SKIN CANCER RECOGNITION

MALIGNANT OR BENIGN?

Origin of the idea

The project aims to successfully identify if the skin cancer is either malignant or benign using VGG16.

This can serve as a tool to assist dermatologists by providing a reliable second opinion, thereby improving diagnostic accuracy and facilitating early intervention.

Modelling process

01

Data preparation and labels vectorization

02

Data Augmentation

03

Constructing and tuning neural network using VGG16 as a baseline model

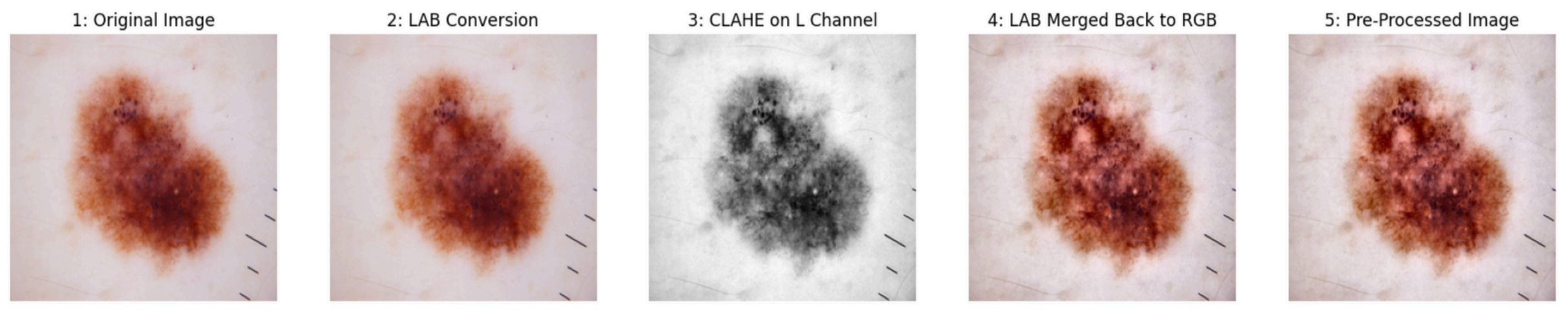
04

Training a model with 15 epochs and assessing the test dataset with the obtained weights

Data Pre-processing

First of all, we need to prepare the raw data in a suitable format for the model:

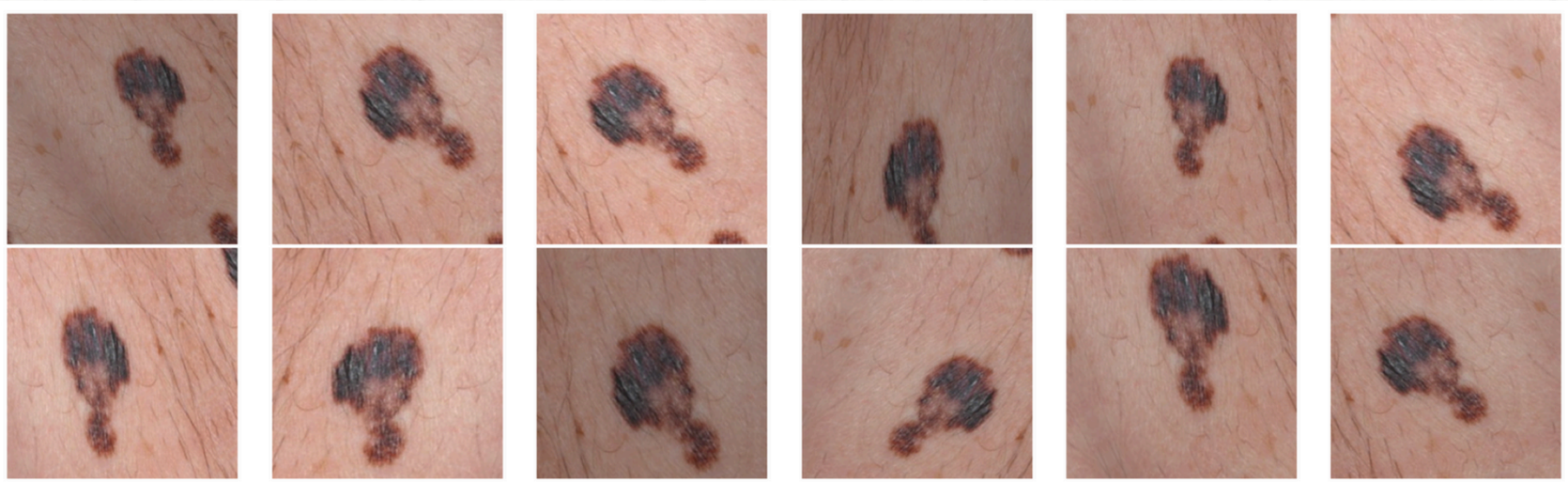
1. Enhanced the contrast of the images by converting to LAB color space and applying CLAHE.
2. Resized the image to 224x224 pixels.
3. Mapped Labels to Numeric Values



Data Augmentation

We used data augmentation to increase the diversity of the training dataset by applying random transformations such as rotations, shifts, flips, etc., to the images.

This overall helped in preventing overfitting



Augmentation Example

```
rescale=1./255,
shear_range=0.2,
zoom_range=0.2,
horizontal_flip=True,
rotation_range=40,
width_shift_range=0.2,
height_shift_range=0.2,
brightness_range=[0.8, 1.2],
fill_mode = "reflect",
validation_split=0.2
```

Neural Network

Sequential Model

Base Model (VGG16)

It captures hierarchical features for recognizing patterns in skin cancer images.

Flatten Layer

Flatten layer converts the 3D feature maps into a 1D vector. This prepares the data for input into the fully connected layers.

Dense Layers

They learn complex patterns and relationships in the extracted features. Multiple dense layers are used to provide the model with sufficient capacity to capture the intricacies of skin lesions.

Batch Normalization

It stabilizes the training process. It normalizes the activations of the previous layer, making training more robust and accelerating convergence.

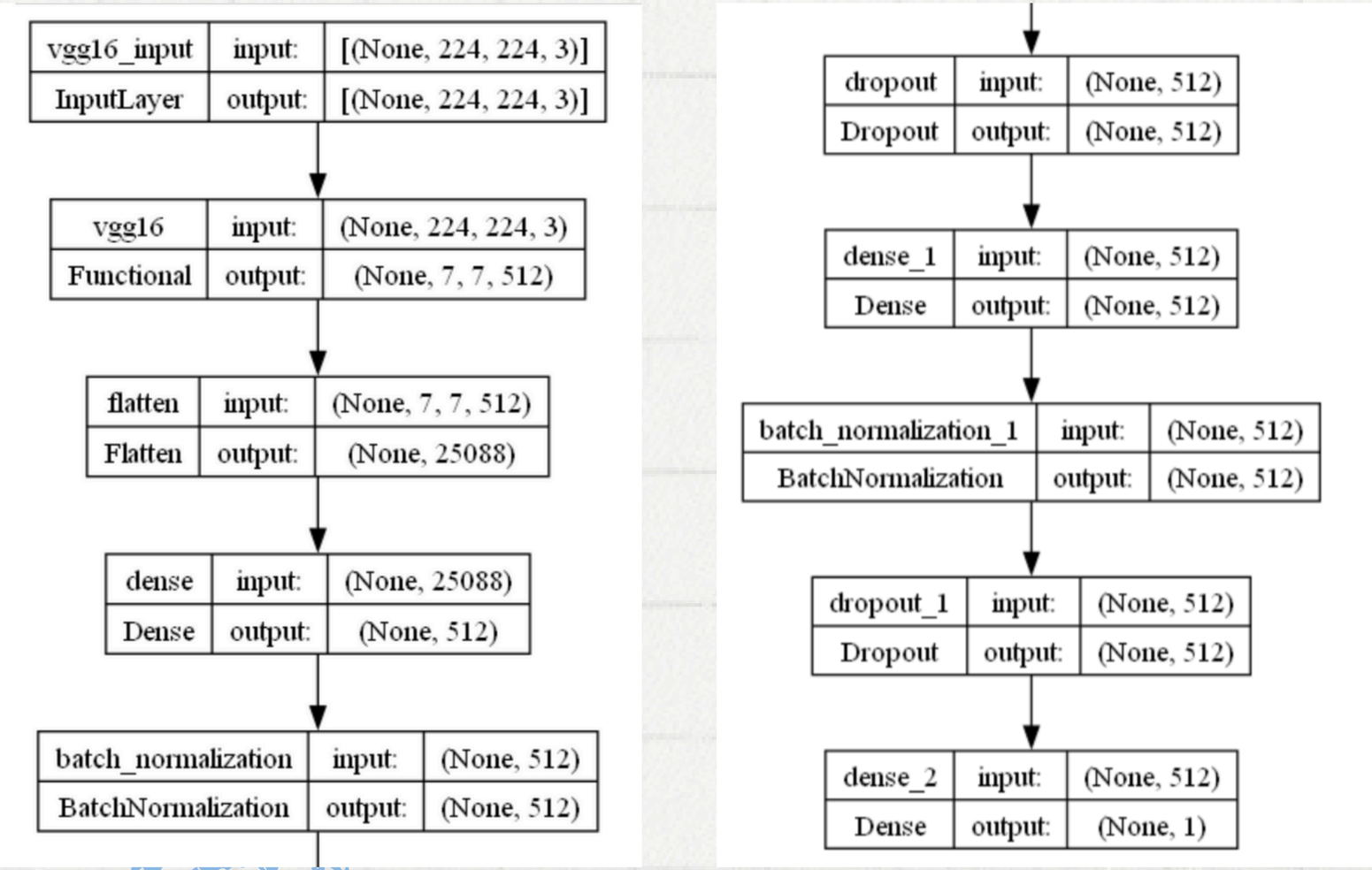
Dropout

It prevents overfitting, learns more robust features, and reduces the risk of memorizing noise in the training data.

Output Layer (Sigmoid Activation)

Sigmoid squashes the output to a value between 0 and 1, representing the probability of malignancy.

VISUAL REPRESENTATION



MODEL TRAINING

COMPILATION

The Adam optimizer with a learning rate of 0.001 is used for updating the network weights during training.

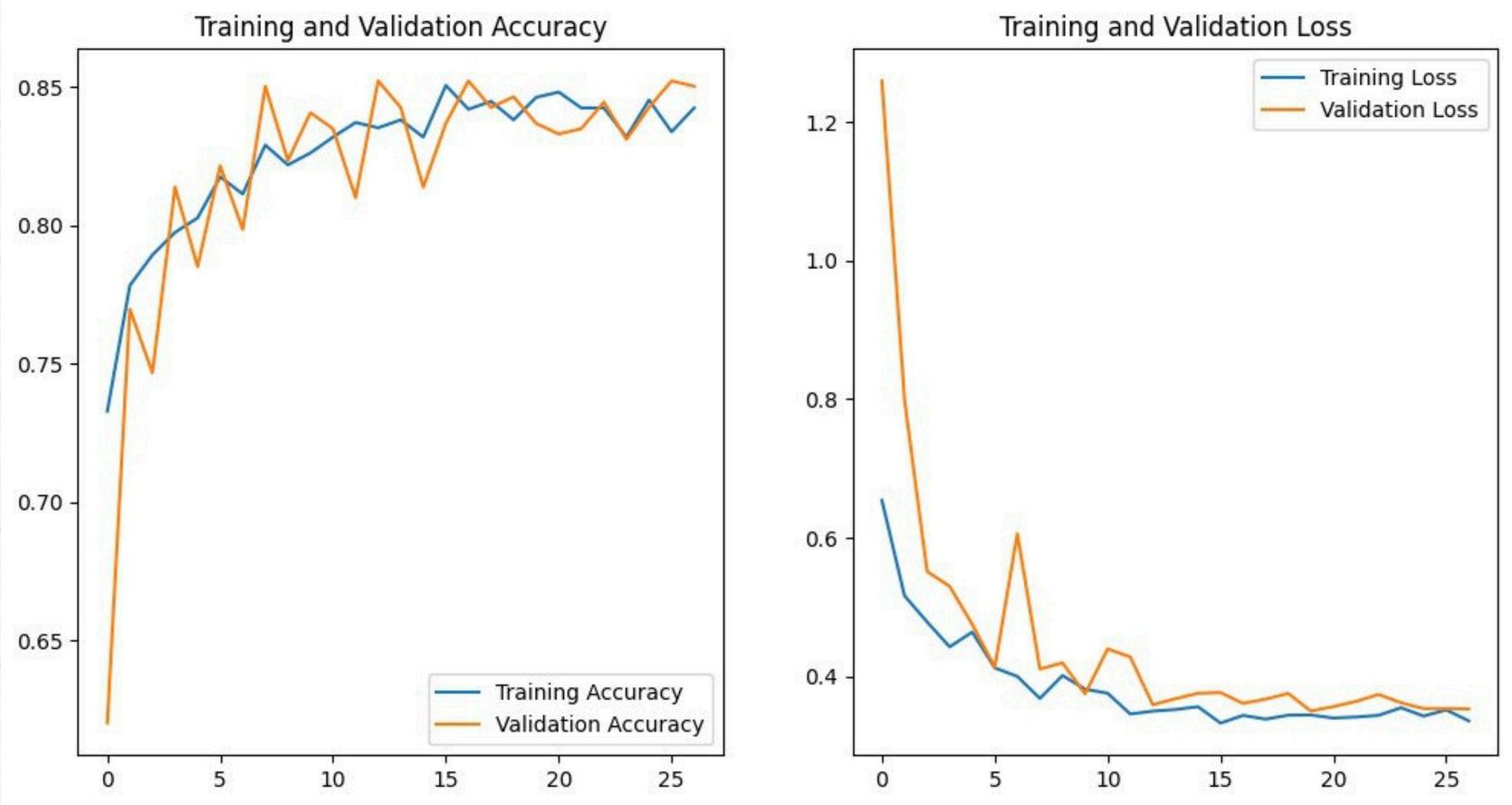
CALLBACKS

The “EarlyStopping” “ReduceLROn- Plateau” callback to control the validation loss. The best model weights are saved to restore the best-performing model

FITTING

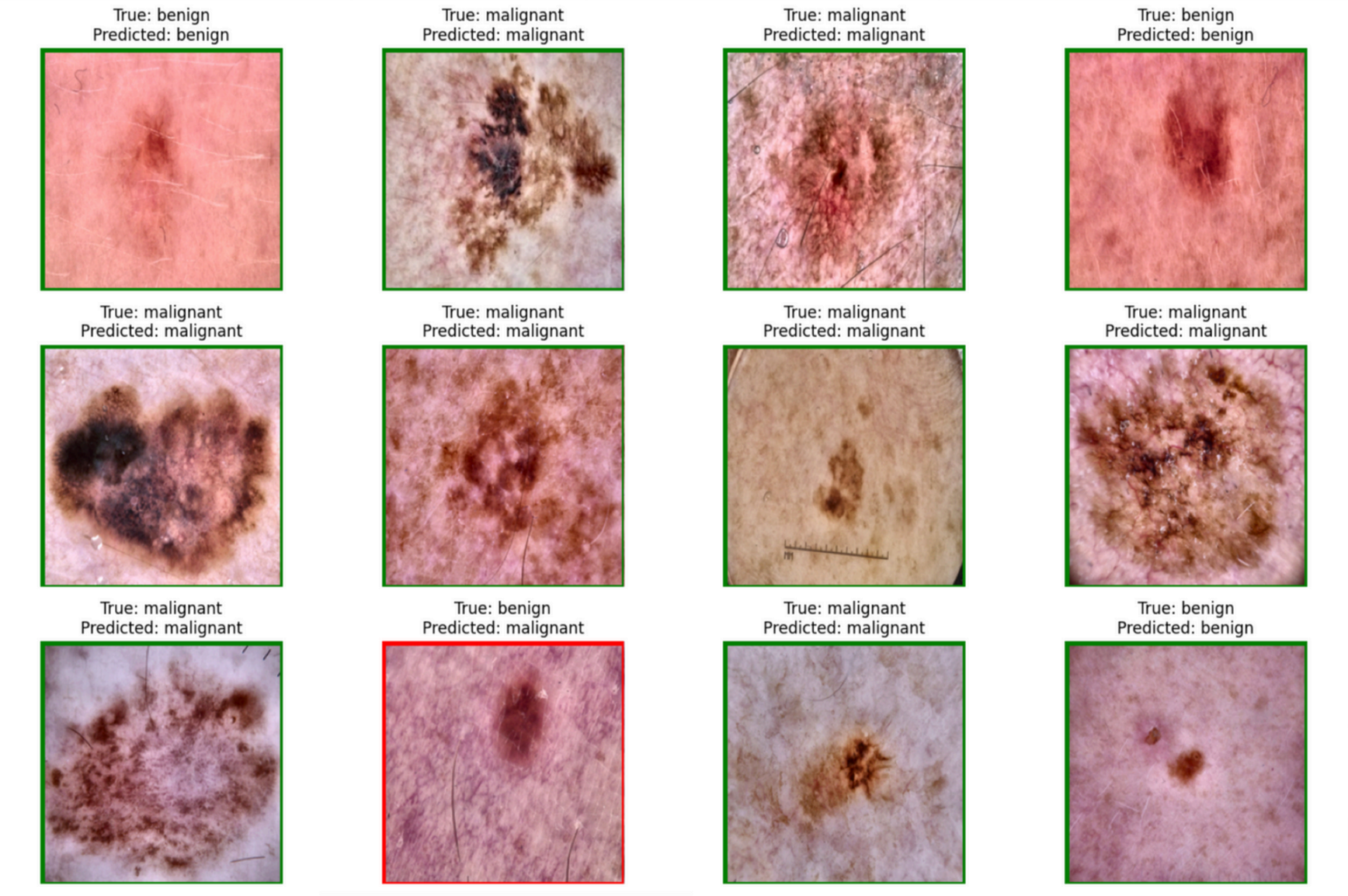
Training the model for 100 epochs on the train data and validating it on the validation data

74%


Training and Validation Accuracy
0.85
0.80
0.75
0.70
0.65
0
5
10
15
20
25
Training Accuracy
Validation Accuracy
Training and Validation Loss
1.2
1.0
0.8
0.6
0.4
0
5
10
15
20
25
Training Loss
Validation Loss

ACCURACY

THE RESULT


True: benign
Predicted: benign
True: malignant
Predicted: malignant
True: malignant
Predicted: malignant
True: benign
Predicted: benign
True: malignant
Predicted: malignant
True: malignant
Predicted: malignant
True: malignant
Predicted: malignant
True: malignant
Predicted: malignant
True: malignant
Predicted: malignant
True: benign
Predicted: malignant
True: malignant
Predicted: malignant
True: benign
Predicted: benign

Future steps

WE AIM TO:

- MAKE A CAMERA-BASED IMPLEMENTATION, SO PEOPLE WOULD BE ABLE TO SCAN THEIR SKIN AND MAKE ACCURATE PREDICTION
- INCREASE THE ACCURACY OF THE MODEL
- EXTEND THE DATABASE WITH OTHER TYPES OF SKIN CANCER