1. Import Necessary Libraries

```
import pandas as pd
import numpy as np
import os
from tensorflow.keras.preprocessing.image import load_img, img_to_array
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
```

2. Load and Preprocess Your Data

```
from google.colab import files
uploaded = files.upload()
```

Choose files nzmsa-2024.zip

- **nzmsa-2024.zip**(application/zip) - 159734390 bytes, last modified: 03/08/2024 - 100% done

```
Saving nzmsa-2024.zip to nzmsa-2024.zip
```

```
import zipfile
# Replace 'your_zip_file.zip' with the name of your uploaded zip file
with zipfile.ZipFile('nzmsa-2024.zip', 'r') as zip_ref:
    zip_ref.extractall('nzmsa-2024 (1)')
```

```
extracted_files = os.listdir('nzmsa-2024 (1)')
print(extracted_files)
```

```
['__MACOSX', 'nzmsa-2024']
```

```
# Load the CSV files
train_df = pd.read_csv('nzmsa-2024 (1)/nzmsa-2024/train.csv')
sample_submission_df = pd.read_csv('nzmsa-2024 (1)/nzmsa-2024/sample_submission.csv')

# Specify directories for train and test images
train_images_dir = 'nzmsa-2024 (1)/nzmsa-2024/cifar10_images/train'
test_images_dir = 'nzmsa-2024 (1)/nzmsa-2024/cifar10_images/test'

# Function to load images from directory based on the dataframe ids
def load_images_from_dir(image_ids, directory, image_size=(32, 32)):
    images = []
    for image_id in image_ids:
        image_path = os.path.join(directory, f'image_{image_id}.png')
        image = load_img(image_path, target_size=image_size)
        image = img_to_array(image)
        images.append(image)
    return np.array(images)

# Load train and test images
X_train = load_images_from_dir(train_df['id'], train_images_dir)
y_train = to_categorical(train_df['label'], num_classes=10)
#X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.2, random_state=42)

X_test = load_images_from_dir(sample_submission_df['id'], test_images_dir)
```

```
# Normalize the pixel values to improve the model's performance:
X_train = X_train / 255.0
X_test = X_test / 255.0
```

```
# Data augmentation artificially increases the size and diversity of the training dataset by applying random transfo
from tensorflow.keras.preprocessing.image import ImageDataGenerator

datagen = ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    horizontal_flip=True
)
```

3. Build the Model

```
from tensorflow.keras.layers import BatchNormalization
# Build a CNN model
model = Sequential([
    Conv2D(64, (3, 3), activation='relu', input_shape=(32, 32, 3)),
    BatchNormalization(),
    MaxPooling2D((2, 2)),
    Dropout(0.25),

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

    Flatten(),
    Dense(256, activation='relu'),
    BatchNormalization(),
    Dropout(0.5),

    Dense(10, activation='softmax')
])

from tensorflow.keras.optimizers import Adam

optimizer = Adam(learning_rate=0.001)

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

4. Train the Model

```
history = model.fit(X_train, y_train,
                    validation_split=0.2,
                    epochs=30,
                    batch_size=32)
```

```
Epoch 1/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 248s 194ms/step - accuracy: 0.3486 - loss: 2.0762 - val_accuracy: 0.3265 - val_los
Epoch 2/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 260s 192ms/step - accuracy: 0.5183 - loss: 1.3599 - val_accuracy: 0.3531 - val_los
Epoch 3/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 270s 198ms/step - accuracy: 0.5698 - loss: 1.2151 - val_accuracy: 0.3479 - val_los
Epoch 4/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 247s 186ms/step - accuracy: 0.5991 - loss: 1.1275 - val_accuracy: 0.4973 - val_los
Epoch 5/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 232s 186ms/step - accuracy: 0.6204 - loss: 1.0826 - val_accuracy: 0.2974 - val_los
Epoch 6/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 263s 187ms/step - accuracy: 0.6355 - loss: 1.0275 - val_accuracy: 0.3453 - val_los
Epoch 7/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 260s 186ms/step - accuracy: 0.6459 - loss: 1.0052 - val_accuracy: 0.5487 - val_los
Epoch 8/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 243s 195ms/step - accuracy: 0.6639 - loss: 0.9497 - val_accuracy: 0.3782 - val_los
Epoch 9/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 250s 185ms/step - accuracy: 0.6724 - loss: 0.9333 - val_accuracy: 0.4270 - val_los
Epoch 10/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 267s 189ms/step - accuracy: 0.6815 - loss: 0.9107 - val_accuracy: 0.5366 - val_los
Epoch 11/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 269s 195ms/step - accuracy: 0.6909 - loss: 0.8828 - val_accuracy: 0.4972 - val_los
Epoch 12/30
```

```
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 250s 185ms/step - accuracy: 0.6956 - loss: 0.8673 - val_accuracy: 0.2760 - val_los
Epoch 13/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 273s 194ms/step - accuracy: 0.7021 - loss: 0.8398 - val_accuracy: 0.5800 - val_los
Epoch 14/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 265s 196ms/step - accuracy: 0.7118 - loss: 0.8199 - val_accuracy: 0.6677 - val_los
Epoch 15/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 254s 190ms/step - accuracy: 0.7143 - loss: 0.8012 - val_accuracy: 0.5903 - val_los
Epoch 16/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 244s 195ms/step - accuracy: 0.7168 - loss: 0.8018 - val_accuracy: 0.6160 - val_los
Epoch 17/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 265s 198ms/step - accuracy: 0.7275 - loss: 0.7724 - val_accuracy: 0.5107 - val_los
Epoch 18/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 238s 191ms/step - accuracy: 0.7283 - loss: 0.7692 - val_accuracy: 0.5226 - val_los
Epoch 19/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 233s 187ms/step - accuracy: 0.7352 - loss: 0.7523 - val_accuracy: 0.5988 - val_los
Epoch 20/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 275s 197ms/step - accuracy: 0.7391 - loss: 0.7404 - val_accuracy: 0.5830 - val_los
Epoch 21/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 255s 191ms/step - accuracy: 0.7396 - loss: 0.7380 - val_accuracy: 0.4131 - val_los
Epoch 22/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 268s 196ms/step - accuracy: 0.7426 - loss: 0.7274 - val_accuracy: 0.5550 - val_los
Epoch 23/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 240s 192ms/step - accuracy: 0.7475 - loss: 0.7077 - val_accuracy: 0.5846 - val_los
Epoch 24/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 235s 188ms/step - accuracy: 0.7487 - loss: 0.7062 - val_accuracy: 0.5504 - val_los
Epoch 25/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 248s 198ms/step - accuracy: 0.7602 - loss: 0.6773 - val_accuracy: 0.6698 - val_los
Epoch 26/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 259s 196ms/step - accuracy: 0.7630 - loss: 0.6740 - val_accuracy: 0.5159 - val_los
Epoch 27/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 262s 196ms/step - accuracy: 0.7634 - loss: 0.6779 - val_accuracy: 0.7092 - val_los
Epoch 28/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 252s 188ms/step - accuracy: 0.7613 - loss: 0.6676 - val_accuracy: 0.5743 - val_los
Epoch 29/30
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 270s 195ms/step - accuracy: 0.7687 - loss: 0.6540 - val_accuracy: 0.5778 - val_los
```

5. Making Predictions

```
# CNN predictions
cnn_predictions = model.predict(X_test)
cnn_pred_labels = np.argmax(cnn_predictions, axis=1)


# Save predictions to CSV (e.g., for submission)
submission_df = pd.DataFrame({
    'id': sample_submission_df['id'],
    'label': cnn_pred_labels
})
submission_df.to_csv('cnn_predictions3.csv', index=False)
```

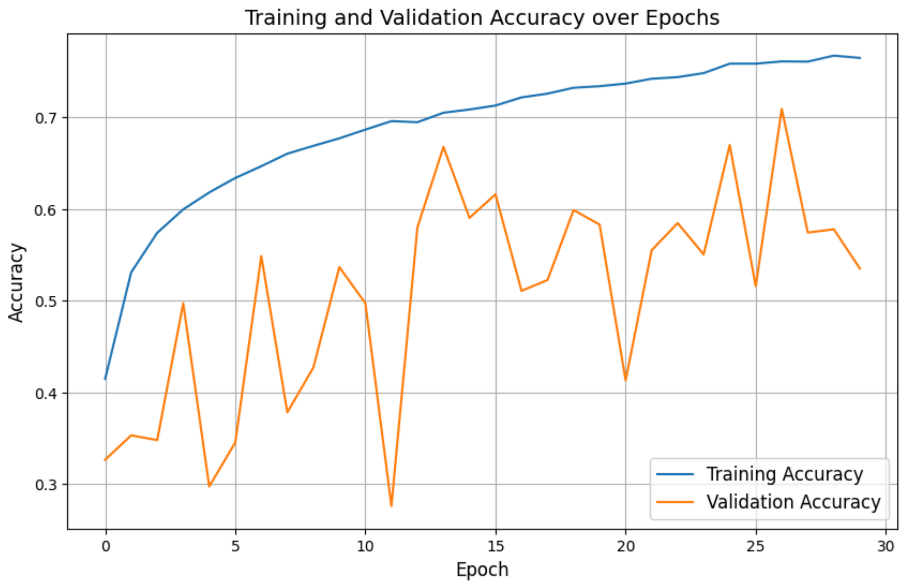
```
157/157 ━━━━━━━━━━━━━━━━━━━━ 8s 48ms/step
```

```
from google.colab import files

files.download('cnn_predictions3.csv')
```

6. Visualize Results

```
# Plotting Training and Validation Accuracy
plt.figure(figsize=(10, 6))
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epoch', fontsize=12)
plt.ylabel('Accuracy', fontsize=12)
plt.title('Training and Validation Accuracy over Epochs', fontsize=14)
plt.legend(loc='lower right', fontsize=12)
plt.grid(True)
plt.show()
```



7. Summary

In this project, I built a Convolutional Neural Network (CNN) to classify images from the CIFAR-10 dataset. The model architecture includes:

Convolutional Layers: Three Conv2D layers with 64, 128, and 256 filters, respectively. Each convolutional layer is followed by BatchNormalization, MaxPooling, and Dropout layers to enhance model performance and reduce overfitting.

Flatten Layer: Converts the 2D feature maps to a 1D vector.

Dense Layers: A Dense layer with 256 neurons and ReLU activation, followed by Dropout.

Output Layer: A Dense layer with 10 neurons and softmax activation for multi-class classification.

The model was compiled using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss, tracking accuracy as the metric during training. This setup is designed to effectively learn and classify the CIFAR-10 images, leveraging the CNN's ability to capture spatial features and the Adam optimizer's efficiency in training deep neural networks.