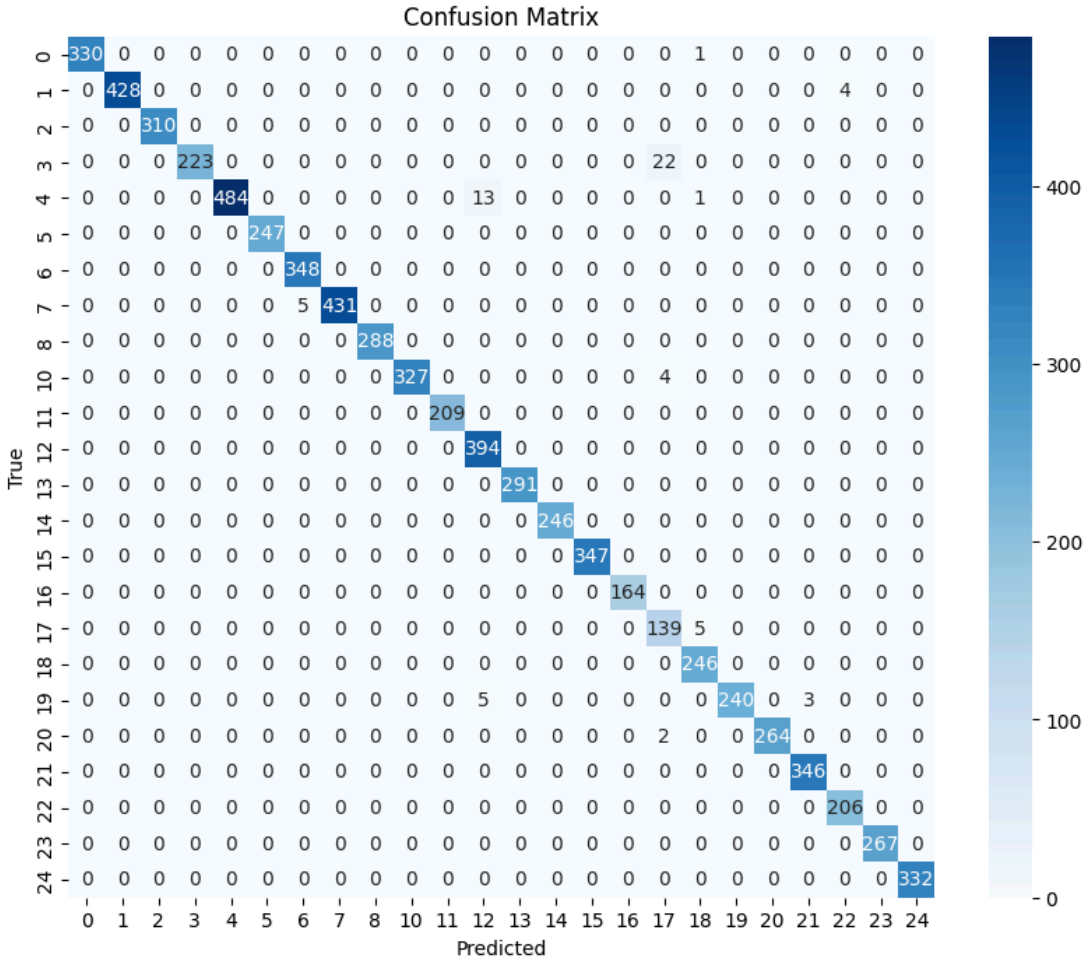
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       331
           1       1.00      0.99      1.00       432
           2       1.00      1.00      1.00       310
           3       1.00      0.91      0.95       245
```

```
                4       1.00      0.97      0.99       498
                5       1.00      1.00      1.00       247
                6       0.99      1.00      0.99       348
                7       1.00      0.99      0.99       436
                8       1.00      1.00      1.00       288
               10       1.00      0.99      0.99       331
               11       1.00      1.00      1.00       209
               12       0.96      1.00      0.98       394
               13       1.00      1.00      1.00       291
               14       1.00      1.00      1.00       246
               15       1.00      1.00      1.00       347
               16       1.00      1.00      1.00       164
               17       0.83      0.97      0.89       144
               18       0.97      1.00      0.99       246
               19       1.00      0.97      0.98       248
               20       1.00      0.99      1.00       266
               21       0.99      1.00      1.00       346
               22       0.98      1.00      0.99       206
               23       1.00      1.00      1.00       267
               24       1.00      1.00      1.00       332

         accuracy                           0.99      7172
        macro avg       0.99      0.99      0.99      7172
     weighted avg       0.99      0.99      0.99      7172
```

```
#Confusion_Matrix
cm = confusion_matrix(true_labels, predicted_labels)
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=label_binarizer.classes_, yticklabels=label_binarizer.classes_)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```



Model Saving

Saving the model allows you to reuse it later for inference, deployment in applications, or further training. The HDF5 format preserves the model's architecture and weights, making it easy to load and use in different environments that support Keras or TensorFlow.

```
def plot_metrics(history):
    plt.figure(figsize=(12, 5))

    # Plotting model accuracy
```