Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers


from keras.applications.densenet import DenseNet121
from keras.applications.xception import Xception
from keras.applications.densenet import preprocess_input
from keras.optimizers import Adam, SGD, Adamax
from keras.models import Model, load_model
from keras.layers import *
from sklearn.model_selection import train_test_split
from keras.callbacks import *

from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Embedding, LSTM, Conv1D, MaxPool1D
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score
from tensorflow.keras import regularizers
from keras.src import callbacks
```

Train test split

```
from google.colab import drive
drive.mount('/content/drive',force_remount=True)
```

```
Mounted at /content/drive
```

```
image_size = (224, 224)
batch_size = 32


train_ds, val_ds = tf.keras.utils.image_dataset_from_directory(
    "/content/drive/MyDrive/BM1000",
    validation_split=0.25,
    subset="both",
    seed=1337,
    image_size=image_size,
    batch_size=batch_size,
)
```

```
Found 5850 files belonging to 7 classes.
Using 4388 files for training.
Using 1462 files for validation.
```

```
train_ds
```

```
<_PrefetchDataset element_spec=(TensorSpec(shape=(None, 224, 224, 3), dtype=tf.float32, name=None), TensorSpec(shape=(None,), dtype=tf.int32, name=None))>
```

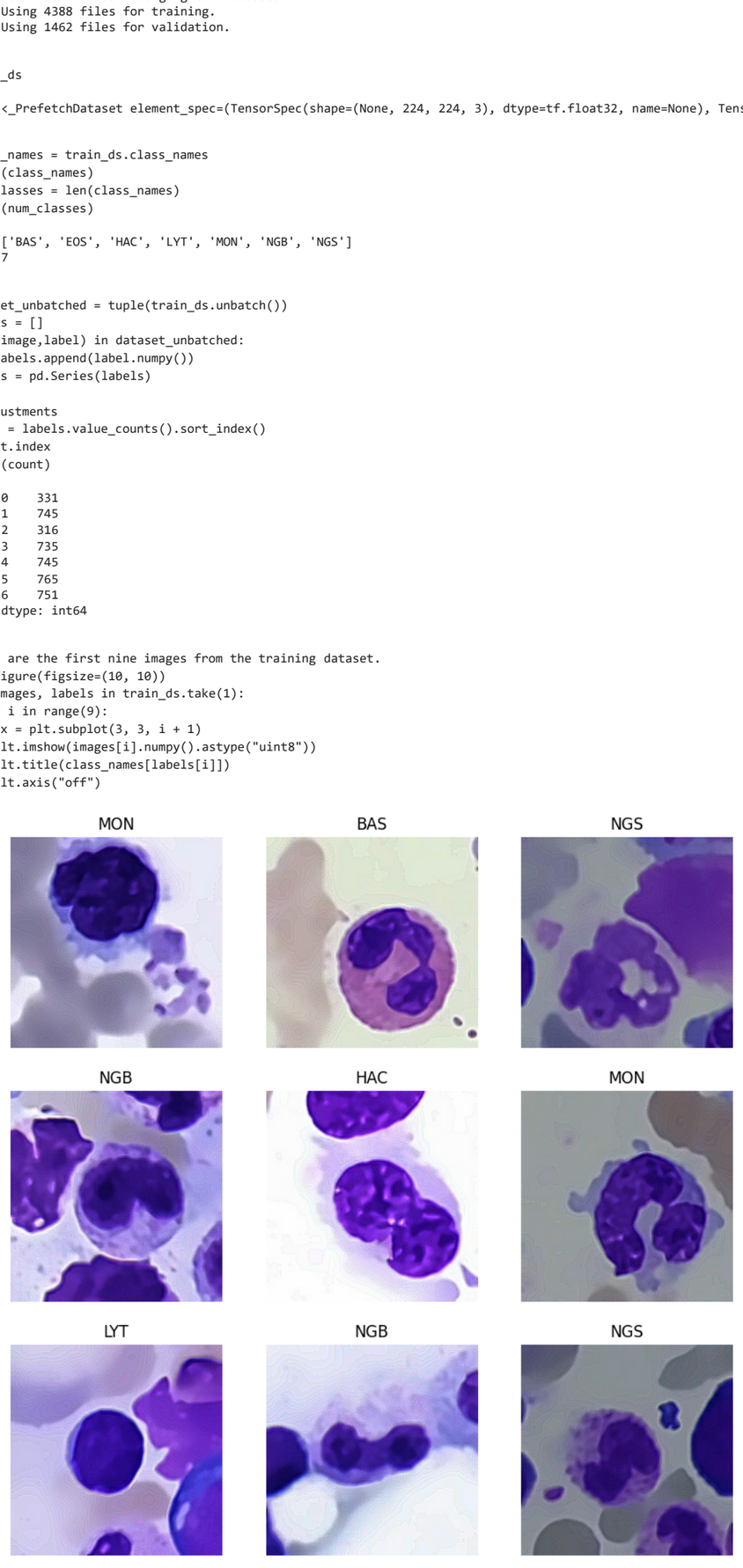
```
class_names = train_ds.class_names
print(class_names)
num_classes = len(class_names)
print(num_classes)
```

```
['BAS', 'EOS', 'HAC', 'LYT', 'MON', 'NGB', 'NGS']
7
```

```
dataset_unbatched = tuple(train_ds.unbatch())
labels = []
for (image,label) in dataset_unbatched:
    labels.append(label.numpy())
labels = pd.Series(labels)

# adjustments
count = labels.value_counts().sort_index()
#count.index
print(count)
```

```
0    331
1    745
2    316
3    735
4    745
5    765
6    751
dtype: int64
```

```
#Here are the first nine images from the training dataset.
plt.figure(figsize=(10, 10))
for images, labels in train_ds.take(1):
  for i in range(9):
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(images[i].numpy().astype("uint8"))
    plt.title(class_names[labels[i]])
    plt.axis("off")
```




```
for image_batch, labels_batch in train_ds:
  print(image_batch.shape)
  print(labels_batch.shape)
  break
```

```
(32, 224, 224, 3)
(32,)
```

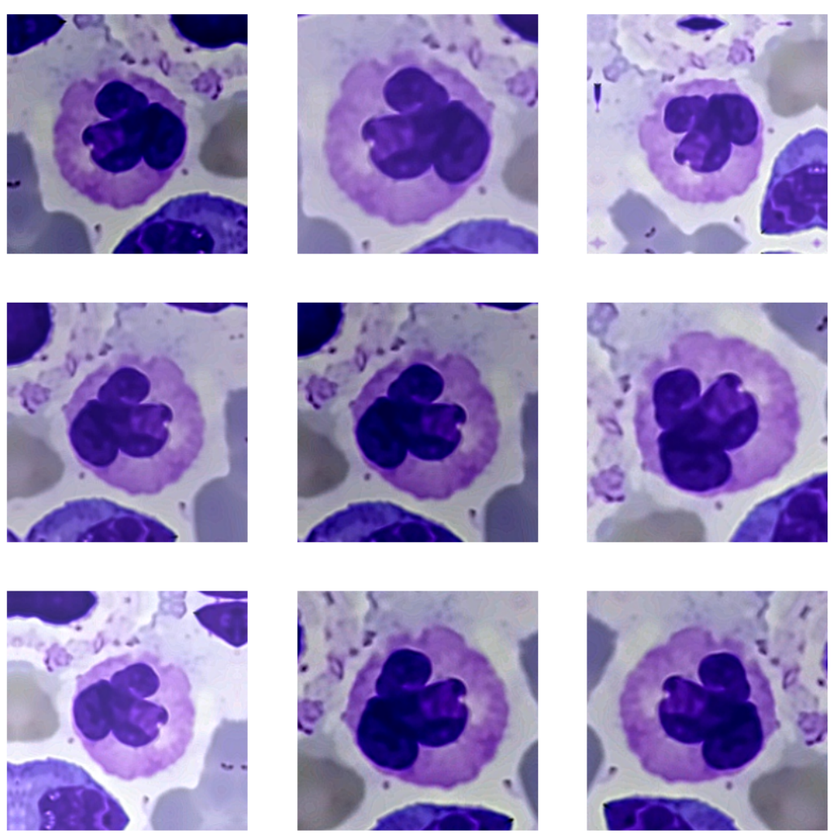
```
image_batch, labels_batch = next(iter(train_ds))
first_image = image_batch[0]
print(first_image)
```

```
tf.Tensor(
[[[102.  44. 224.]
  [102.  47. 228.]
  [ 95.  41. 225.]
  ...
  [189. 179. 239.]
  [199. 188. 246.]
  [197. 186. 244.]]

 [[105.  47. 227.]
  [102.  47. 228.]
  [ 94.  40. 222.]
  ...
  [187. 177. 237.]
  [193. 183. 243.]
  [191. 181. 241.]]

 [[103.  45. 227.]
```

```
       [101.  46. 227.]
       [ 96.  43. 223.]
       ...
       [199. 190. 253.]
       [206. 197. 255.]
       [205. 196. 255.]]

      ...

      [[220. 214. 252.]
       [219. 213. 251.]
       [221. 213. 254.]
       ...
       [208. 196. 246.]
       [204. 191. 244.]
       [206. 193. 247.]]

      [[221. 217. 254.]
       [218. 212. 250.]
       [221. 213. 252.]
       ...
       [195. 183. 231.]
       [205. 191. 242.]
       [206. 189. 241.]]

      [[217. 213. 250.]
       [220. 216. 253.]
       [220. 212. 251.]
       ...
       [202. 190. 236.]
       [205. 189. 238.]
       [228. 210. 255.]]], shape=(224, 224, 3), dtype=float32)
```

Data Augmentation

```
data_augmentation = keras.Sequential(
  [
    layers.RandomFlip("horizontal",
                      input_shape=(224,
                                   224,
                                   3)),
    layers.RandomRotation(0.2),
    layers.RandomZoom(0.2),
    layers.RandomContrast(0.2),
    layers.RandomBrightness(0.2)
  ]
)

#Visualize a few augmented examples by applying data augmentation to the same image several times:
plt.figure(figsize=(10, 10))
for images, _ in train_ds.take(1):
  for i in range(9):
    augmented_images = data_augmentation(images)
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(augmented_images[0].numpy().astype("uint8"))
    plt.axis("off")
```



```
train_ds = train_ds.map(
  lambda x, y: (data_augmentation(x, training=True), y))
```

Configure the dataset for performance

Make sure to use buffered prefetching, so you can yield data from disk without having I/O become blocking. These are two important methods you should use when loading data:

Dataset.cache keeps the images in memory after they're loaded off disk during the first epoch. This will ensure the dataset does not become a bottleneck while training your model. If your dataset is too large to fit into memory, you can also use this method to create a performant on-disk cache.

Dataset.prefetch overlaps data preprocessing and model execution while training.

```
AUTOTUNE = tf.data.AUTOTUNE

train_ds = train_ds.cache().shuffle(1000).prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.cache().prefetch(buffer_size=AUTOTUNE)
```

Early Stopping

```
# Define EarlyStopping callback
early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)
```

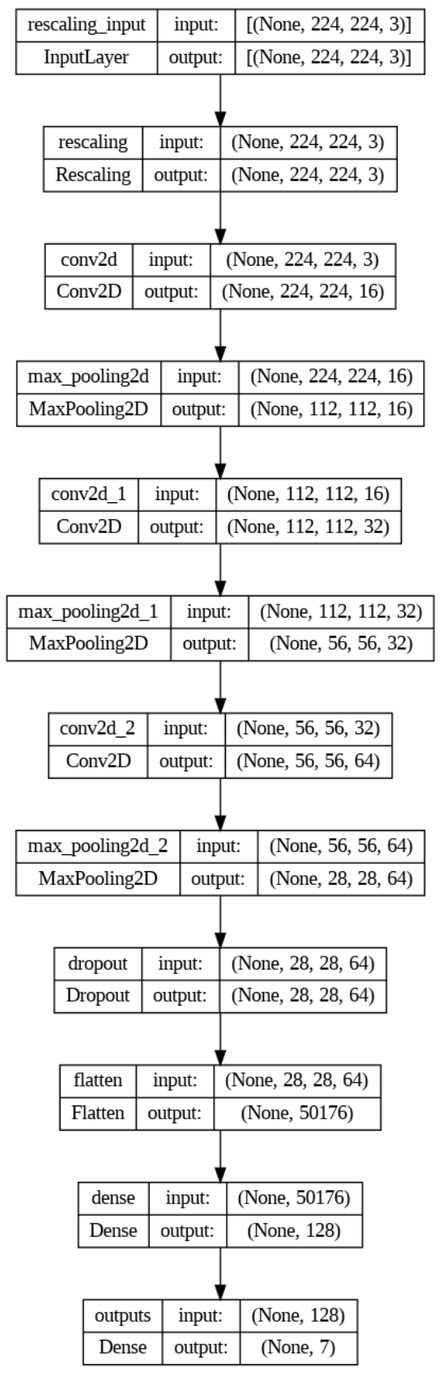
Sequential Model 1

```
model = Sequential([
  layers.Rescaling(1./255, input_shape=(224, 224, 3)),
  layers.Conv2D(16, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu', kernel_regularizer=regularizers.l2(l=0.01)),
  layers.MaxPooling2D(),
  layers.Dropout(0.5),
  layers.Flatten(),
  layers.Dense(128, activation='relu',kernel_regularizer=regularizers.l2(l=0.01)),
  layers.Dense(7, activation='softmax', name="outputs")
])


model.compile(Adamax(learning_rate= 0.001), loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=False), metrics= ['accuracy'])

model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling (Rescaling)       (None, 224, 224, 3)       0

 conv2d (Conv2D)             (None, 224, 224, 16)      448

 max_pooling2d (MaxPooling2  (None, 112, 112, 16)      0
 D)

 conv2d_1 (Conv2D)           (None, 112, 112, 32)      4640

 max_pooling2d_1 (MaxPoolin  (None, 56, 56, 32)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 56, 56, 64)        18496

 max_pooling2d_2 (MaxPoolin  (None, 28, 28, 64)        0
 g2D)
```

```
 dropout (Dropout)           (None, 28, 28, 64)        0

 flatten (Flatten)           (None, 50176)             0

 dense (Dense)               (None, 128)               6422656

 outputs (Dense)             (None, 7)                 903

=================================================================
Total params: 6447143 (24.59 MB)
Trainable params: 6447143 (24.59 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
keras.utils.plot_model(model, show_shapes=True)
```




```
epochs = 70
history = model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs,
  batch_size=256,
  callbacks=[early_stopping]
)
```

```
    Epoch 1/70
    138/138 [==============================] - 95s 216ms/step - loss: 3.0430 - accuracy: 0.2359 - val_loss: 2.4720 - val_accuracy: 0.3495
    Epoch 2/70
    138/138 [==============================] - 6s 45ms/step - loss: 2.3499 - accuracy: 0.3336 - val_loss: 2.1710 - val_accuracy: 0.4001
    Epoch 3/70
    138/138 [==============================] - 6s 45ms/step - loss: 2.1544 - accuracy: 0.3546 - val_loss: 2.0539 - val_accuracy: 0.4049
    Epoch 4/70
    138/138 [==============================] - 6s 46ms/step - loss: 2.0373 - accuracy: 0.3751 - val_loss: 2.0113 - val_accuracy: 0.3495
    Epoch 5/70
    138/138 [==============================] - 6s 45ms/step - loss: 1.9520 - accuracy: 0.3838 - val_loss: 1.8541 - val_accuracy: 0.4220
    Epoch 6/70
    138/138 [==============================] - 6s 45ms/step - loss: 1.8773 - accuracy: 0.3906 - val_loss: 1.8111 - val_accuracy: 0.4337
    Epoch 7/70
    138/138 [==============================] - 6s 46ms/step - loss: 1.8185 - accuracy: 0.4191 - val_loss: 1.7925 - val_accuracy: 0.4193
    Epoch 8/70
    138/138 [==============================] - 6s 45ms/step - loss: 1.7857 - accuracy: 0.4309 - val_loss: 1.7430 - val_accuracy: 0.4316
    Epoch 9/70
    138/138 [==============================] - 6s 46ms/step - loss: 1.7280 - accuracy: 0.4464 - val_loss: 1.6406 - val_accuracy: 0.4836
    Epoch 10/70
    138/138 [==============================] - 6s 45ms/step - loss: 1.6919 - accuracy: 0.4505 - val_loss: 1.6554 - val_accuracy: 0.4740
    Epoch 11/70
    138/138 [==============================] - 7s 48ms/step - loss: 1.6459 - accuracy: 0.4756 - val_loss: 1.6161 - val_accuracy: 0.4822
    Epoch 12/70
    138/138 [==============================] - 6s 47ms/step - loss: 1.5792 - accuracy: 0.5021 - val_loss: 1.5628 - val_accuracy: 0.5021
    Epoch 13/70
    138/138 [==============================] - 6s 46ms/step - loss: 1.5339 - accuracy: 0.5312 - val_loss: 1.5778 - val_accuracy: 0.4850
    Epoch 14/70
    138/138 [==============================] - 6s 47ms/step - loss: 1.4890 - accuracy: 0.5558 - val_loss: 1.5733 - val_accuracy: 0.5048
    Epoch 15/70
    138/138 [==============================] - 6s 47ms/step - loss: 1.4568 - accuracy: 0.5675 - val_loss: 1.6176 - val_accuracy: 0.4973
    Epoch 16/70
    138/138 [==============================] - 7s 47ms/step - loss: 1.4197 - accuracy: 0.5932 - val_loss: 1.5258 - val_accuracy: 0.5321
    Epoch 17/70
    138/138 [==============================] - 6s 46ms/step - loss: 1.3787 - accuracy: 0.6051 - val_loss: 1.5325 - val_accuracy: 0.5417
    Epoch 18/70
    138/138 [==============================] - 7s 48ms/step - loss: 1.3363 - accuracy: 0.6335 - val_loss: 1.5519 - val_accuracy: 0.5308
    Epoch 19/70
    138/138 [==============================] - 6s 47ms/step - loss: 1.2957 - accuracy: 0.6522 - val_loss: 1.5460 - val_accuracy: 0.5472
    Epoch 20/70
    138/138 [==============================] - 7s 47ms/step - loss: 1.2407 - accuracy: 0.6718 - val_loss: 1.4924 - val_accuracy: 0.5800
    Epoch 21/70
    138/138 [==============================] - 7s 47ms/step - loss: 1.2095 - accuracy: 0.6823 - val_loss: 1.5973 - val_accuracy: 0.5595
    Epoch 22/70
    138/138 [==============================] - 6s 47ms/step - loss: 1.1660 - accuracy: 0.7053 - val_loss: 1.5541 - val_accuracy: 0.5636
    Epoch 23/70
    138/138 [==============================] - 7s 48ms/step - loss: 1.1397 - accuracy: 0.7217 - val_loss: 1.6633 - val_accuracy: 0.5404
    Epoch 24/70
    138/138 [==============================] - 6s 47ms/step - loss: 1.0961 - accuracy: 0.7297 - val_loss: 1.5710 - val_accuracy: 0.5711
    Epoch 25/70
    138/138 [==============================] - 7s 48ms/step - loss: 1.0514 - accuracy: 0.7523 - val_loss: 1.6110 - val_accuracy: 0.5698
    Epoch 26/70
    138/138 [==============================] - 7s 47ms/step - loss: 1.0366 - accuracy: 0.7596 - val_loss: 1.6294 - val_accuracy: 0.5554
    Epoch 27/70
    138/138 [==============================] - 7s 48ms/step - loss: 1.0002 - accuracy: 0.7755 - val_loss: 1.6467 - val_accuracy: 0.5527
    Epoch 28/70
    138/138 [==============================] - 7s 48ms/step - loss: 0.9601 - accuracy: 0.7892 - val_loss: 1.6799 - val_accuracy: 0.5458
    Epoch 29/70
    138/138 [==============================] - 7s 49ms/step - loss: 0.9578 - accuracy: 0.7890 - val_loss: 1.7277 - val_accuracy: 0.5568
```

```
#Create plots of the loss and accuracy on the training and validation sets:
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(acc, label='Training Accuracy')
plt.plot(val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(loss, label='Training Loss')
plt.plot(val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title('Training and Validation Loss')
plt.show()
```


```
y_test = np.concatenate([y for x, y in val_ds], axis=0)
y_pred = model.predict(val_ds)
y_pred_classes = np.argmax(y_pred, axis=1)
accuracy_score(y_test, y_pred_classes)
```

```
46/46 [==============================] - 1s 11ms/step
0.5800273597811217
```

```
print(classification_report(y_test, y_pred_classes, target_names=class_names))
```

```
                  precision    recall  f1-score   support

             BAS       0.44      0.16      0.24       110
             EOS       0.60      0.67      0.63       255
             HAC       0.60      0.56      0.58        93
             LYT       0.69      0.74      0.71       265
             MON       0.53      0.63      0.57       255
             NGB       0.51      0.41      0.45       235
             NGS       0.57      0.62      0.59       249

        accuracy                           0.58      1462
       macro avg       0.56      0.54      0.54      1462
    weighted avg       0.57      0.58      0.57      1462
```