
Data Mining Course Project

Grapevine Leaves Classification



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[Link to Google Colaboratory](#)

1. Loading The Dataset and Pre-processing

1.1. Load the Dataset

Attribute Information:

This dataset is a collection of png pictures of five class of grapevine leaves. Namely **Ak**, **Ala Idris**, **Nazli**, **Buzgulu**, and **Dimnit**.

We first mount the google colab to google drive and use the dataset uploaded there.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype  
---  -- 
 0   images   500 non-null    object 
 1   label    500 non-null    object 
 2   path     500 non-null    object 
 dtypes: object(3)
memory usage: 11.8+ KB
```

We store the dataset in a dataframe where each row is consist of the label and the path to the picture.

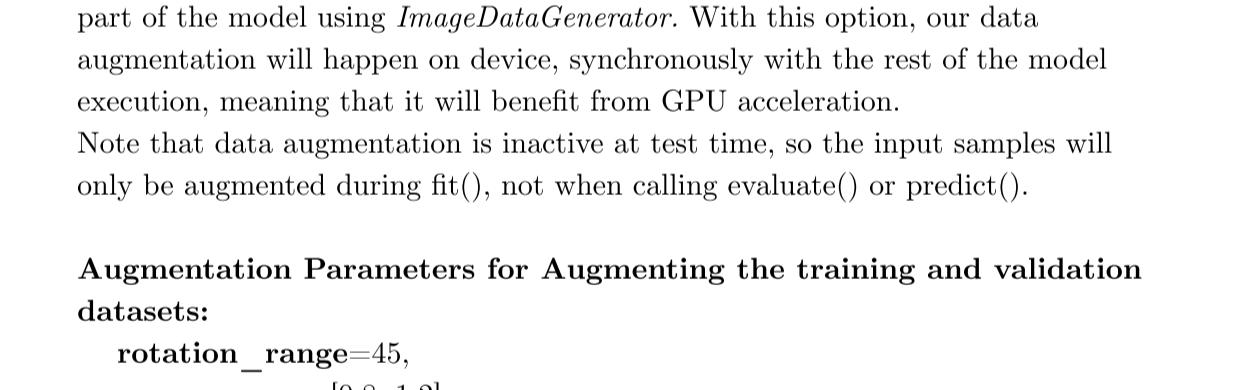
	images	label	path
0	Ak (51).png	Ak	/content/Grapevine_Leaves_Image_Dataset/Ak/Ak ...
1	Ak (21).png	Ak	/content/Grapevine_Leaves_Image_Dataset/Ak/Ak ...
2	Ak (4).png	Ak	/content/Grapevine_Leaves_Image_Dataset/Ak/Ak ...
3	Ak (10).png	Ak	/content/Grapevine_Leaves_Image_Dataset/Ak/Ak ...
4	Ak (69).png	Ak	/content/Grapevine_Leaves_Image_Dataset/Ak/Ak ...

Number of Leaves Classes: 5

Number of Leaves in Each Class:
Ak 100
Ala_Idris 100
Buzgulu 100
Dimnit 100
Nazli 100
Name: label, dtype: int64

As we can see the dataset is completely balanced and we have 100 pictures for each class of leaves.

Below are some instances of our dataset.



1.2. Split Train, Test, and Validation Data

We split our dataset into test and train sets using `train_test_split` of scikit-learn.

```
Num train images: 320
Num validation images: 80
Num test images: 100
Num classes: 5
Num iterations per epoch: 10
```

1.3. Data Augmentation

Since we don't have a large image dataset, it's a good practice to artificially introduce sample diversity by applying random yet realistic transformations to the training images, such as random horizontal flipping or small random rotations.

This helps expose the model to different aspects of the training data while slowing down overfitting. We should also standardize the data. Our pictures RGB channel values are in the [0, 255] range. This is not ideal for a neural network; in general we should seek to make your input values small. Here, we will standardize values to be in the [0, 1] by using a Rescaling layer at the start of our model. We make it part of the model using `ImageDataGenerator`. With this option, our data

augmentation will happen on device, synchronously with the rest of the model execution, meaning that it will benefit from GPU acceleration.

Note that data augmentation is inactive at test time, so the input samples will only be augmented during `fit()`, not when calling `evaluate()` or `predict()`.

Augmentation Parameters for Augmenting the training and validation datasets:

```
rotation_range=45,
zoom_range=[0.8, 1.2],
brightness_range=[0.5, 1.5],
channel_shift_range=0.5,
width_shift_range=0.15,
height_shift_range=0.15,
shear_range=0.15,
horizontal_flip=True,
vertical_flip=True,
fill_mode='constant',
cval=0.0)
```

For each model, we also pass a preprocessing function to the `ImageDataGenerator`. This function would perform the appropriate scaling on the data. We call `flow_from_dataframe` on the generators to get and argument the data.

Note that we won't augment the test dataset but we still use the preprocessing function on them.

Using augmentation we get:



The left-most column is the real data and the others are the augmented.

2. Pre-trained Convolutional Neural Network -Transfer Learning-

2.1. Introduction

Transfer learning is a technique in machine learning where we can take a model developed on one task and use it as a starting point in some other similar but different tasks. Transfer learning is extremely popular in Deep Learning since the "transfer" of knowledge from one "parent" model to a "child" model means that the "child" model can be trained to high accuracies with a much smaller dataset compared to the "parent" model.

Most Image Classification Deep Learning tasks today will start by downloading one of these 18 pre-trained models, modify the model slightly to suit the task on hand, and train only the custom modifications while freezing the layers in the pre-trained model. This approach gives very high accuracy on real-world image classification tasks since "ImageNet" collects many real-world images.

However, choosing which of the 18 pre-trained models to use is not always an exact science. Many developers stick to the models they are familiar with and gave them good results in the past.

Pre-trained model available on *Keras*:

```
DenseNet121  
DenseNet169  
DenseNet201  
EfficientNetB0  
EfficientNetB1  
EfficientNetB2  
EfficientNetB3  
EfficientNetB4  
EfficientNetB5  
EfficientNetB6  
EfficientNetB7  
EfficientNetV2B0  
EfficientNetV2B1  
EfficientNetV2B2  
EfficientNetV2B3  
EfficientNetV2L  
EfficientNetV2M  
EfficientNetV2S  
InceptionResNetV2  
InceptionV3  
MobileNet  
MobileNetV2  
MobileNetV3Large  
MobileNetV3Small  
NASNetLarge  
NASNetMobile  
ResNet101  
ResNet101V2  
ResNet152  
ResNet152V2  
ResNet50  
ResNet50V2  
VGG16  
VGG19  
Xception
```

In general, there are two competing criteria while doing any machine learning task in the industry:

1. **Accuracy** of the model: Higher Better
2. **Speed** of Model Training and Predictions: Faster Better

The two criteria are pretty straightforward. We want the model that gives us the highest accuracy on validation data since it can make useful predictions. We also want the model to train and predict as fast as possible because, in production, we might need to serve hundreds or thousands of predictions every second.

Unfortunately, to get higher accuracy, we need to use a "deeper" or larger model. But a larger model has many more parameters that make it slower to execute. So there is a **tradeoff** between the accuracy and size/number of operations of the model.

Training on the *cats_vs_dogs* dataset we have:

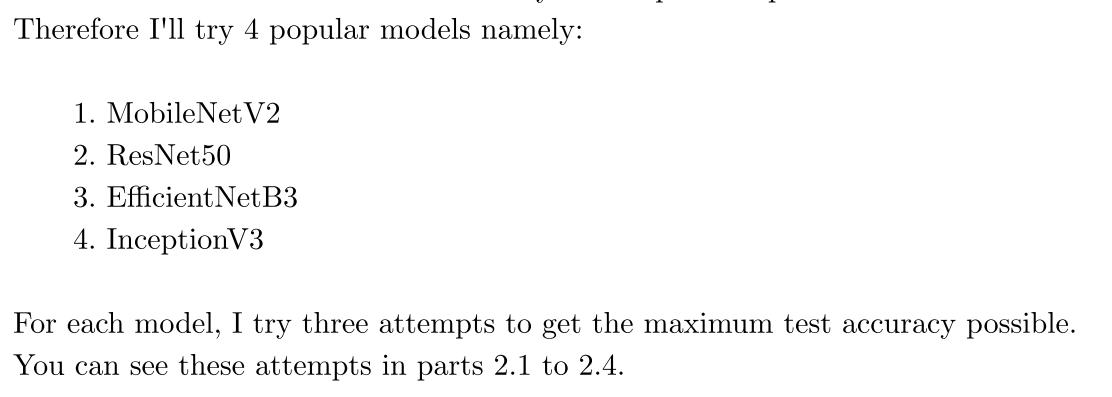


Figure 1: [reference](#)

Due to hardware limitations I cannot try all the possible pre-trained models. Therefore I'll try 4 popular models namely:

1. MobileNetV2
2. ResNet50
3. EfficientNetB3
4. InceptionV3

For each model, I try three attempts to get the maximum test accuracy possible.

You can see these attempts in parts 2.1 to 2.4.

In parts 3 and 4 I use autoencoder and 10 fold cross validation only on the best performing model with the highest test accuracy (again due to time and GPU limits.)

In part 5 I try to use some techniques to improve accuracy and further fine tune the models.

2. Pre-trained Convolutional Neural Network -Transfer Learning-

2.2. ResNet50

△First Attempt△

Validation Accuracy = 81.25%

Test Accuracy = 75%

● Parameters:

Optimization Algorithm: adam

Learning Rate: NA

Momentum: NA

Epoch: 150

Pooling: avg

Number of trainable layers of the base model: 5

Activation: softmax

● Model Summary:

Model: "sequential_10"

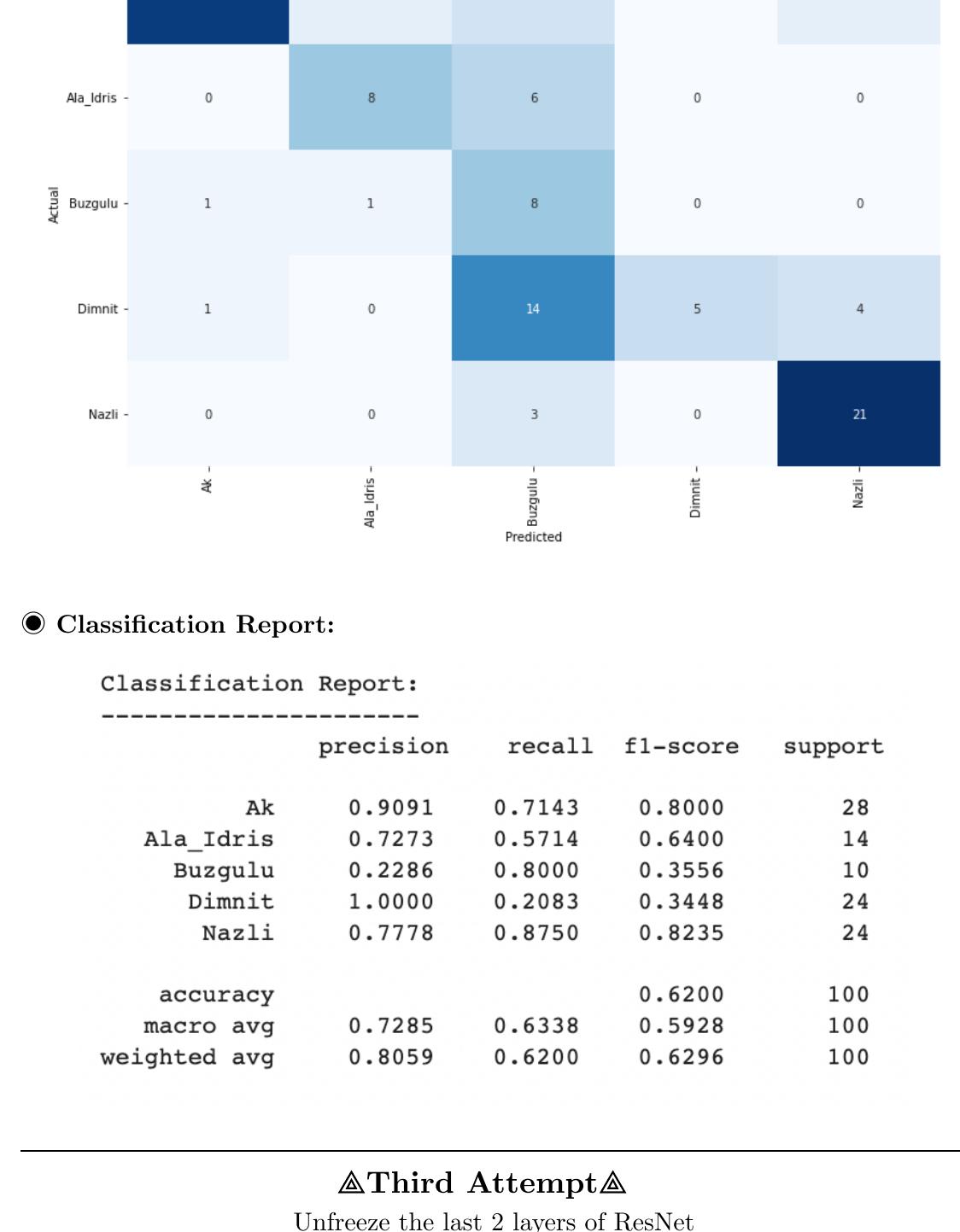
Layer (type)	Output Shape	Param #
resnet50 (Functional)	(None, 2048)	23587712
dense_12 (Dense)	(None, 512)	1049088
dropout_9 (Dropout)	(None, 512)	0
dense_13 (Dense)	(None, 512)	262656
dropout_10 (Dropout)	(None, 512)	0
dense_14 (Dense)	(None, 5)	2565

Total params: 24,902,021
Trainable params: 2,369,029
Non-trainable params: 22,532,992

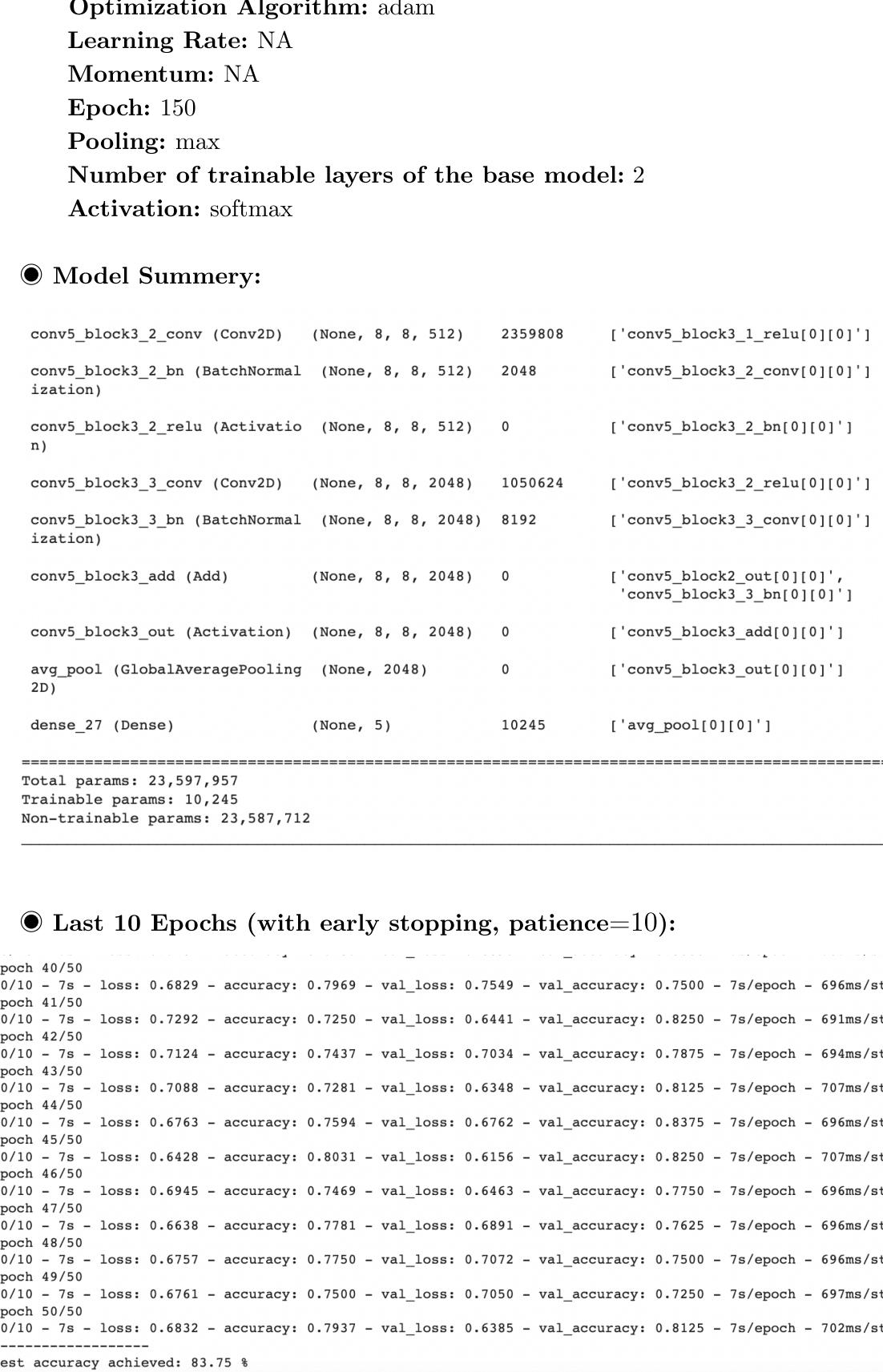
● Last 10 Epochs (with early stopping, patience=10):

```
1/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 2/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 3/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 4/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 5/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 6/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 7/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 8/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 9/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 10/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 11/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 12/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 13/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 14/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 15/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 16/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 17/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 18/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 19/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 20/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 21/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 22/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 23/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 24/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 25/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 26/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 27/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 28/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 29/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 30/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 31/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 32/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 33/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 34/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Epoch 35/10 - 7s - loss: 0.6769 - accuracy: 0.7154 - val_loss: 0.7465 - val_accuracy: 0.7125
Best accuracy achieved: 81.25 %
```

● Training And Validation Loss/Accuracy:



● Confusion Matrix:



● Classification Report:

Classification Report:

	precision	recall	f1-score	support
Ak	0.8421	0.5714	0.6809	28
Ala_Idris	0.9000	0.6429	0.7500	14
Buzgulu	0.3750	0.9000	0.5294	10
Dimmit	0.7917	0.7917	0.7917	24
Nazli	0.9565	0.9167	0.9362	24
accuracy			0.7500	100
macro avg	0.7731	0.7645	0.7376	100
weighted avg	0.8189	0.7500	0.7633	100

△Second Attempt△

Changing the CNN architecture in hope of better accuracy.

Validation Accuracy = 78%

Test Accuracy = 62%

● Parameters:

Optimization Algorithm: adam

Learning Rate: NA

Momentum: NA

Epoch: 150

Pooling: max

Number of trainable layers of the base model: 0

Activation: softmax

● Model Summary:

```
conv5_block3_2_conv (Conv2D) (None, 8, 8, 512) 2359808 ['conv5_block3_1_relu[0][0]']
conv5_block3_2_bn (BatchNormal) (None, 8, 8, 512) 2048 ['conv5_block3_2_conv[0][0]']
conv5_block3_2_relu (Activation) (None, 8, 8, 512) 0 ['conv5_block3_2_bn[0][0]']
conv5_block3_3_conv (Conv2D) (None, 8, 8, 2048) 1050624 ['conv5_block3_2_relu[0][0]']
conv5_block3_3_bn (BatchNormal) (None, 8, 8, 2048) 8192 ['conv5_block3_3_conv[0][0]']
conv5_block3_3_add (Add) (None, 8, 8, 2048) 0 ['conv5_block2_out[0][0]', 'conv5_block3_3_bn[0][0]']
conv5_block3_out (Activation) (None, 8, 8, 2048) 0 ['conv5_block3_3_out[0][0]']
global_average_pooling2d_14 (G (None, 2048) 0 ['conv5_block3_out[0][0]']
dense_21 (Dense) (None, 5) 10245 ['global_average_pooling2d_14[0][0]']

Total params: 23,597,957
Trainable params: 10,245
Non-trainable params: 23,587,712
```

● Last 10 Epochs (with early stopping, patience=10):

```
Epoch 40/50
10/10 - 7s - loss: 0.7256 - accuracy: 0.7500 - val_loss: 0.5910 - val_accuracy: 0.8500 - 7s/epoch - 69ms/step
Epoch 41/50
10/10 - 7s - loss: 0.7609 - accuracy: 0.7469 - val_loss: 0.7122 - val_accuracy: 0.7250 - 7s/epoch - 690ms/step
Epoch 42/50
10/10 - 7s - loss: 0.6678 - accuracy: 0.7719 - val_loss: 0.6365 - val_accuracy: 0.8125 - 7s/epoch - 694ms/step
Epoch 43/50
10/10 - 7s - loss: 0.6678 - accuracy: 0.7719 - val_loss: 0.6365 - val_accuracy: 0.8125 - 7s/epoch - 695ms/step
Epoch 44/50
10/10 - 7s - loss: 0.6648 - accuracy: 0.7969 - val_loss: 0.6489 - val_accuracy: 0.8000 - 7s/epoch - 693ms/step
Epoch 45/50
10/10 - 7s - loss: 0.6594 - accuracy: 0.7755 - val_loss: 0.6716 - val_accuracy: 0.7000 - 7s/epoch - 698ms/step
Epoch 46/50
10/10 - 7s - loss: 0.6652 - accuracy: 0.7789 - val_loss: 0.6762 - val_accuracy: 0.8125 - 7s/epoch - 704ms/step
Epoch 47/50
10/10 - 7s - loss: 0.6725 - accuracy: 0.7719 - val_loss: 0.6567 - val_accuracy: 0.8000 - 7s/epoch - 698ms/step
Epoch 48/50
10/10 - 7s - loss: 0.6763 - accuracy: 0.7719 - val_loss: 0.6567 - val_accuracy: 0.8000 - 7s/epoch - 698ms/step
Epoch 49/50
10/10 - 7s - loss: 0.6763 - accuracy: 0.7719 - val_loss: 0.6567 - val_accuracy: 0.8000 - 7s/epoch - 695ms/step
Epoch 50/50
Restoring model weights from the end of the best epoch: 40.
10/10 - 7s - loss: 0.6213 - accuracy: 0.8062 - val_loss: 0.6599 - val_accuracy: 0.7875 - 7s/epoch - 708ms/step
Epoch 50/50: early stopping
```

● Training And Validation Loss/Accuracy:

● Classification Report:

Classification Report:

	precision	recall	f1-score	support
Ak	0.9091	0.7143	0.8000	28
Ala_Idris	0.4074	0.5714	0.5366	14
Buzgulu	0.2286	0.8000	0.3556	10
Dimmit	1.0000	0.2083	0.3448	24
Nazli	0.7778	0.8750	0.8235	24
accuracy			0.6200	100
macro avg	0.72			

2. Pre-trained Convolutional Neural Network -Transfer Learning-

2.3. EfficientNetB3

▲First Attempt▲

Validation Accuracy = 72.5%

Test Accuracy = 72.00%

● Parameters:

Optimization Algorithm: adam

Learning Rate: NA

Momentum: NA

Epoch: 150

Pooling: max

Number of trainable layers of the base model: 2

Activation: softmax

● Model Summary:

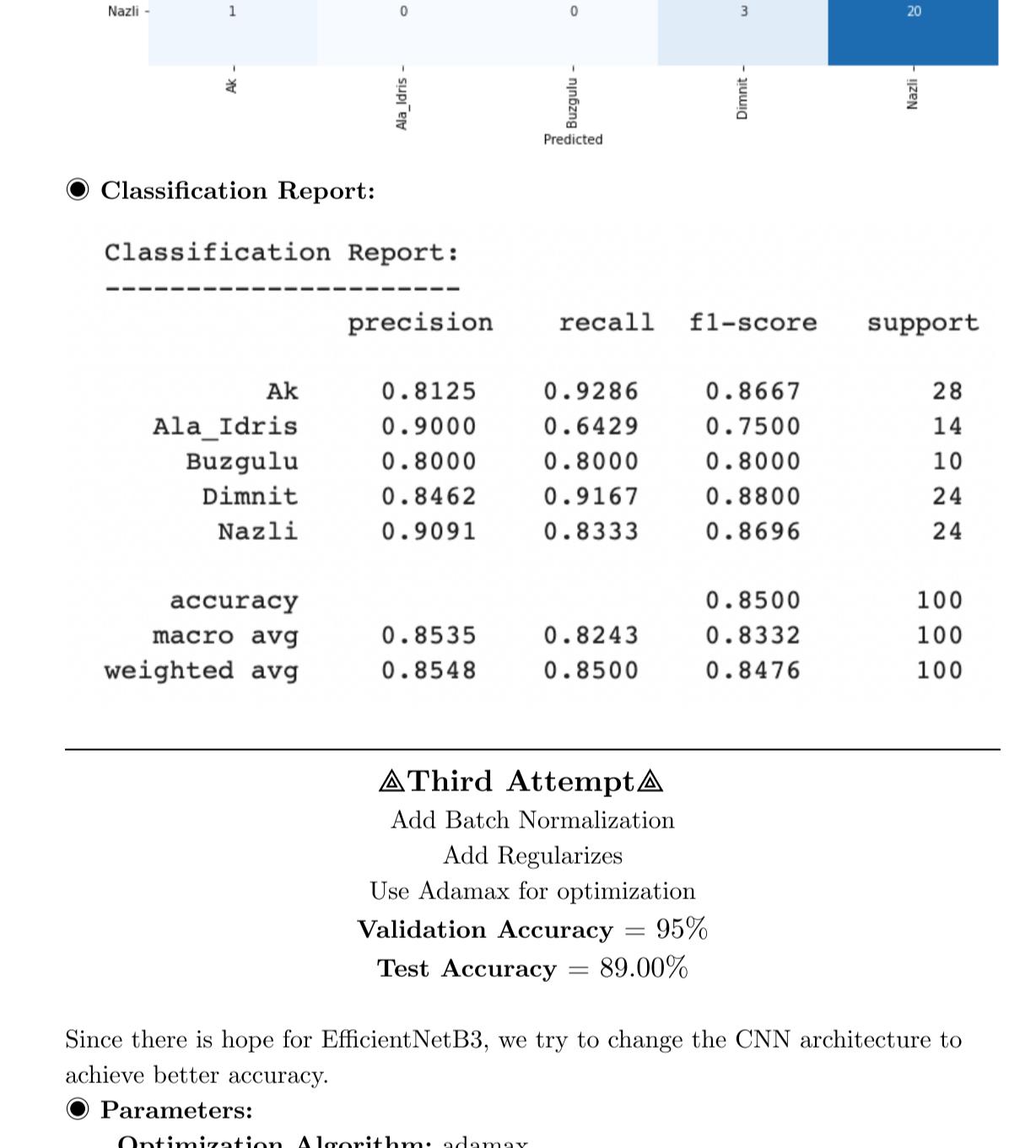
Model: "sequential_15"

Layer (type)	Output Shape	Param #
=====		
efficientnetb3 (Functional)	(None, 1536)	10783535
dense_31 (Dense)	(None, 512)	786944
dropout_15 (Dropout)	(None, 512)	0
dense_32 (Dense)	(None, 512)	262656
dropout_16 (Dropout)	(None, 512)	0
dense_33 (Dense)	(None, 5)	2565
=====		
Total params: 11,835,700		
Trainable params: 1,052,165		
Non-trainable params: 10,783,535		

● Last 10 Epochs (with early stopping, patience=10):

```
Epoch 32/50
10/10 - 7s - loss: 1.1771 - accuracy: 0.5281 - val_loss: 0.9315 - val_accuracy: 0.6375 - 7s/epoch - 695ms/step
Epoch 33/50
10/10 - 7s - loss: 1.1746 - accuracy: 0.5000 - val_loss: 0.9766 - val_accuracy: 0.7250 - 7s/epoch - 681ms/step
Epoch 34/50
10/10 - 7s - loss: 1.1553 - accuracy: 0.5094 - val_loss: 0.0333 - val_accuracy: 0.6250 - 7s/epoch - 680ms/step
Epoch 35/50
10/10 - 7s - loss: 1.2255 - accuracy: 0.4938 - val_loss: 1.1132 - val_accuracy: 0.4875 - 7s/epoch - 683ms/step
Epoch 36/50
10/10 - 7s - loss: 1.1731 - accuracy: 0.5031 - val_loss: 0.0142 - val_accuracy: 0.6125 - 7s/epoch - 681ms/step
Epoch 37/50
10/10 - 7s - loss: 1.1563 - accuracy: 0.5625 - val_loss: 0.0107 - val_accuracy: 0.6625 - 7s/epoch - 686ms/step
Epoch 38/50
10/10 - 7s - loss: 1.1834 - accuracy: 0.5112 - val_loss: 0.0117 - val_accuracy: 0.6875 - 7s/epoch - 684ms/step
Epoch 39/50
10/10 - 7s - loss: 1.1388 - accuracy: 0.5125 - val_loss: 1.1877 - val_accuracy: 0.5000 - 7s/epoch - 684ms/step
Epoch 40/50
10/10 - 7s - loss: 1.0822 - accuracy: 0.5750 - val_loss: 0.0385 - val_accuracy: 0.6000 - 7s/epoch - 689ms/step
Epoch 41/50
10/10 - 7s - loss: 1.1311 - accuracy: 0.5156 - val_loss: 0.0961 - val_accuracy: 0.6125 - 7s/epoch - 687ms/step
Resting model weights from the end of the best epoch: 32.
Epoch 42/50
10/10 - 7s - loss: 1.1773 - accuracy: 0.5375 - val_loss: 0.0056 - val_accuracy: 0.6125 - 7s/epoch - 698ms/step
Epoch 42/ early stopping
Best accuracy achieved: 72.5 %
```

● Training And Validation Loss/Accuracy:



● Confusion Matrix:

		Confusion Matrix				
		Ak	Ala_Idris	Buzgulu	Dimnit	Nazli
Actual	Ak	16	4	1	3	4
	Ala_Idris	0	9	5	0	0
	Buzgulu	0	2	7	0	1
	Dimnit	1	0	1	21	1
	Nazli	1	0	3	1	19
	Ak	16	4	1	3	4

● Classification Report:

Classification Report:

	precision	recall	f1-score	support
Ak	0.8889	0.5714	0.6957	28
Ala_Idris	0.6000	0.6429	0.6207	14
Buzgulu	0.4118	0.7000	0.5185	10
Dimnit	0.8400	0.8750	0.8571	24
Nazli	0.7600	0.7917	0.7755	24
accuracy			0.7200	100
macro avg	0.7001	0.7162	0.6935	100
weighted avg	0.7581	0.7200	0.7254	100

▲Second Attempt▲

Removing a dropout layer unfreezing more pre-trained layer.

Validation Accuracy = 83.75%

Test Accuracy = 85.00%

● Parameters:

Optimization Algorithm: adamax

Learning Rate: NA

Momentum: NA

Epoch: 150

Pooling: max

Number of trainable layers of the base model: 10

Activation: softmax

● Model Summary:

```
Model: "sequential_17"
Layer (type)          Output Shape       Param #
=====
efficientnetb3 (Functional) (None, 1536)    10783535
dense_36 (Dense)      (None, 512)        786944
dropout_18 (Dropout)   (None, 512)        0
dense_37 (Dense)      (None, 5)          2565
=====
Total params: 11,573,044
Trainable params: 2,491,397
Non-trainable params: 9,081,647
```

● Last 10 Epochs (with early stopping, patience=10):

```
Epoch 17/50
10/10 - 7s - loss: 0.6197 - accuracy: 0.7937 - val_loss: 0.4523 - val_accuracy: 0.7750 - 7s/epoch - 703ms/step
Epoch 18/50
10/10 - 7s - loss: 0.8332 - accuracy: 0.8906 - val_loss: 0.9523 - val_accuracy: 0.6750 - 7s/epoch - 698ms/step
Epoch 19/50
10/10 - 7s - loss: 0.7998 - accuracy: 0.9000 - val_loss: 0.9766 - val_accuracy: 0.7250 - 7s/epoch - 680ms/step
Epoch 20/50
10/10 - 7s - loss: 0.7314 - accuracy: 0.7250 - val_loss: 0.6698 - val_accuracy: 0.7750 - 7s/epoch - 688ms/step
Epoch 21/50
10/10 - 7s - loss: 0.6023 - accuracy: 0.7688 - val_loss: 0.4776 - val_accuracy: 0.8375 - 7s/epoch - 686ms/step
Epoch 22/50
10/10 - 7s - loss: 0.5786 - accuracy: 0.7971 - val_loss: 0.5189 - val_accuracy: 0.8125 - 7s/epoch - 684ms/step
Epoch 23/50
10/10 - 7s - loss: 0.5599 - accuracy: 0.7781 - val_loss: 0.6936 - val_accuracy: 0.7375 - 7s/epoch - 694ms/step
Epoch 24/50
10/10 - 7s - loss: 0.6600 - accuracy: 0.7500 - val_loss: 0.7200 - val_accuracy: 0.7000 - 7s/epoch - 690ms/step
Epoch 25/50
10/10 - 7s - loss: 0.5661 - accuracy: 0.7844 - val_loss: 0.5588 - val_accuracy: 0.7500 - 7s/epoch - 690ms/step
Epoch 26/50
10/10 - 7s - loss: 0.6146 - accuracy: 0.7625 - val_loss: 0.6625 - val_accuracy: 0.7625 - 7s/epoch - 691ms/step
Epoch 27/50
10/10 - 7s - loss: 0.6102 - accuracy: 0.7719 - val_loss: 0.6564 - val_accuracy: 0.7875 - 7s/epoch - 694ms/step
Resting model weights from the end of the best epoch: 17.
Epoch 27: early stopping
Best accuracy achieved: 83.75 %
```

● Training And Validation Loss/Accuracy:

● Confusion Matrix :

		Confusion Matrix				
		Ak	Ala_Idris	Buzgulu	Dimnit	Nazli
Actual	Ak	26	0	0	1	1
	Ala_Idris	3	9	2	0	0
	Buzgulu	1	1	8	0	0
	Dimnit	1	0	0	22	1
	Nazli	1	0	0	3	20
	Ak	26	0	0	1	1

● Classification Report:

Classification Report:

	precision	recall	f1-score	support
Ak	1.0000	0.9286	0.8867	28
Ala_Idris	0.9000	0.6429	0.7500	14
Buzgulu	0.8000	0.8000	0.8000	10
Dimnit	0.8462	0.9167	0.8800	24
Nazli	0.9091	0.8333	0.8696	24
accuracy			0.8500	100
macro avg	0.9121	0.9155	0.9030	100
weighted avg	0.9179	0.8900	0.8915	100

▲Third Attempt▲

Add Batch Normalization

Add Regularizes

Use Adamax for optimization

Validation Accuracy = 95%

Test Accuracy = 89.00%

Best Parameters:

Optimization Algorithm: adamax

Learning Rate: 0.001

Momentum: 0.99

Epoch: 150

Pooling: max

Number of trainable layers of the base model: 10

Activation: softmax

Best Validation Accuracy:

2. Pre-trained Convolutional Neural Network -Transfer Learning-

2.4. InceptionV3

△First Attempt△

Validation Accuracy = 83.75%
Test Accuracy = 79.00%

● Parameters:

Optimization Algorithm: adamax
Learning Rate: 0.001
Momentum: 0.99
Epoch: 150
Pooling: max
Number of trainable layers of the base model: 0
Activation: softmax

● Model Summary:

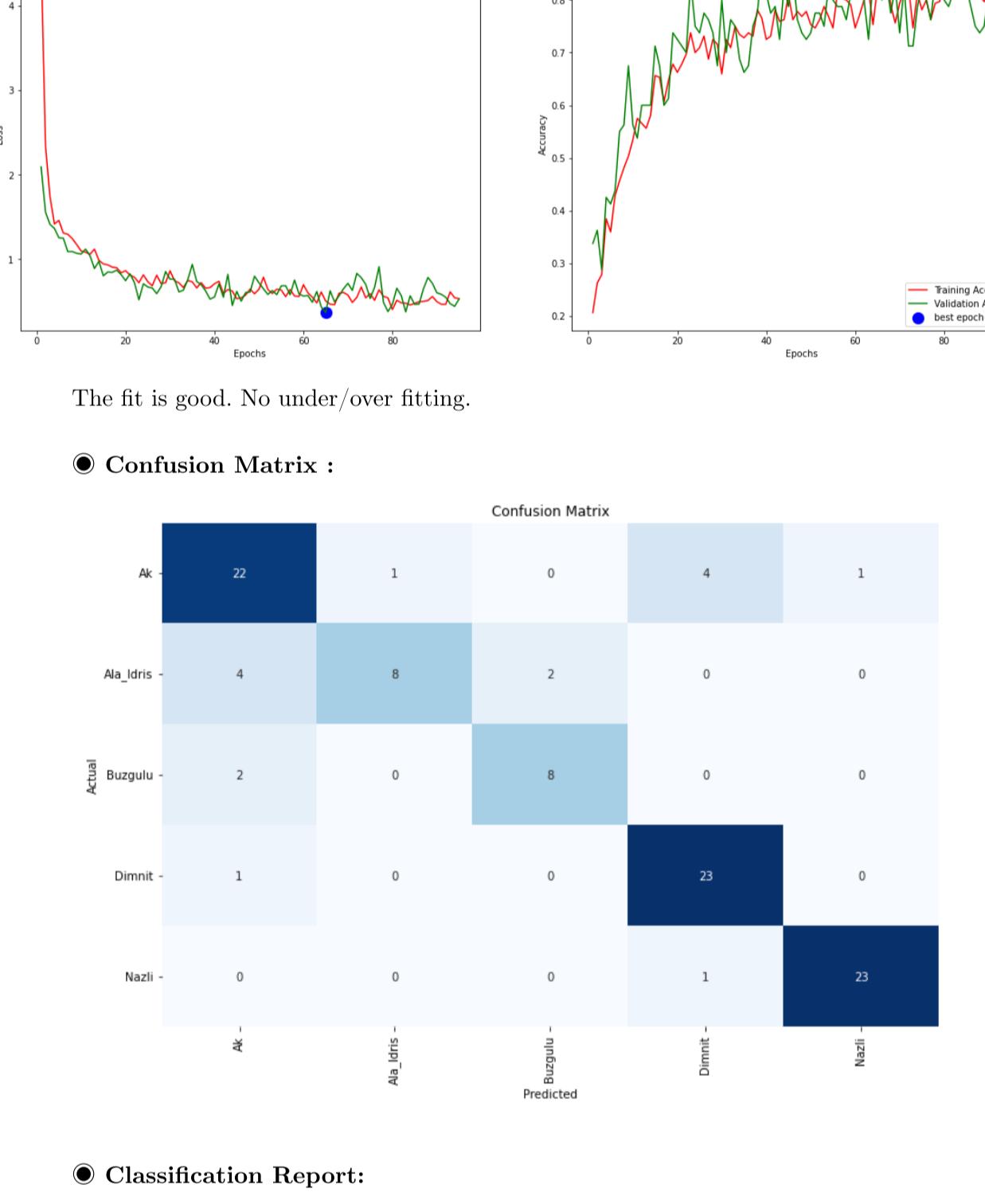
```
activation_273 (Activation) (None, 5, 5, 320) 0      ['batch_normalization_277[0][0]']
mixed9_1 (Concatenate)      (None, 5, 5, 768) 0      ['activation_275[0][0]', 
'activation_276[0][0]']
concatenate_5 (Concatenate) (None, 5, 5, 768) 0      ['activation_279[0][0]', 
'activation_280[0][0]']
activation_281 (Activation) (None, 5, 5, 192) 0      ['batch_normalization_285[0][0]']
mixed10 (Concatenate)      (None, 5, 5, 2048) 0      ['activation_281[0][0]', 
'mixed9_1[0][0]', 
'concatenate_5[0][0]', 
'activation_280[0][0]']
global_max_pooling2d_2 (Global MaxPooling2D) (None, 2048) 0      ['mixed10[0][0]']
batch_normalization_286 (Batch Normalization) (None, 2048) 8192      ['global_max_pooling2d_2[0][0]']
dense_46 (Dense)           (None, 256) 524544      ['batch_normalization_286[0][0]']
dropout_23 (Dropout)       (None, 256) 0          ['dense_46[0][0]']
dense_47 (Dense)           (None, 5) 1285        ['dropout_23[0][0]']

=====
Total params: 22,336,805
Trainable params: 529,925
Non-trainable params: 21,806,880
```

● Last 10 Epochs (with early stopping, patience=10):

```
Epoch 140/150
10/10 - 7s - loss: 1.3218 - accuracy: 0.7875 - val_loss: 1.3364 - val_accuracy: 0.8125 - 7s/epoch - 680ms/step
Epoch 141/150
10/10 - 7s - loss: 1.2697 - accuracy: 0.8125 - val_loss: 1.3673 - val_accuracy: 0.7000 - 7s/epoch - 676ms/step
Epoch 142/150
10/10 - 7s - loss: 1.2539 - accuracy: 0.8188 - val_loss: 1.3119 - val_accuracy: 0.7750 - 7s/epoch - 693ms/step
Epoch 143/150
10/10 - 7s - loss: 1.3093 - accuracy: 0.7844 - val_loss: 1.4207 - val_accuracy: 0.7000 - 7s/epoch - 679ms/step
Epoch 144/150
10/10 - 7s - loss: 1.3023 - accuracy: 0.7686 - val_loss: 1.4110 - val_accuracy: 0.8000 - 7s/epoch - 679ms/step
Epoch 145/150
10/10 - 7s - loss: 1.2952 - accuracy: 0.7969 - val_loss: 1.4207 - val_accuracy: 0.7125 - 7s/epoch - 674ms/step
Epoch 146/150
10/10 - 7s - loss: 1.3054 - accuracy: 0.7906 - val_loss: 1.4101 - val_accuracy: 0.7000 - 7s/epoch - 674ms/step
Epoch 147/150
10/10 - 7s - loss: 1.2828 - accuracy: 0.7750 - val_loss: 1.3782 - val_accuracy: 0.7875 - 7s/epoch - 677ms/step
Epoch 148/150
10/10 - 7s - loss: 1.2646 - accuracy: 0.8062 - val_loss: 1.2809 - val_accuracy: 0.7625 - 7s/epoch - 690ms/step
Epoch 149/150
10/10 - 7s - loss: 1.2279 - accuracy: 0.8031 - val_loss: 1.2831 - val_accuracy: 0.8000 - 7s/epoch - 676ms/step
Epoch 150/150
10/10 - 7s - loss: 1.2570 - accuracy: 0.8031 - val_loss: 1.3409 - val_accuracy: 0.8000 - 7s/epoch - 672ms/step
-----
Best accuracy achieved: 83.75 %
```

● Training And Validation Loss/Accuracy:



Best accuracy achieved: 83.75 %

● Confusion Matrix:

		Confusion Matrix				
		Ak	Ala_Idris	Buzgulu	Dimnit	Nazli
Actual	Ak	19	3	0	5	1
	Ala_Idris	1	10	3	0	0
Actual	Buzgulu	1	1	8	0	0
	Dimnit	0	0	1	23	0
Actual	Nazli	0	0	0	5	19
	All	22	12	8	23	23
		Ak	Ala_Idris	Buzgulu	Dimnit	Nazli
		Predicted				

● Classification Report:

```
Classification Report:
-----
precision    recall    f1-score   support
-----
Ak          0.9048   0.6786   0.7755     28
Ala_Idris   0.7143   0.7143   0.7143     14
Buzgulu    0.6667   0.8000   0.7273     10
Dimnit     0.6970   0.9583   0.8070     24
Nazli       0.9500   0.7917   0.8636     24
accuracy    0.7865   0.7886   0.7775     100
macro avg   0.7865   0.7886   0.7775     100
weighted avg 0.8153   0.7900   0.7908     100
```

△Second Attempt△

Try a different CNN architecture
Increase the patience
Unfreeze more layers

Validation Accuracy = 88.75%

Test Accuracy = 84%

● Parameters:

Optimization Algorithm: adamax
Learning Rate: 0.001
Momentum: 0.99
Epoch: 150
Pooling: max
Number of trainable layers of the base model: 15
Activation: softmax

● Model Summary:

```
Model: "sequential_26"
-----
```

```
Layer (type)      Output Shape     Param #
-----
```

```
inception_v3 (Functional) (None, 2048) 21802784
```

```
batch_normalization_1699 (B (None, 2048) 8192
```

```
batchNormalization
```

```
flatten_7 (Flatten) (None, 2048) 0
```

```
dropout_45 (Dropout) (None, 2048) 0
```

```
dense_73 (Dense) (None, 128) 262272
```

```
dropout_46 (Dropout) (None, 128) 0
```

```
dense_74 (Dense) (None, 256) 33024
```

```
dropout_47 (Dropout) (None, 256) 0
```

```
dense_75 (Dense) (None, 5) 1285
```

```
=====
Total params: 23,117,093
Trainable params: 1,708,805
Non-trainable params: 21,408,288
```

● Last 10 Epochs (with early stopping, patience=30):

```
Epoch 85/150
10/10 - 7s - loss: 0.4801 - accuracy: 0.8406 - val_loss: 0.4688 - val_accuracy: 0.8250 - 7s/epoch - 668ms/step
Epoch 86/150
10/10 - 7s - loss: 0.4992 - accuracy: 0.8062 - val_loss: 0.4716 - val_accuracy: 0.7875 - 7s/epoch - 670ms/step
Epoch 87/150
10/10 - 7s - loss: 0.8493 - accuracy: 0.9530 - val_loss: 0.9903 - val_accuracy: 0.8125 - 7s/epoch - 670ms/step
Epoch 88/150
10/10 - 7s - loss: 0.5037 - accuracy: 0.8156 - val_loss: 0.6544 - val_accuracy: 0.7500 - 7s/epoch - 671ms/step
Epoch 89/150
10/10 - 7s - loss: 0.5142 - accuracy: 0.8094 - val_loss: 0.7862 - val_accuracy: 0.7375 - 7s/epoch - 675ms/step
Epoch 90/150
10/10 - 7s - loss: 0.5613 - accuracy: 0.7969 - val_loss: 0.7166 - val_accuracy: 0.7500 - 7s/epoch - 680ms/step
Epoch 91/150
10/10 - 7s - loss: 0.5006 - accuracy: 0.8125 - val_loss: 0.6057 - val_accuracy: 0.8125 - 7s/epoch - 674ms/step
Epoch 92/150
10/10 - 7s - loss: 0.4699 - accuracy: 0.8125 - val_loss: 0.5873 - val_accuracy: 0.7500 - 7s/epoch - 672ms/step
Epoch 93/150
10/10 - 7s - loss: 0.5236 - accuracy: 0.8062 - val_loss: 0.6256 - val_accuracy: 0.8375 - 7s/epoch - 672ms/step
Epoch 94/150
10/10 - 7s - loss: 0.5129 - accuracy: 0.8031 - val_loss: 0.6256 - val_accuracy: 0.8375 - 7s/epoch - 671ms/step
Epoch 95/150
10/10 - 7s - loss: 0.5396 - accuracy: 0.8031 - val_loss: 0.5318 - val_accuracy: 0.8350 - 7s/epoch - 672ms/step
Epoch 96/150
10/10 - 7s - loss: 0.5318 - accuracy: 0.8031 - val_loss: 0.5318 - val_accuracy: 0.8350 - 7s/epoch - 672ms/step
-----
Best accuracy achieved: 88.75 %
```

● Training And Validation Loss/Accuracy:

● Confusion Matrix :

		Confusion Matrix				
		Ak	Ala_Idris	Buzgulu	Dimnit	Nazli
Actual	Ak	22	1	0	4	1
	Ala_Idris	4	8	2	0	0
Actual	Buzgulu	2	0	8	0	0
	Dimnit	0	0	0	23	0
Actual	Nazli	0	1	0	1	23
	All	22	12	8	23	23
		Ak	Ala_Idris	Buzgulu	Dimnit	Nazli
		Predicted				

● Classification Report:

```
Classification Report:
-----
precision    recall    f1-score   support
-----
Ak          0.9524   0.7143   0.7719     28
Ala_Idris   0.8899   0.5714   0.6957     14
Buzgulu    0.8000   0.8000   0.8000     10
Dimnit     0.8214   0.9583   0.8846     24
Nazli       0.9583   0.9583   0.9583     24
accuracy    0.8440   0.8400   0.8358     100
macro avg   0.8440   0.8400   0.8358     100
weighted avg 0.8937   0.8800   0.8788     100
```

△Third Attempt△

Add dropouts

Add regularization

Add BatchNormalization

Validation Accuracy = 91.25%

Test Accuracy = 88%

● Parameters:

Optimization Algorithm: adamax
Learning Rate: 0.001
Momentum: 0.99
Epoch: 150
Pooling: max
Number of trainable layers of the base model: 15
Activation: softmax

● Model Summary:

```
Model: "sequential_26"
```

```
-----
```

```
Layer (type)      Output Shape     Param #
-----
```

```
inception_v3 (Functional) (None, 2048) 21802784
```

```
batch_normalization_1699 (B (None, 2048) 8192
```

```
batchNormalization
```

```
flatten_7 (Flatten) (None, 2048) 0
```

```
dropout_45 (Dropout) (None, 2048) 0
```

```
dense_73 (Dense) (None, 128) 262272
```

```
dropout_46 (Dropout) (None, 128) 0
```

```
dense_74 (Dense) (None, 256) 33024
```

```
dropout_47 (Dropout) (None, 256) 0
```

```
dense_75 (Dense) (None, 5) 1285
```

```
=====
Total params: 22,107,557
Trainable params: 695,17
```


4. 10 Fold Cross Validation

Cross-validation is a statistical method used to estimate the skill of machine learning models.

In 10 fold cross validation, we shuffle and split the training set into 10 parts and take one of those parts for validation and the rest for training. Thus we train our model 10 times on 10 different sets of train and validation datasets. Finally we announce the average of the validation accuracies as the final accuracy of the model.

We use the **stratified cross validation** to ensure that each fold of dataset has the same proportion of observations with a given label. Simply *StratifiedKFold* is the improved version of *KFold*

We use our second to best performing models so far which is **InceptionV3** to calculate accuracy using the 10 fold cross validation. The reason we don't do this for **EfficientNetB3** is that it has a very large number of trainable parameters and doing 10 fold cross validation would probably ban me from colab :)

4.1. InceptionV3

Since cross validation is very time consuming, specially for deep layers with high epochs, I had to limit the model to only 20 epochs. Thus we don't get the 91% accuracy we had before.

Result of the 10 fold cross validation on 20 epochs are as follows:

	1st Fold	2nd Fold	3rd Fold	4th Fold	5th Fold	6th Fold	7th Fold	8th Fold	9th Fold	10th Fold	Average
InceptionV3	62.5	67.5	65.0	67.5	70.0	57.5	72.5	80.0	65.0	60.0	66.75

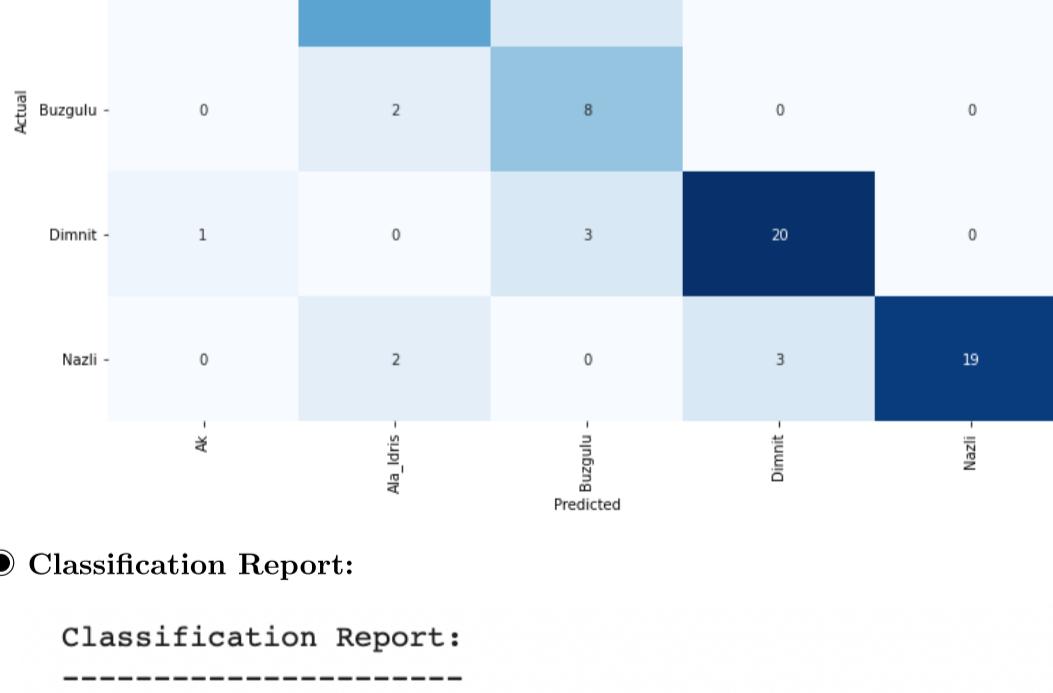
Validation Accuracy:
66.75% (+/- 5.84%)
Validation Loss:
3.19% (+/- 0.26%)

Best model number is 8 with validation accuracy of 80 %.

Running the best model on our test data set we get a test accuracy of 76%

Validation Accuracy = 80%
Test Accuracy = 76%

● Confusion Matrix:



● Classification Report:

Classification Report:

	precision	recall	f1-score	support
Ak	0.9375	0.5357	0.6818	28
Ala_Idris	0.6111	0.7857	0.6875	14
Buzgulu	0.4444	0.8000	0.5714	10
Dimnit	0.7143	0.8333	0.7692	24
Nazli	0.9500	0.7917	0.8636	24
accuracy			0.7300	100
macro avg	0.7315	0.7493	0.7147	100
weighted avg	0.7919	0.7300	0.7362	100

5. Improving The Accuracy (Extra Credit)

In this section I try various techniques in hope of reaching a better test accuracy.

5.1. Unfreezing All the Pre-trained Layers

One idea is to unfreeze all layers of a pre-trained model so it can fully learn our dataset and find the best weight for our purpose and not just the ImageNet.

We try this method with **EfficientNetB3**. To avoid overfitting we use BatchNormalization.

△Extra Attempt△

Add Batch Normalization

Add Regularizes

Use Adamax for optimization

Unfreeze all layers

Validation Accuracy = 90%

Test Accuracy = 97%

● Parameters:

Optimization Algorithm: adamax

Learning Rate: 0.001

Momentum: 0.99

Epoch: 150

Pooling: max

Number of trainable layers of the base model: all layers of EfficientNetB3

Activation: softmax

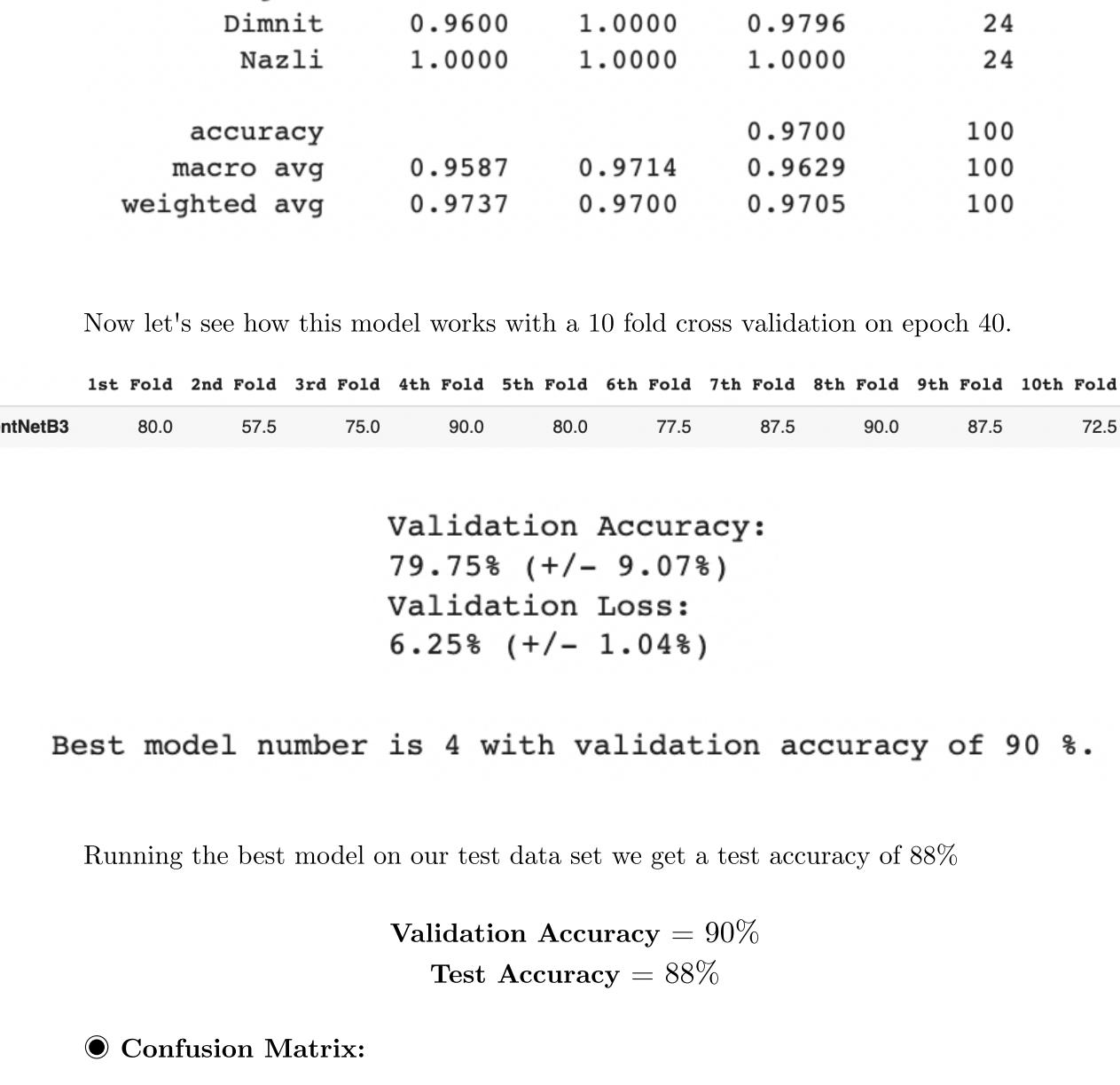
● Model Summary:

block7b_drop (Dropout)	(None, 8, 8, 384)	0	['block7b_project_bn[0][0]']
block7b_add (Add)	(None, 8, 8, 384)	0	['block7b_drop[0][0]', 'block7a_project_bn[0][0]']
top_conv (Conv2D)	(None, 8, 8, 1536)	589824	['block7b_add[0][0]']
top_bn (BatchNormalization)	(None, 8, 8, 1536)	6144	['top_conv[0][0]']
top_activation (Activation)	(None, 8, 8, 1536)	0	['top_bn[0][0]']
max_pool (GlobalMaxPooling2D)	(None, 1536)	0	['top_activation[0][0]']
batch_normalization_195 (Batch Normalization)	(None, 1536)	6144	['max_pool[0][0]']
dense_12 (Dense)	(None, 256)	393472	['batch_normalization_195[0][0]']
dropout_8 (Dropout)	(None, 256)	0	['dense_12[0][0]']
dense_13 (Dense)	(None, 5)	1285	['dropout_8[0][0]']
<hr/>			
Total params:	11,184,436		
Trainable params:	11,094,061		
Non-trainable params:	90,375		

● Last 10 Epochs (with early stopping, patience=10):

```
Epoch 30/40
10/10 - 9s - loss: 3.5053 - accuracy: 0.9937 - val_loss: 3.8413 - val_accuracy: 0.8375 - 9s/epoch - 945ms/step
Epoch 31/40
10/10 - 9s - loss: 3.4445 - accuracy: 0.9875 - val_loss: 3.9489 - val_accuracy: 0.8250 - 9s/epoch - 926ms/step
Epoch 32/40
10/10 - 9s - loss: 3.3108 - accuracy: 0.9844 - val_loss: 3.7579 - val_accuracy: 0.7875 - 9s/epoch - 939ms/step
Epoch 33/40
10/10 - 9s - loss: 3.2156 - accuracy: 0.9937 - val_loss: 3.6626 - val_accuracy: 0.8625 - 9s/epoch - 936ms/step
Epoch 34/40
10/10 - 10s - loss: 3.1784 - accuracy: 0.9719 - val_loss: 3.6152 - val_accuracy: 0.8125 - 10s/epoch - 971ms/step
Epoch 35/40
10/10 - 10s - loss: 3.0806 - accuracy: 0.9781 - val_loss: 3.3866 - val_accuracy: 0.9000 - 10s/epoch - 1s/step
Epoch 36/40
10/10 - 9s - loss: 2.9736 - accuracy: 0.9875 - val_loss: 3.1875 - val_accuracy: 0.8875 - 9s/epoch - 938ms/step
Epoch 37/40
10/10 - 9s - loss: 2.9017 - accuracy: 0.9781 - val_loss: 3.0624 - val_accuracy: 0.9000 - 9s/epoch - 937ms/step
Epoch 38/40
10/10 - 9s - loss: 2.8080 - accuracy: 0.9937 - val_loss: 3.1155 - val_accuracy: 0.8625 - 9s/epoch - 928ms/step
Epoch 39/40
10/10 - 10s - loss: 2.7203 - accuracy: 0.9875 - val_loss: 2.9546 - val_accuracy: 0.8875 - 10s/epoch - 991ms/step
Epoch 40/40
10/10 - 11s - loss: 2.6686 - accuracy: 0.9812 - val_loss: 2.8894 - val_accuracy: 0.8875 - 11s/epoch - 1s/step
-----
Best accuracy achieved: 90.0 %
```

● Training And Validation Loss/Accuracy:



Although this looks like a bad case of overfit but it has a wonderful result on the test dataset!

● Confusion Matrix :

Confusion Matrix					
Actual	Ak	Ala_Idris	Buzgulu	Dimnit	Nazli
Ak	26	0	1	1	0
Ala_Idris	0	13	1	0	0
Buzgulu	0	0	10	0	0
Dimnit	0	0	0	24	0
Nazli	0	0	0	0	24

● Classification Report:

Classification Report:

	precision	recall	f1-score	support
Ak	1.0000	0.9286	0.9630	28
Ala_Idris	1.0000	0.9286	0.9630	14
Buzgulu	0.8333	1.0000	0.9091	10
Dimnit	0.9600	1.0000	0.9796	24
Nazli	1.0000	1.0000	1.0000	24
accuracy			0.9700	100
macro avg	0.9587	0.9714	0.9629	100
weighted avg	0.9737	0.9700	0.9705	100

Now let's see how this model works with a 10 fold cross validation on epoch 40.

	1st Fold	2nd Fold	3rd Fold	4th Fold	5th Fold	6th Fold	7th Fold	8th Fold	9th Fold	10th Fold	Average
EfficientNetB3	80.0	57.5	75.0	90.0	80.0	77.5	87.5	90.0	87.5	72.5	79.75

Validation Accuracy:

79.75% (+/- 9.07%)

Validation Loss:

6.25% (+/- 1.04%)

Best model number is 4 with validation accuracy of 90 %.

Running the best model on our test data set we get a test accuracy of 88%.

Validation Accuracy = 90%

Test Accuracy = 88%

● Confusion Matrix:

Confusion Matrix					
Actual	Ak	Ala_Idris	Buzgulu	Dimnit	Nazli
Ak	25	0	0	3	0
Ala_Idris	1	7	6	0	0
Buzgulu	1	0	9	0	0
Dimnit	0	0	0	24	0
Nazli	1	0	0	0	23

● Classification Report:

Classification Report:

	precision	recall	f1-score	support
Ak	0.8929	0.8929	0.8929	28
Ala_Idris	1.0000	0.5000	0.6667	14
Buzgulu	0.6000	0.9000	0.7200	10
Dimnit	0.8889	1.0000	0.9412	24
Nazli	1.0000	0.9583	0.9787	24
accuracy			0.8800	100
macro avg	0.8763	0.8502	0.8399	100
weighted avg	0.9033	0.8800	0.8761	100

6. Conclusion

In this section I summarize my work on this project.

6.1. Transform Learning

We used transform learning to train on top of 4 pre-trained models. Namely, MobileNetV2, ResNet50, EfficientNetB3, and InceptionV3.

For each model we attempted 3 times to increase the test accuracy.

Notes from the attempts:

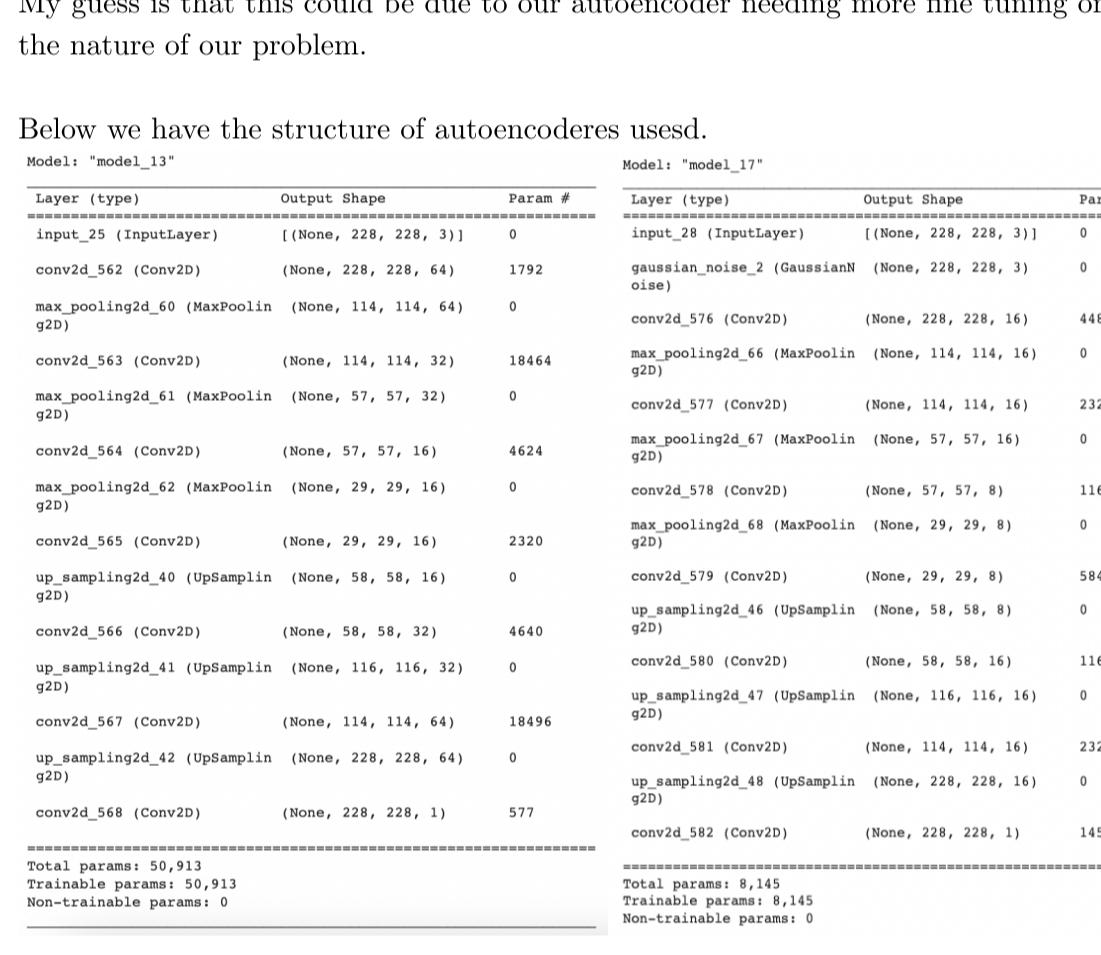
1. Adding dropout layers can reduce overfitting.
2. Adding more dense layers or unfreezing the last layers of our base model can help with underfitting.
3. Using a call back function with a low patience can also prevent overfitting.
4. Adding batch normalization and regularizing layers will help with overfitting.
5. Finding a good optimization algorithms can help the accuracy of our model.

In the table below we can see the comparison of their performance.

Model_Name	Num_Trainable_Params	Validation_Accuracy	Test_Accuracy
2 EfficientNetB3	2099717	96	89
3 InceptionV3	695173	91	88
0 MobileNetV2	921093	90	80
1 ResNet50	2369029	81	75

We can see that without any advanced hyperparameter tuning, **EfficientNetB3** has a quite good test accuracy.

In the picture below we can see the test accuracy compared to the number of trainable parameters of each model.



Notes we can take from this plot:

1. High number of trainable parameters does not necessarily lead to higher accuracy.
2. There are no one network that fits all, some network would perform better on some datasets and we can only find our optimal network by practice.
3. Considering both accuracy and training time, one would choose the **InceptionV3** network.

6.2. Autoencoders

I trained two autoencoders for denoising and feature extraction purposes on the training dataset. Then I discarded the decoder and used the predicted images from the encoder to feed to EfficientNetB3, but it did not change the accuracy in any significant value.

My guess is that this could be due to our autoencoder needing more fine tuning or the nature of our problem.

Below we have the structure of autoencoderes used.

Model: "model_13"			Model: "model_17"		
Layer (type)	Output Shape	Param #	Layer (type)	Output Shape	Param #
input_25 (Inputlayer)	[None, 228, 228, 3]	0	input_28 (Inputlayer)	[None, 228, 228, 3]	0
conv2d_562 (Conv2D)	(None, 228, 228, 64)	1792	gaussian_noise_2 (GaussianNoise)	(None, 228, 228, 3)	0
max_pooling2d_60 (MaxPool2D)	(None, 114, 114, 64)	0	conv2d_576 (Conv2D)	(None, 228, 228, 16)	448
conv2d_563 (Conv2D)	(None, 114, 114, 32)	18464	max_pooling2d_66 (MaxPool2D)	(None, 114, 114, 16)	0
max_pooling2d_61 (MaxPool2D)	(None, 57, 57, 32)	0	conv2d_577 (Conv2D)	(None, 114, 114, 16)	2320
conv2d_564 (Conv2D)	(None, 57, 57, 16)	4624	max_pooling2d_67 (MaxPool2D)	(None, 57, 57, 16)	0
max_pooling2d_62 (MaxPool2D)	(None, 29, 29, 16)	0	conv2d_578 (Conv2D)	(None, 57, 57, 8)	1160
conv2d_565 (Conv2D)	(None, 29, 29, 16)	2320	max_pooling2d_68 (MaxPool2D)	(None, 29, 29, 8)	0
up_sampling2d_40 (UpSampling2D)	(None, 58, 58, 16)	0	conv2d_579 (Conv2D)	(None, 29, 29, 8)	584
up_sampling2d_41 (UpSampling2D)	(None, 116, 116, 32)	0	up_sampling2d_46 (UpSampling2D)	(None, 58, 58, 8)	0
conv2d_567 (Conv2D)	(None, 114, 114, 64)	18496	conv2d_580 (Conv2D)	(None, 58, 58, 16)	1168
up_sampling2d_42 (UpSampling2D)	(None, 228, 228, 64)	0	up_sampling2d_47 (UpSampling2D)	(None, 116, 116, 16)	0
conv2d_568 (Conv2D)	(None, 228, 228, 1)	577	conv2d_581 (Conv2D)	(None, 114, 114, 16)	2320
			up_sampling2d_48 (UpSampling2D)	(None, 228, 228, 16)	0
			conv2d_582 (Conv2D)	(None, 228, 228, 1)	145

Figure 1: Autoencoder

Figure 2: Denoising Autoencoder

6.3. Cross Validation

Since cross validation is very time consuming, specially for deep layers with high epochs, I had to limit the model to only 20 epochs. Thus we don't get the 91% accuracy we had before.

1st Fold	2nd Fold	3rd Fold	4th Fold	5th Fold	6th Fold	7th Fold	8th Fold	9th Fold	10th Fold	Average	
InceptionV3	62.5	67.5	65.0	67.5	70.0	57.5	72.5	80.0	65.0	60.0	66.75

Validation Accuracy:

66.75% (+/- 5.84%)

Validation Loss:

3.19% (+/- 0.26%)

Best model number is 8 with validation accuracy of 80 %.

Maximum Validation Accuracy = 80%

Test Accuracy = 76%

6.4. Improving The Accuracy

In this part I unfroze all layers of pre-trained **EfficientNetB3**, so it can fully learn our dataset and find the best weight for our purpose and not just the ImageNet.

To avoid overfitting I used BatchNormalization.

The result was amazing!

Now we have:

Model_Name	Num_Trainable_Params	Validation_Accuracy	Test_Accuracy
4 Fully Trainable EfficientNetB3	11094061	90	97
2 EfficientNetB3	2099717	96	89
3 InceptionV3	695173	91	88
0 MobileNetV2	921093	90	80
1 ResNet50	2369029	81	75

The paper achieved an accuracy of 97.5% and I got a test accuracy of 97% so pretty close! Performing more hyperparameter tuning and doing more experiments would probably result in higher accuracy.

This is a very interesting fact! Although transfer learning can save us time and resource by providing us with the pre-trained weights, using the state of the art architecture of CNN models can lead us to very high accuracies because neurons would learn exactly our dataset and not ImageNet.

To make sure the accuracy was reliable, I performed 10 fold cross validation on this model. The result:

1st Fold	2nd Fold	3rd Fold	4th Fold	5th Fold	6th Fold	7th Fold	8th Fold	9th Fold	10th Fold	Average	
EfficientNetB3	80.0	57.5	75.0	90.0	80.0	77.5	87.5	90.0	87.5	72.5	79.75

Validation Accuracy:

79.75% (+/- 9.07%)

Validation Loss:

6.25% (+/- 1.04%)

And it turned out that the model is good most of the times but fails terribly at some folds! So we should always perform cross validation to make sure our accuracy is reliable.