Computer Vision Midterm Assignment

Introduction

Welcome to your Computer Vision midterm project! Here, you'll get hands-on experience building an image recognition model using Convolutional Neural Networks and transfer learning.

Install Necessary Libraries:

```
!pip install tensorflow
!pip install keras
!pip install numpy
!pip install matplotlib
```

```
Requirement already satisfied: tensorflow in /usr/local/lib/python3.10/dist-packages (2.17.1)
Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.4.0)
Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.6.3)
Requirement already satisfied: flatbuffers>=24.3.25 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (24.3.25)
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.6.0
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Requirement already satisfied: ml-dtypes<0.5.0,>=0.3.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.4.1)
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Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.37
Requirement already satisfied: numpy<2.0.0,>=1.23.5 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.26.4)
Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.10/dist-packages (from astunparse>=1.6.0->tensorflow) (0.4
Requirement already satisfied: rich in /usr/local/lib/python3.10/dist-packages (from keras>=3.2.0->tensorflow) (13.9.4)
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Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tensorfl
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Requirement already satisfied: absl-py in /usr/local/lib/python3.10/dist-packages (from keras) (1.4.0)
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Requirement already satisfied: typing-extensions>=4.5.0 in /usr/local/lib/python3.10/dist-packages (from optree->keras) (4.12.2)
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Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (4.55.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.7)
```

```
import numpy as np
import matplotlib.pyplot as plt
```

```
import tensorflow as tf
import numpy as np

from tensorflow. keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Model, Sequential
from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Dropout
from tensorflow.keras.applications import VGG16, ResNet50, MobileNetV2  # Choose a pre-trained model
from tensorflow.keras.callbacks import ModelCheckpoint

# Additional libraries for data loading (if using a custom dataset)
# from skimage.io import imread  # Example for loading images
```

Dataset Selection and Loading

- **Choose Your Dataset**
    - **Standard Datasets:** CIFAR-10, CIFAR-100, or a suitable subset of ImageNet are good starting points. You can use built-in functions to load them.
    - **Custom Dataset:** If you propose a custom dataset, ensure it has sufficient images per class, good quality, and accurate labeling. You'll need to upload it to Colab.
    - **Select your dataset and uncomment the appropriate loading code.**
    - **If you are using a custom dataset, make sure you have uploaded it to Colab and adjust the file path.**

```
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
import numpy as np

from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Model, Sequential
from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Dropout
from tensorflow.keras.applications import VGG16, ResNet50, MobileNetV2  # Choose a pre-trained model
from tensorflow.keras.callbacks import ModelCheckpoint
# Import the cifar10 dataset
from tensorflow.keras.datasets import cifar10


# Additional libraries for data loading (if using a custom dataset)
# from skimage.io import imread  # Example for loading images
```

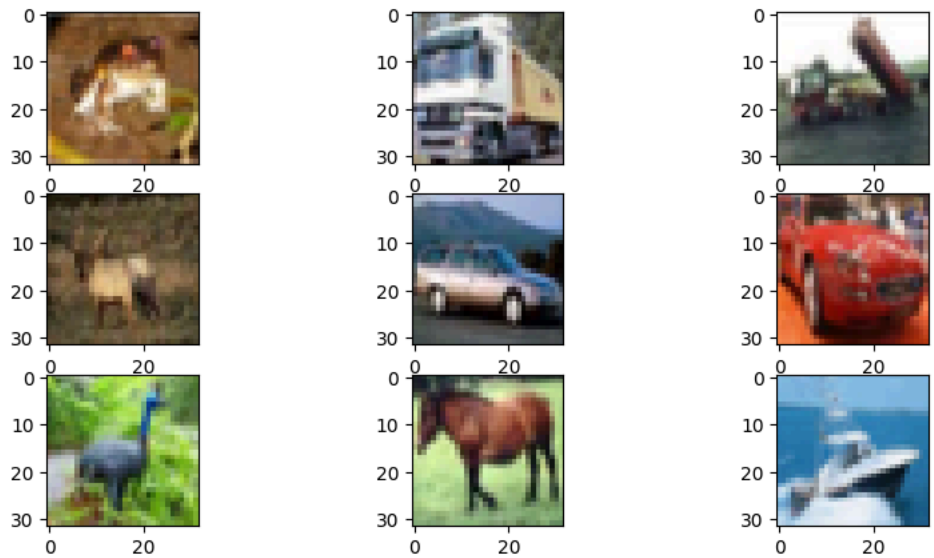
Markdown Cell: Exploratory Data Analysis (EDA)

- **Instructions:**
    - Visualize a few random images from your dataset to understand its content and overall quality.
    - Check the shape of your data to confirm the number of images and their dimensions.

```
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
import numpy as np

from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Model, Sequential
from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Dropout
from tensorflow.keras.applications import VGG16, ResNet50, MobileNetV2  # Choose a pre-trained model
from tensorflow.keras.callbacks import ModelCheckpoint
# Import the cifar10 dataset
from tensorflow.keras.datasets import cifar10
from collections import Counter


# Additional libraries for data loading (if using a custom dataset)
# from skimage.io import imread  # Example for loading images


# Load the CIFAR-10 dataset first
(x_train, y_train), (x_test, y_test) = cifar10.load_data()

# Now you can display sample images
plt.figure(figsize=(10, 5))
for i in range(9):
```

```
    plt.subplot(3, 3, i+1)
    plt.imshow(x_train[i])
plt.show()
#
print('Training data shape:', x_train.shape)
print('Training labels shape:', y_train.shape)
print('Test data shape:', x_test.shape)
print('Test labels shape:', y_test.shape)

# Explore class distribution (if using a standard dataset)
print('Class Distribution (Top 10):')
print(Counter(np.argmax(y_train, axis=1)).most_common(10))
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 ━━━━━━━━━━━━━━━━━━━━ 3s 0us/step
```



```
Training data shape: (50000, 32, 32, 3)
Training labels shape: (50000, 1)
Test data shape: (10000, 32, 32, 3)
Test labels shape: (10000, 1)
Class Distribution (Top 10):
[(0, 50000)]
```

Image Preprocessing

- **Instructions:**
  1. **Normalization:**
     - Normalize pixel values (usually to the range of 0-1 or -1 to 1)
  2. **Resizing:**
     - Resize images to a consistent size for model input.

```
# Insert code here to normalize images
# Normalize the data
x_train = x_train.astype('float32') / 255.0
x_test = x_test.astype('float32') / 255.0

# Resize images if needed (adjust input_shape in model building accordingly)
# x_train = tf.image.resize(x_train, (224, 224))  # Example for resizing to 224x224
# x_test = tf.image.resize(x_test, (224, 224))

# Insert code here to resize images, if needed
```

** Data Augmentation **

- **Instructions:**

1. Experiment with Parameters: The code below has some example data augmentation parameters. Try changing the values within these parameters, or even adding new augmentation techniques! Here's a short guide:

- Hint 1: Start with small adjustments to see the effects clearly.
- Hint 2: Consider which augmentations make sense for your dataset. Flipping images of letters might be okay, but rotating them too much could make them unreadable!
- Explore more: Try adding things like shear_range (for shearing transformations) or zoom_range (for random zooming).

2. Visualize the Effects: After setting up your ImageDataGenerator, add a few lines of code to display some randomly augmented images from your dataset. This will help you see how your chosen parameters change the images.

- Hint: Use a small sample of images so it's easy to compare the originals with the augmented versions.

```
datagen = ImageDataGenerator(
       rotation_range=20,
       width_shift_range=0.1,
       height_shift_range=0.1,
       horizontal_flip=True,
       # Add more augmentations if desired
)
datagen.fit(x_train) # Fit the augmentation parameters to the training data
```

Model Building (Transfer Learning)

```
# Choose a pre-trained model suitable for object recognition (VGG16, ResNet50, MobileNetV2 are all options)
from tensorflow.keras.applications.vgg16 import VGG16
from tensorflow.keras.layers import Flatten, Dense
from tensorflow.keras.models import Model

base_model = VGG16(weights='imagenet', include_top=False, input_shape=x_train.shape[1:])

# Freeze some layers of the pre-trained model (optional)
for layer in base_model.layers[:10]:
   layer.trainable = False  # Adjust the number of layers to freeze as needed

# Add custom top layers
x = base_model.output
x = Flatten()(x)

num_classes =  10

predictions = Dense(num_classes, activation='softmax')(x)  # Adjust num_classes for your dataset

model = Model(inputs=base_model.input, outputs=predictions)

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

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16_weights_tf_dim_ordering_tf_kernels_notop.
58889256/58889256 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
```

Model Training

```
# ipython-input-8-4698ae1c4f81
# ipython-input-23-6fd226214be7 (Continued from your code)
from tensorflow.keras.layers import Dense # Import Dense here

# ... [9](Your existing code for base_model and Flatten) ...

# Define the number of classes in your dataset
num_classes = 10  # Replace 10 with the actual number of classes in your dataset

# Add a Dense layer for classification
predictions = Dense(num_classes, activation='softmax')(x)  # num_classes should be the number of your classes

# Create the final model
from tensorflow.keras.models import Model
model = Model(inputs=base_model.input, outputs=predictions)
```

```
# Compile the model
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy']) # Adjust optimizer, loss, and metrics as neede

# Now you can use model.fit in the next cell (ipython-input-22-6fd226214be7)
```

Enhanced Training

Implement data augmentation within the training loop. Add callbacks to monitor progress and save the best performing model. Modify the Training Code: If you haven't already, we need to make a few changes to your training loop:

1. Integrate the Data Augmentation: Replace the direct use of x_train with datagen.flow(x_train, y_train, batch_size=32). This will apply your augmentations in real-time during training
2. Use the Validation Set: We already have validation_data=(x_test, y_test).
3. Save the Best Model: We're using a ModelCheckpoint callback to automatically save the model if its performance on the validation set improves

- Hint: Experiment with different batch sizes as well.

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator  # Import from tensorflow.keras
from keras.callbacks import ModelCheckpoint

# Data Augmentation with ImageDataGenerator
datagen = ImageDataGenerator(
       rotation_range=20,
       width_shift_range=0.1,
       height_shift_range=0.1,
       horizontal_flip=True)

#  Modify the model fitting to use real-time augmentation
history = model.fit(datagen.flow(x_train, y_train, batch_size=32),
                   epochs=15,
                   validation_data=(x_test, y_test),  # Use the test set for validation
                   callbacks=[ModelCheckpoint('best_model.keras', save_best_only=True, monitor='val_loss')]) # Changed the filepath to e
```

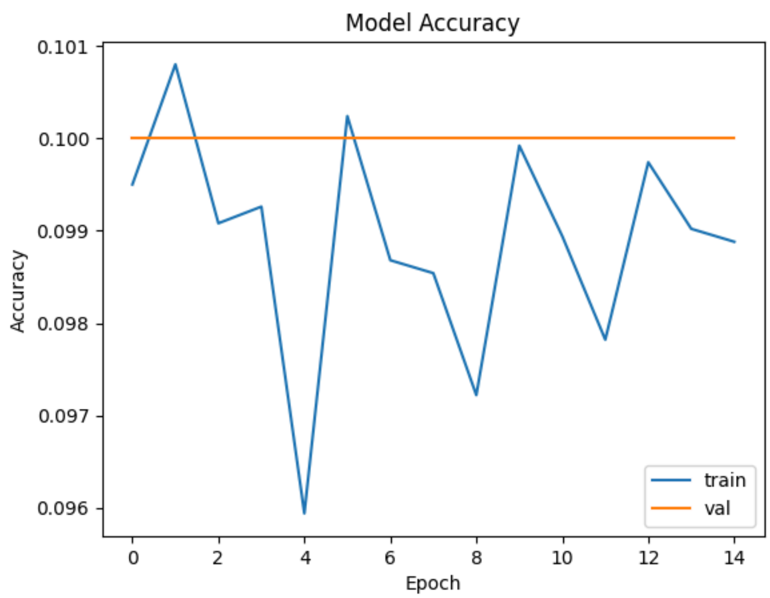
```
Epoch 1/15
/usr/local/lib/python3.10/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:122: UserWarning: Your `PyDataset` class
  self._warn_if_super_not_called()
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 64s 37ms/step - accuracy: 0.1040 - loss: 2.3126 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 2/15
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 72s 33ms/step - accuracy: 0.1023 - loss: 2.3027 - val_accuracy: 0.1000 - val_loss: 2.3027
Epoch 3/15
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 82s 33ms/step - accuracy: 0.0983 - loss: 2.3028 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 4/15
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 82s 33ms/step - accuracy: 0.0998 - loss: 2.3028 - val_accuracy: 0.1000 - val_loss: 2.3027
Epoch 5/15
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 83s 34ms/step - accuracy: 0.0979 - loss: 2.3027 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 6/15
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 80s 33ms/step - accuracy: 0.1013 - loss: 2.3027 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 7/15
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 54s 35ms/step - accuracy: 0.0981 - loss: 2.3027 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 8/15
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 54s 34ms/step - accuracy: 0.0967 - loss: 2.3028 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 9/15
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 52s 33ms/step - accuracy: 0.0945 - loss: 2.3028 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 10/15
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 53s 34ms/step - accuracy: 0.1014 - loss: 2.3027 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 11/15
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 81s 33ms/step - accuracy: 0.1027 - loss: 2.3027 - val_accuracy: 0.1000 - val_loss: 2.3027
Epoch 12/15
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 52s 33ms/step - accuracy: 0.0966 - loss: 2.3028 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 13/15
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 83s 33ms/step - accuracy: 0.0999 - loss: 2.3028 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 14/15
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 53s 34ms/step - accuracy: 0.1007 - loss: 2.3027 - val_accuracy: 0.1000 - val_loss: 2.3026
Epoch 15/15
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 53s 34ms/step - accuracy: 0.1008 - loss: 2.3028 - val_accuracy: 0.1000 - val_loss: 2.3026
```

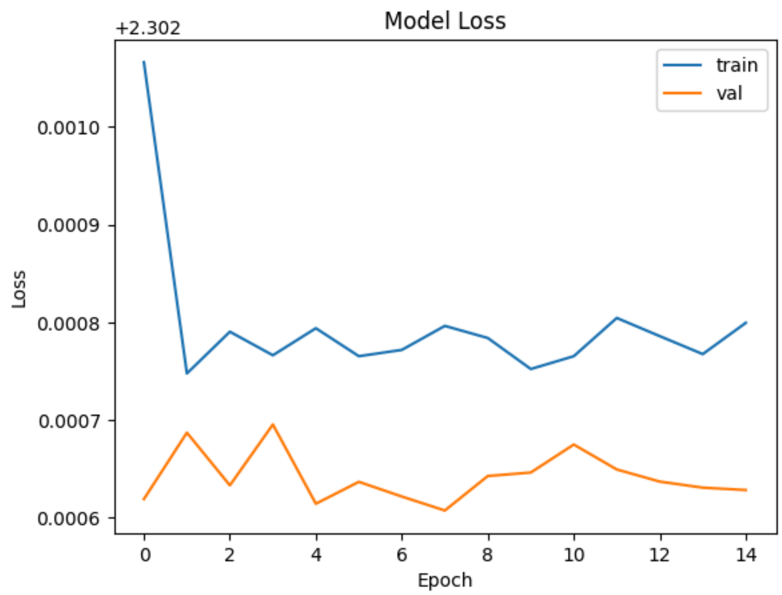
Visualizing Training Progress

Importance of Monitoring: Explain why tracking validation metrics helps identify overfitting or underfitting.

- Plot training and validation accuracy/loss curves.

```
# Plot training and validation curves
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['train', 'val'], loc='lower right')
plt.show()

# Plot the loss curves
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['train', 'val'], loc='upper right')
plt.show()
```





Evaluation on the Test Set

Discuss how test set metrics provide the most unbiased assessment of model performance.

```
from tensorflow.keras.models import load_model  # Import load_model

best_model = load_model('best_model.keras') # Also change .h5 to .keras to match filename in ModelCheckpoint
test_loss, test_acc = best_model.evaluate(x_test, y_test)

print('Test Loss:', test_loss)
print('Test Accuracy:', test_acc)
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 3s 8ms/step - accuracy: 0.0988 - loss: 2.3026
Test Loss: 2.302607536315918
Test Accuracy: 0.10000000149011612
```

Hyperparameter Tuning

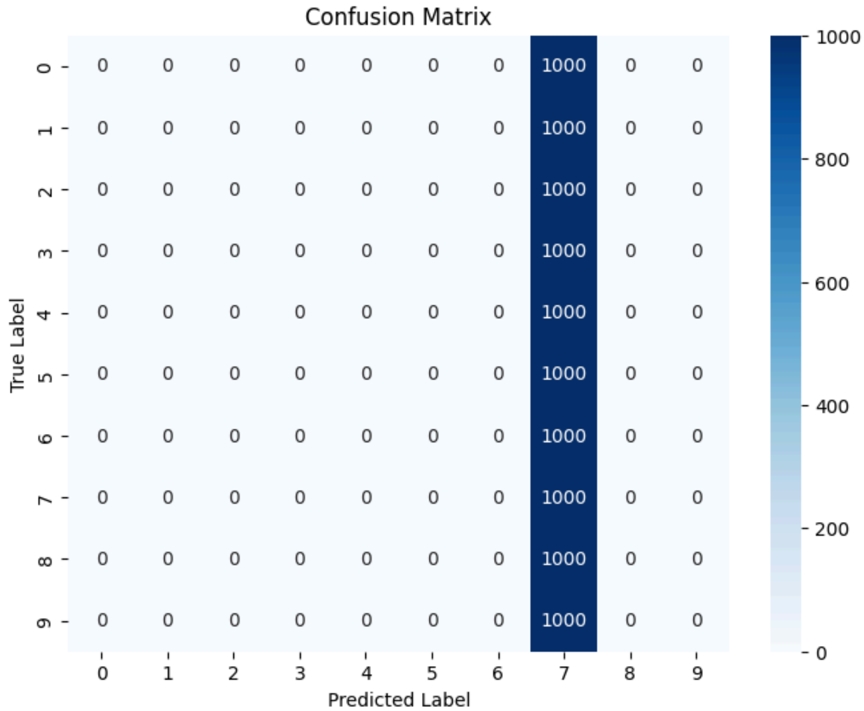
> Exploring Learning Rates: In the provided code, we're iterating through different learning rates.
>
> - Hint 1: A good starting range for the learning rate is often between 0.01 and 0.0001.
> - Hint 2: Pay close attention to how quickly the validation loss starts to increase (if it does), which might signal a learning rate that's too high.

```
def create_model(learning_rate=0.01):
    # ... (Code to build your model, using the learning_rate parameter)
    return model

# Basic parameter exploration
for lr in [0.01, 0.001, 0.0001]:
    model = create_model(learning_rate=lr)
    # ... (Training the model)
```

Confusion Matrx

```
from sklearn.metrics import confusion_matrix
import seaborn as sn

y_pred = best_model.predict(x_test)
y_pred_classes = np.argmax(y_pred, axis=1)

cm = confusion_matrix(y_test, y_pred_classes)

plt.figure(figsize=(8, 6))
sn.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix')
plt.show()
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step
```



Discussion and Further Exploration

Questions to consider:

1. How does the choice of pre-trained model (VGG16, ResNet50, etc.) affect the results?
2. Analyze the confusion matrix: Are errors more common between certain classes? What might explain this?
3. Experiment with different degrees of fine-tuning (freezing more/fewer layers of the pre-trained model).
4. If applicable to your dataset, can you collect more data for classes with higher error rates? What are other ways to potentially improve accuracy? (e.g., ensembling models, exploring advanced augmentation strategies, class-weighted training)

Sources towardsdatascience.com/build-your-own-deep-learning-classification-model-in-keras-511f647980d6
stackoverflow.com/questions/69997327/tensorflow-valueerror-input-0-is-incompatible-with-layer-model-expected-shape