


Analyze SoftMax and Sigmoid activation function in ResNet-50 model for classifying malaria in human blood cells.

BY

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Introduction

- Malaria is a mosquito-borne disease caused by a plasmodium parasite transmitted by the bite of infected mosquitoes.
 - Worldwide, an estimated 300–500 million people contract malaria each year, resulting in 1.5–2.7 million deaths annually .
 - Malaria is a deadly disease which is more frequently found in rural areas where medical diagnosis and health care options are not easily accessible.
 - Early detection is the most effective way to reduce deaths.
 - Early diagnosis requires an accurate and reliable procedure to distinguish between healthy and infected cells..
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Objectives and importance

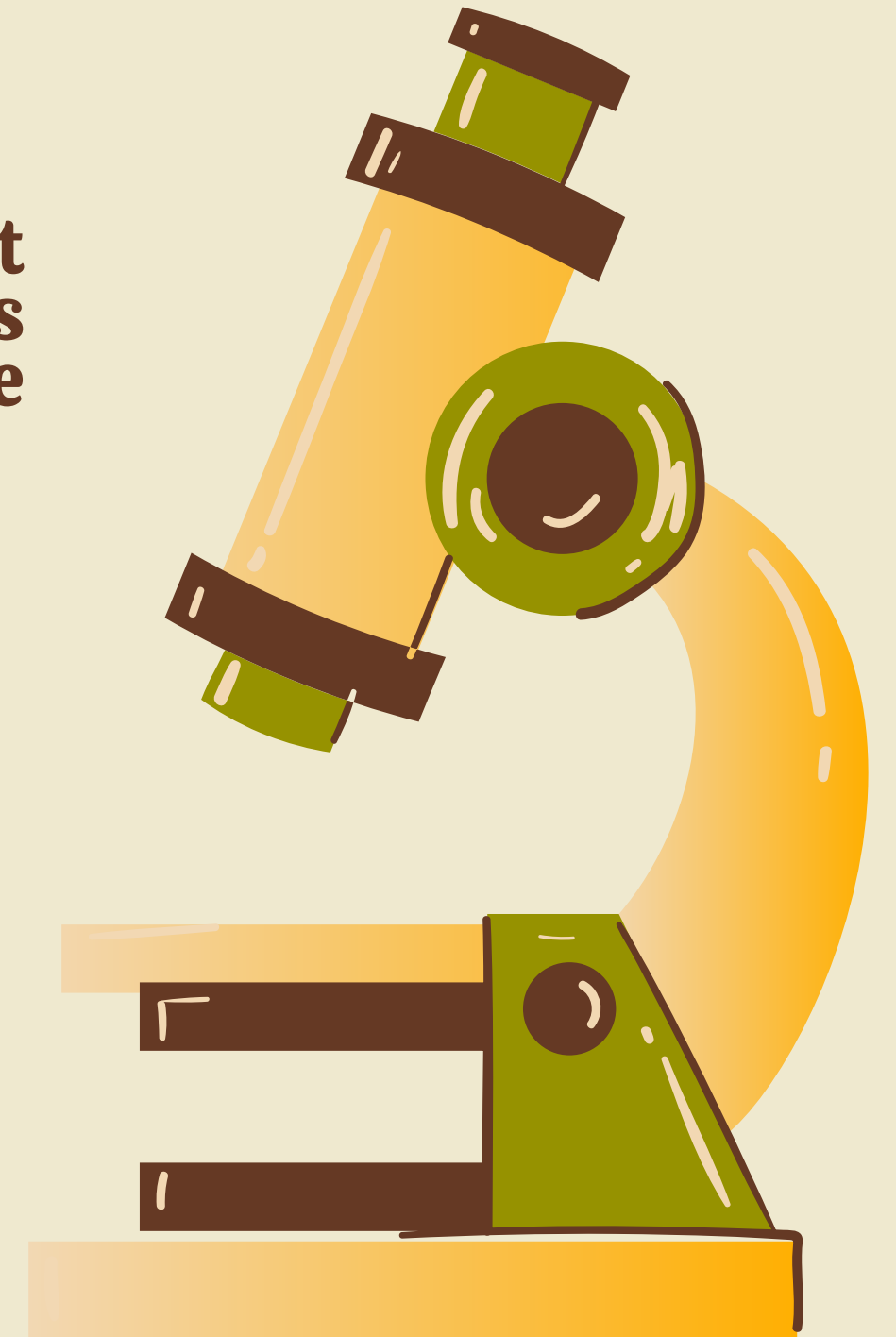
Malaria is a female Anopheles mosquito-borne disease that transmits a motile infective form to the host body such as humans, which reproduce asexually in the blood cells of the host.

The typical symptoms of malaria are fever, headache, tiredness, and vomiting. In severe cases may lead to coma and death.

In this research, we used deep neural networks to detect the malaria virus in human blood cells.

Traditional malaria detection techniques require experts to test blood cells under a microscope. The shortage of skilled technicians and the unavailability of required equipment and infrastructure result in false diagnoses leading to an increase in mortality rate.

We have customised the dataset which was made by taking random 1000 images from the cell images dataset downloaded from Kaggle Website. We have done preprocessing of data. We split the data into 60:10:30 for training, validation and testing datasets respectively.



Scope

We have successfully completed all the objectives in the detection of malaria parasites. We have explored our image dataset and split the dataset into training, validation and testing datasets in the ratio of 60:10:30. As all the images present in the dataset won't be in the same image dimensions we resize the images. We built CNN from scratch and then worked on Residual Neural networks. In ResNet-50 we applied it in two different ways. One is using softmax activation function and the other is using sigmoid activation function in dense layers. This report will explain the details of the literature used in this project (the list of references used and the review of some key reference journals/papers) and how the proposed model is different and better from the pre-existing ones, the limitations of the pre-existing and the proposed model and the future scope of how the proposed model can be improved. We will explain the implementation of this project with a diagrammatic explanation, the results derived after the implementation as well as the performance evaluation of the models.

Existing Works

Rajaraman et al. proposed the use of ensemble learning using three pre-trained models (VGG19, Squeeze Net, and InceptionResNet-V2) and a custom trained CNN model. Features of those four models were put together before final classification to discriminate between images that are infected with the malaria parasite and those that are healthy. In addition, the pre-trained models were also trained independently, and a comparison was made.



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LIBRARIES USED

RESNET-50 MODEL

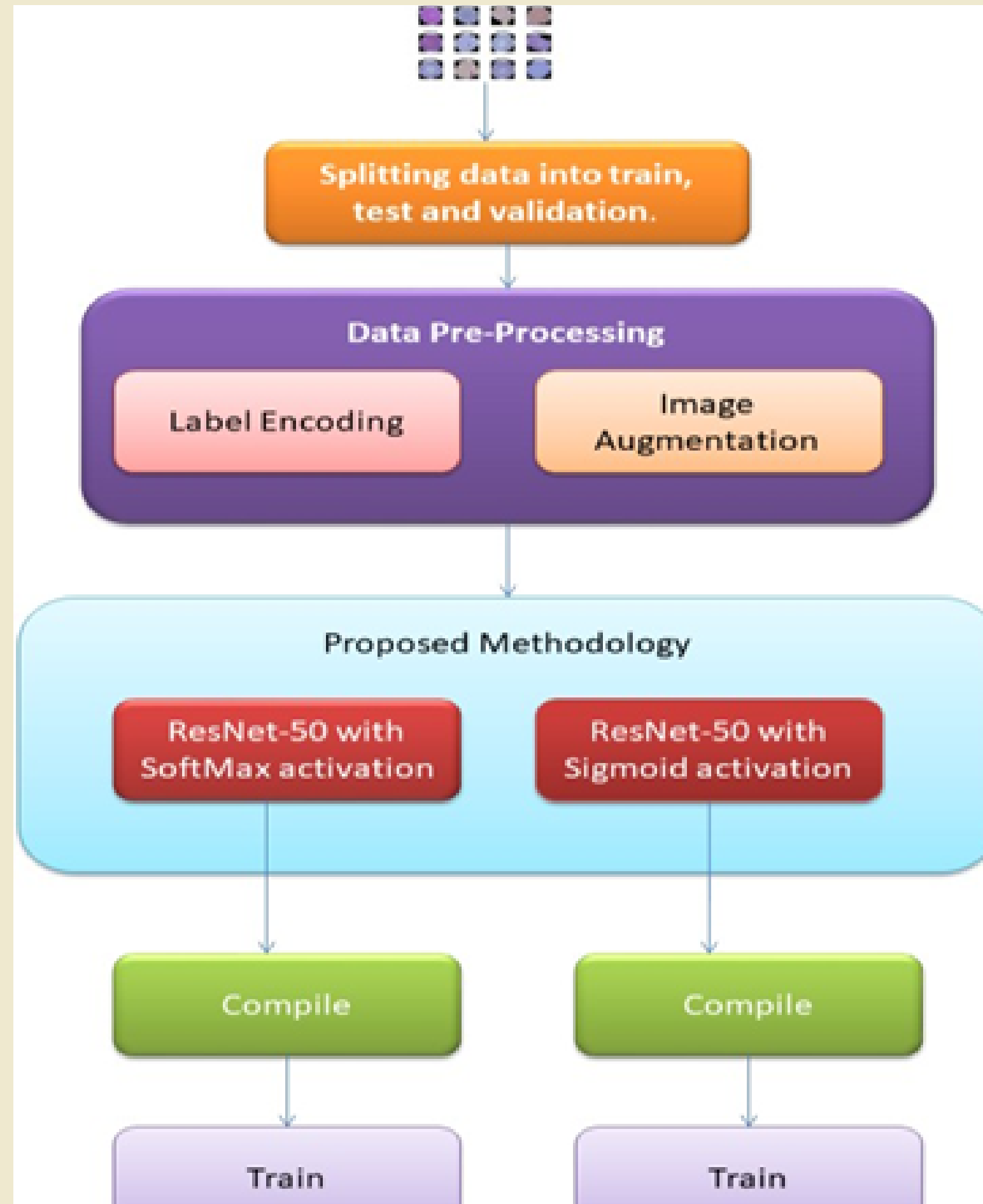
DATASETS

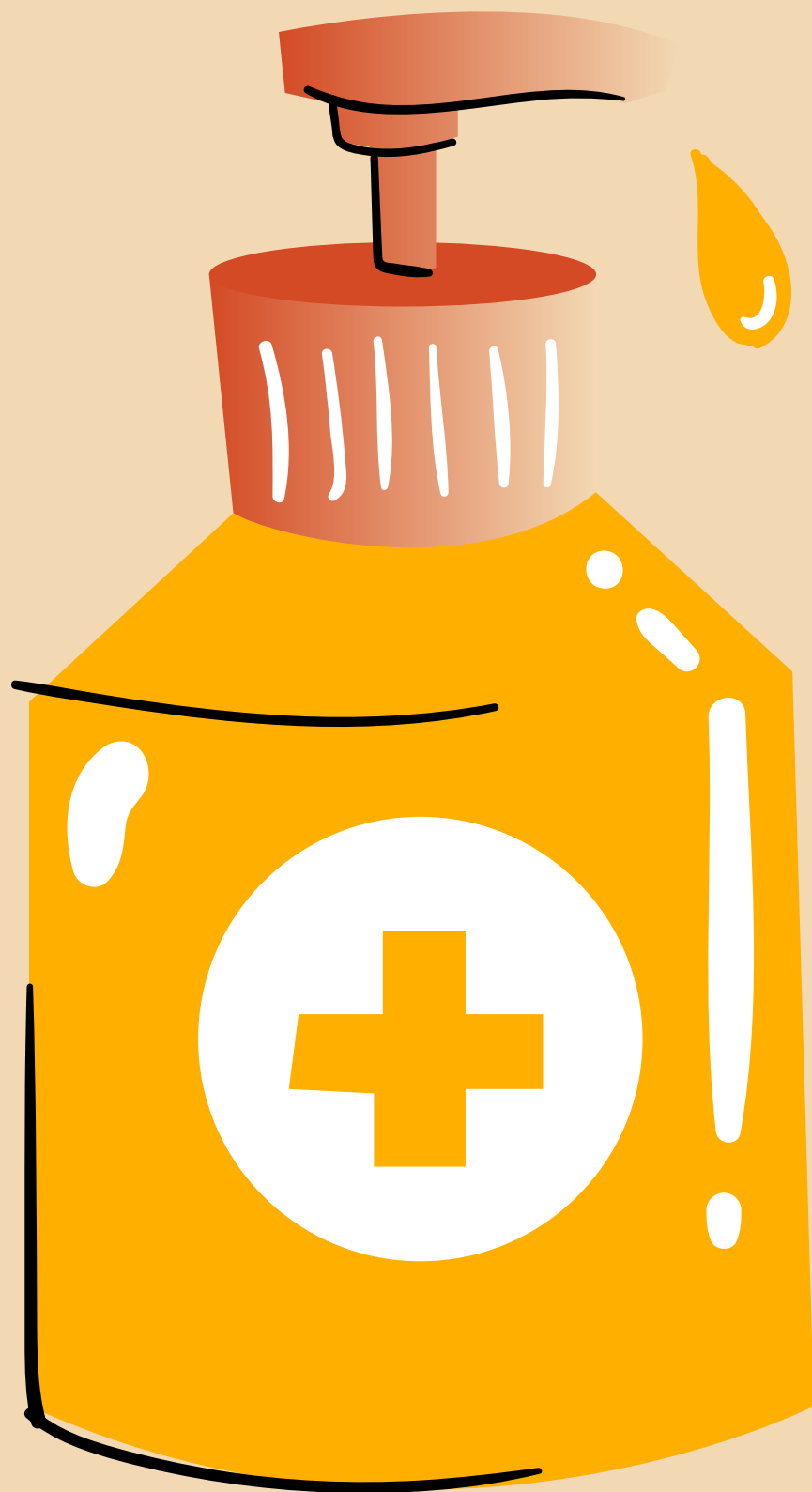
MODEL EVALUATION

CNN MODEL

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Libraries used



NUMPY

PANDAS



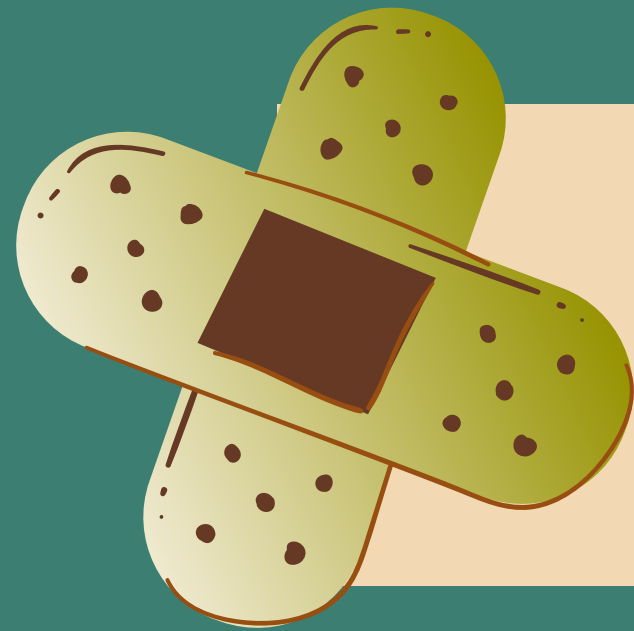
MATPLOTLIB

SEABORN

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KERAS

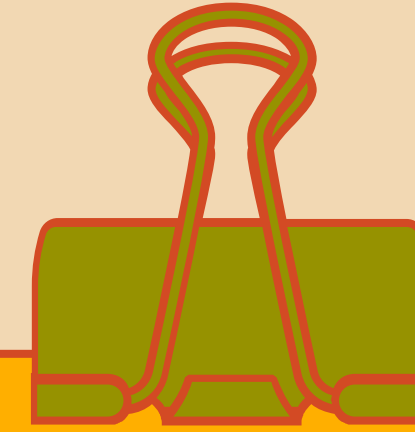
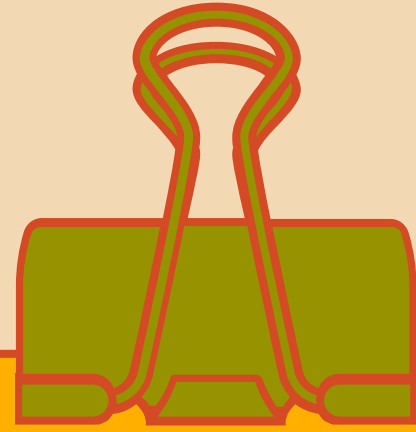
DATA SET



Cell images dataset which is publicly available for researchers is customized. The original dataset consists of 27,558 images in which 13779 images are parasitized and 13779 images are infected.

There are 1000 images in our dataset , where 500 images are parasitized and 500 images are infected.





Data preprocessing

We merged files of both non-infected images and parasitized images and labelled them as healthy and infected for the respective files. The dataset is divided into three sets for training, validation, and testing. The ratio of train to validation to test is 60:10:30. Malaria dataset

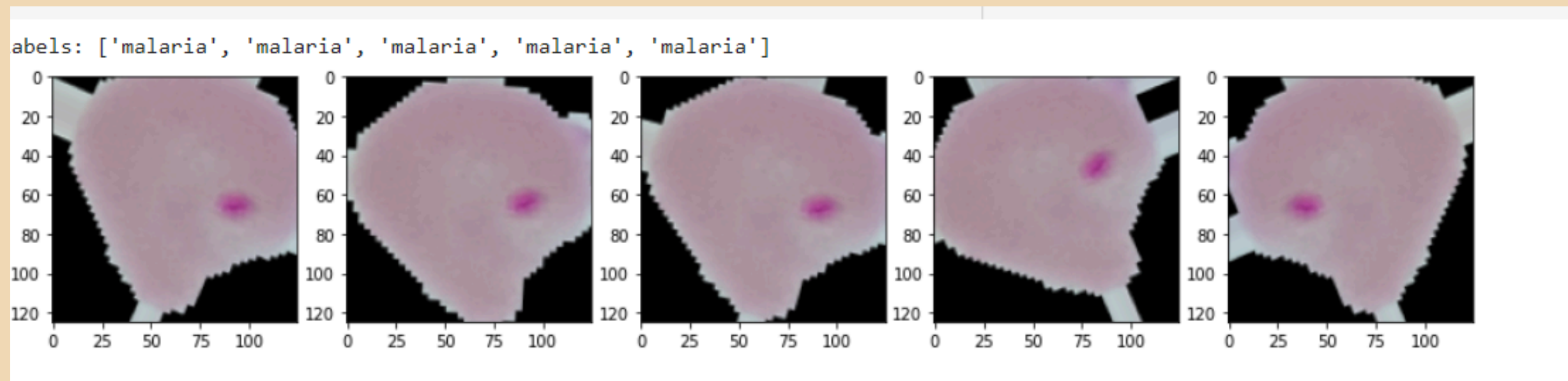
The training dataset consists of 60 percent of dataset which has 317 healthy cells and 313 infected cells, validation dataset is of 10 percent and has 39 healthy cells and 31 infected cells, and the testing dataset consists of 30 percent of the whole dataset and has 144 healthy cells and 156 infected cells.

Label Encoding

Label Encoding is a technique of converting categorical variables to a numeric value. Each value in the column is converted to a number. In this research, we used label encoding to encode the target dataset. The labels malaria and healthy are encoded as 1 and 0, respectively. The label encoder is implemented only on the training and validation datasets.

Image Augmentation

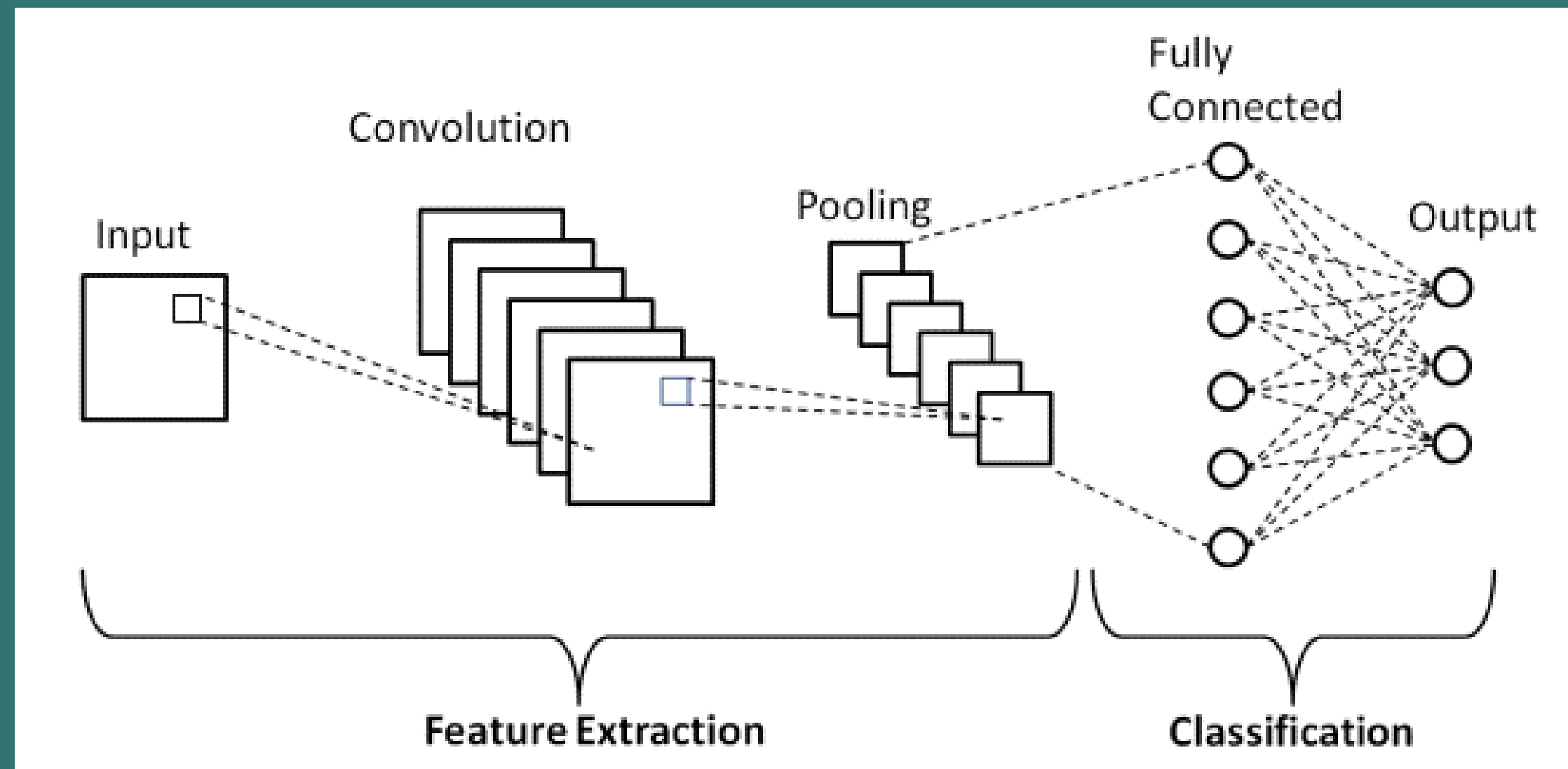
Image Augmentation is a technique that is applied to the dataset to increase the variety of data available for training models. It has been used in various medical datasets to improve classification performance. Majorly the dataset with small size uses data augmentation to increase the number of samples to improve the model performance by supplying variable data values for the model to train on. The dataset consists of equal instances in different classes keeping it a balanced dataset is performed on the training dataset which eliminates the chances of having similarity with the test dataset.



Convolutional Neural Networks

Computer sees images in the form of array values. The dimension of array is $60 \times 60 \times 3$, here 3 refers to RGB values. 3 means color images and 1 means gray scale image. CNN layers reduce the number of parameters and speed up the training of model. There are three types of CNN layers. They are:

- Convolutional layer
- Relu layer
- Pooling Layer

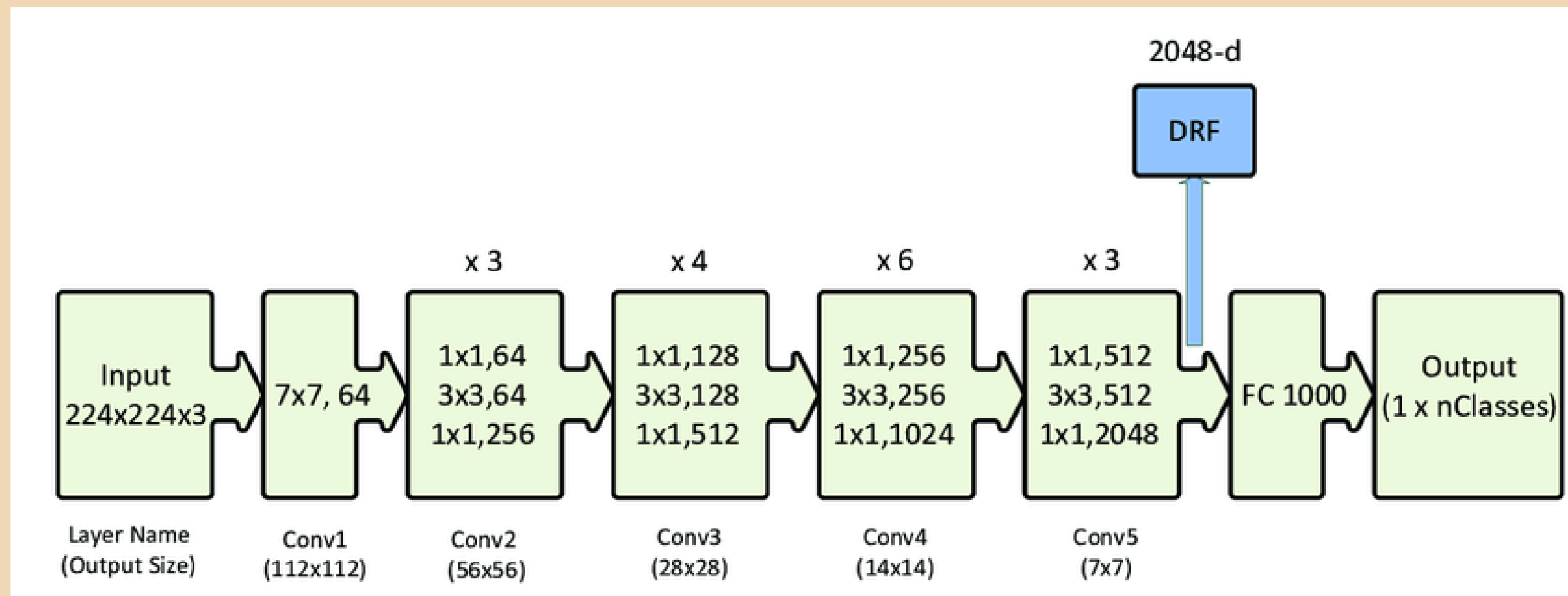


Fully Connected Layer in CNN

This is the layer where image classification actually happens. Here we convert the filtered images into a one-dimensional array. We need to convert the 2D images into a 1D array if we want to perform classification. So we convert the images into a 1D array and give it to a fully connected layer.

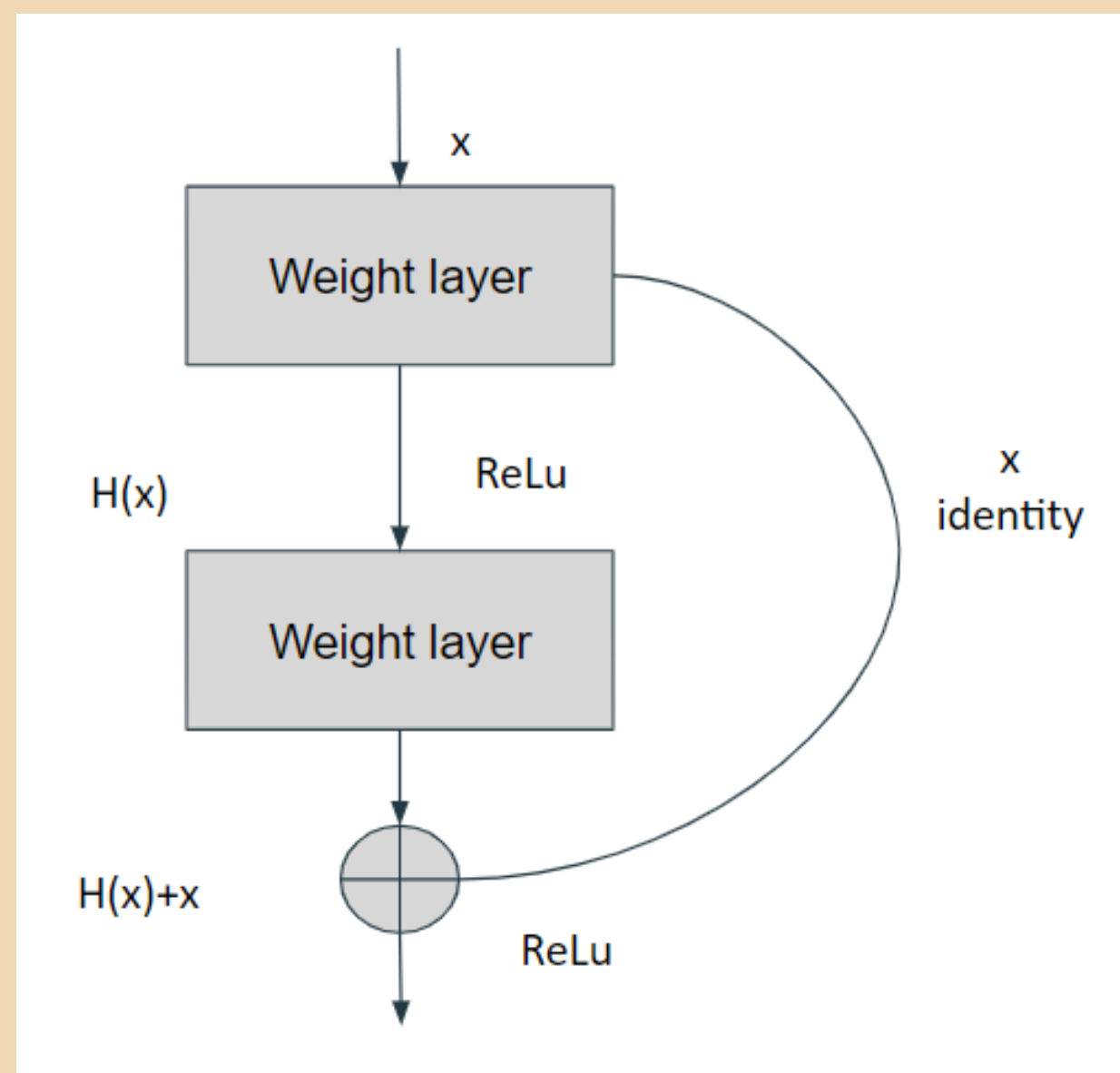
Residual Neural Network

The ResNet-50 model consists of 5 stages, each with a convolution block and identity block. Each convolution block has three convolution layers, and each identity block also has three convolution layers. The ResNet-50 has over 25 million trainable parameters.



ResNet or residual networks and these Resnets are made up from Residual Blocks.

The very first thing we notice to be different is that there is a direct connection which skips some layers(may vary in different models) in between. This connection is called 'skip connection' and is the core of residual blocks. Due to this skip connection, the output of the layer is not the same now. Without using this skip connection, the input 'x' gets multiplied by the weights of the layer followed by adding a bias term.



Model Evaluation

Convolutional Neural Networks model

The adjacent figure is a confusion matrix of CNN model:

This shows that it has 27 “type 1 errors” and 33 “type 2 errors”.

Type 2 errors are the worst as they predict that the patient is not infected with malaria when in real, they are infected.



ResNet-50 using Softmax activation

The adjacent figure is a confusion matrix of ResNet-50 model:

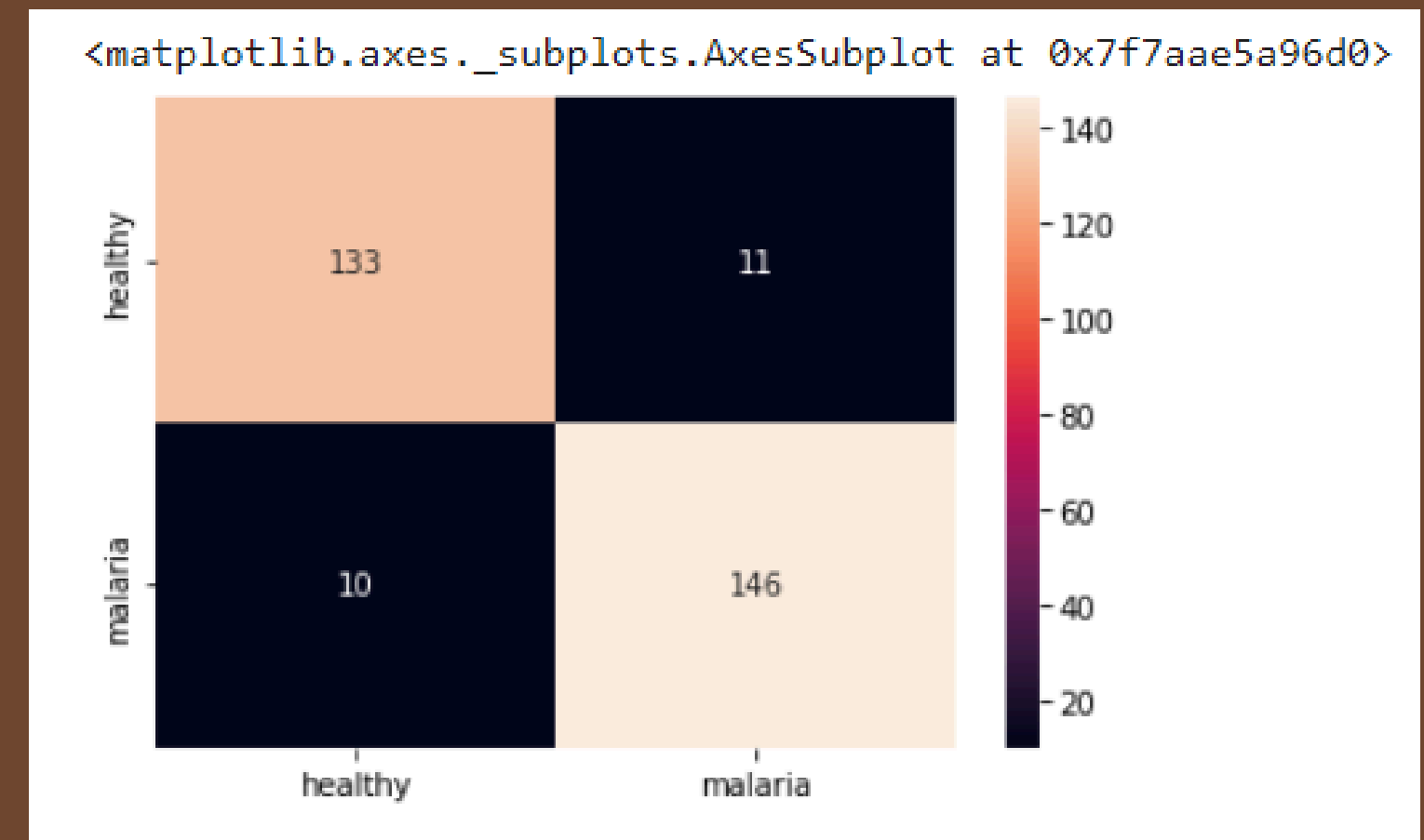
This shows that it has 5 “type 1 errors” and 23 “type 2 errors”.



ResNet-50 using sigmoid activation

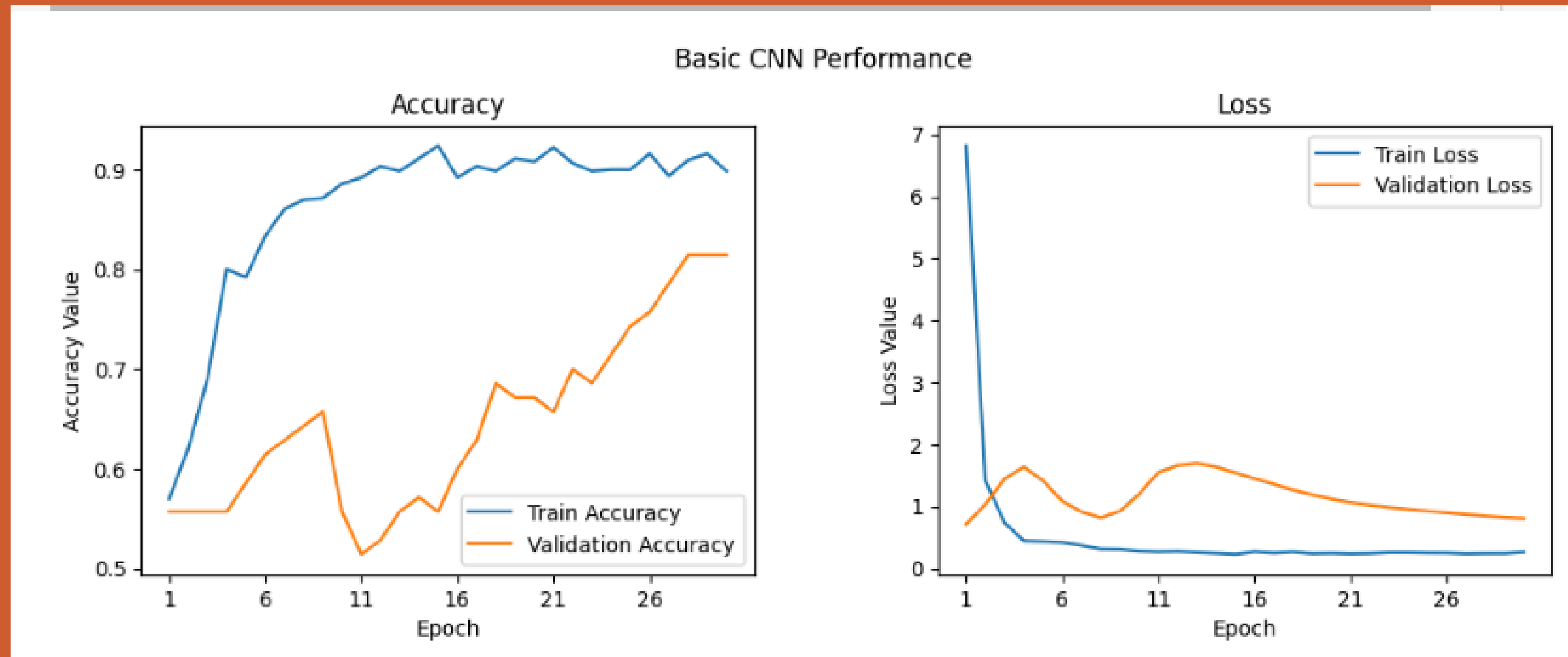
The adjacent figure is a confusion matrix of ResNet-50 model:

This shows that it has 11 “type 1 errors” and 10 “type 2 errors”.



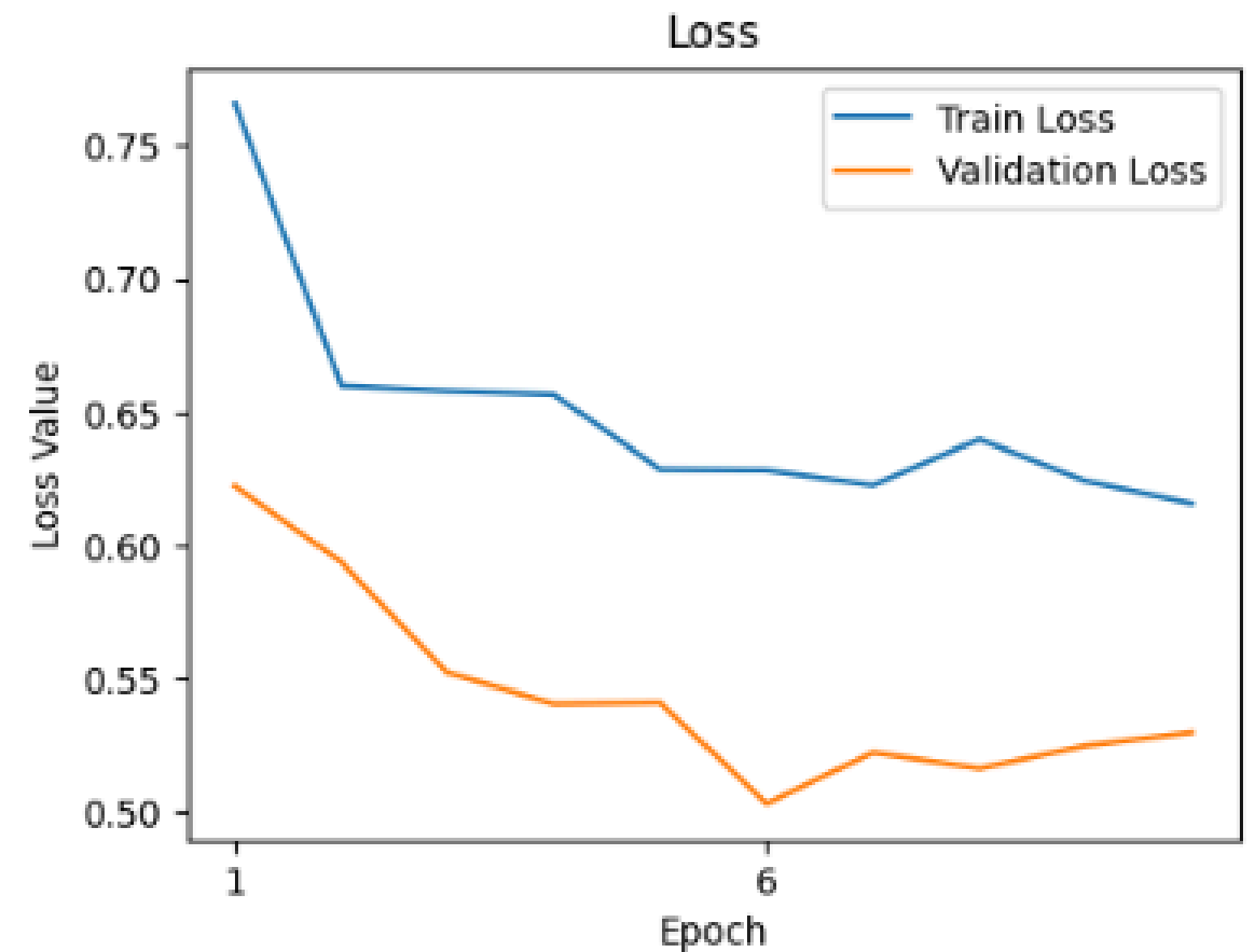
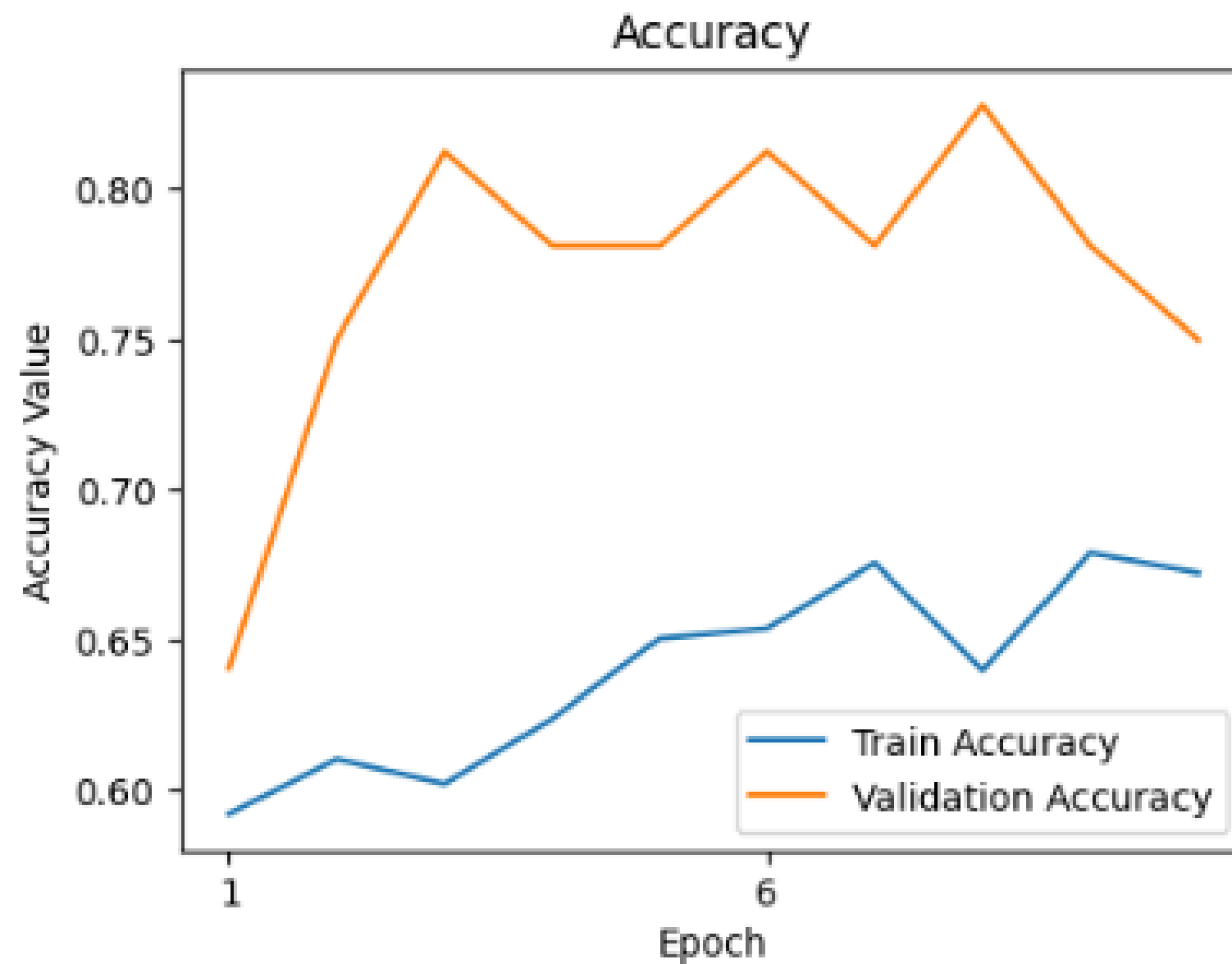
Model Accuracy and Model Loss

Convolutional Neural Networks model



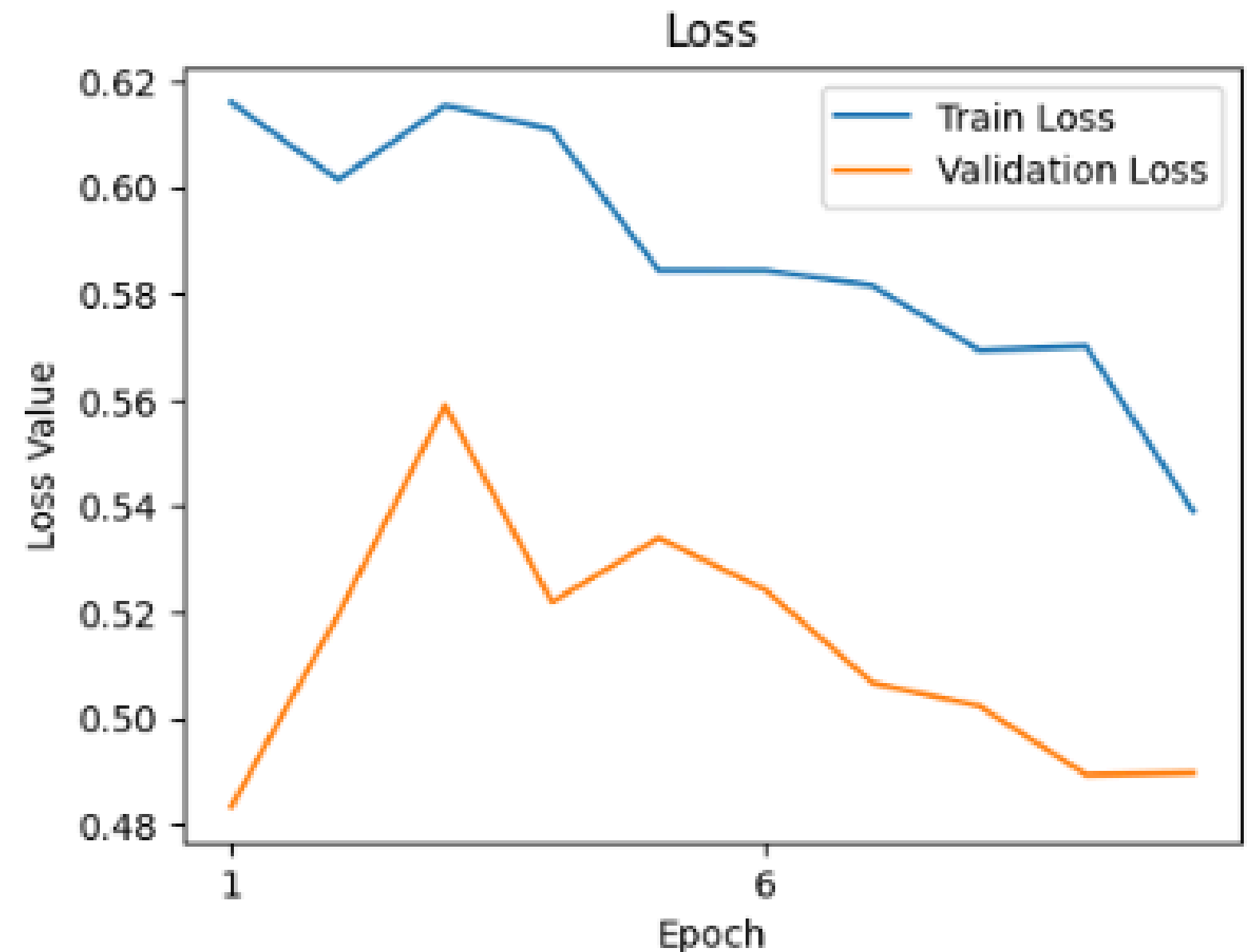
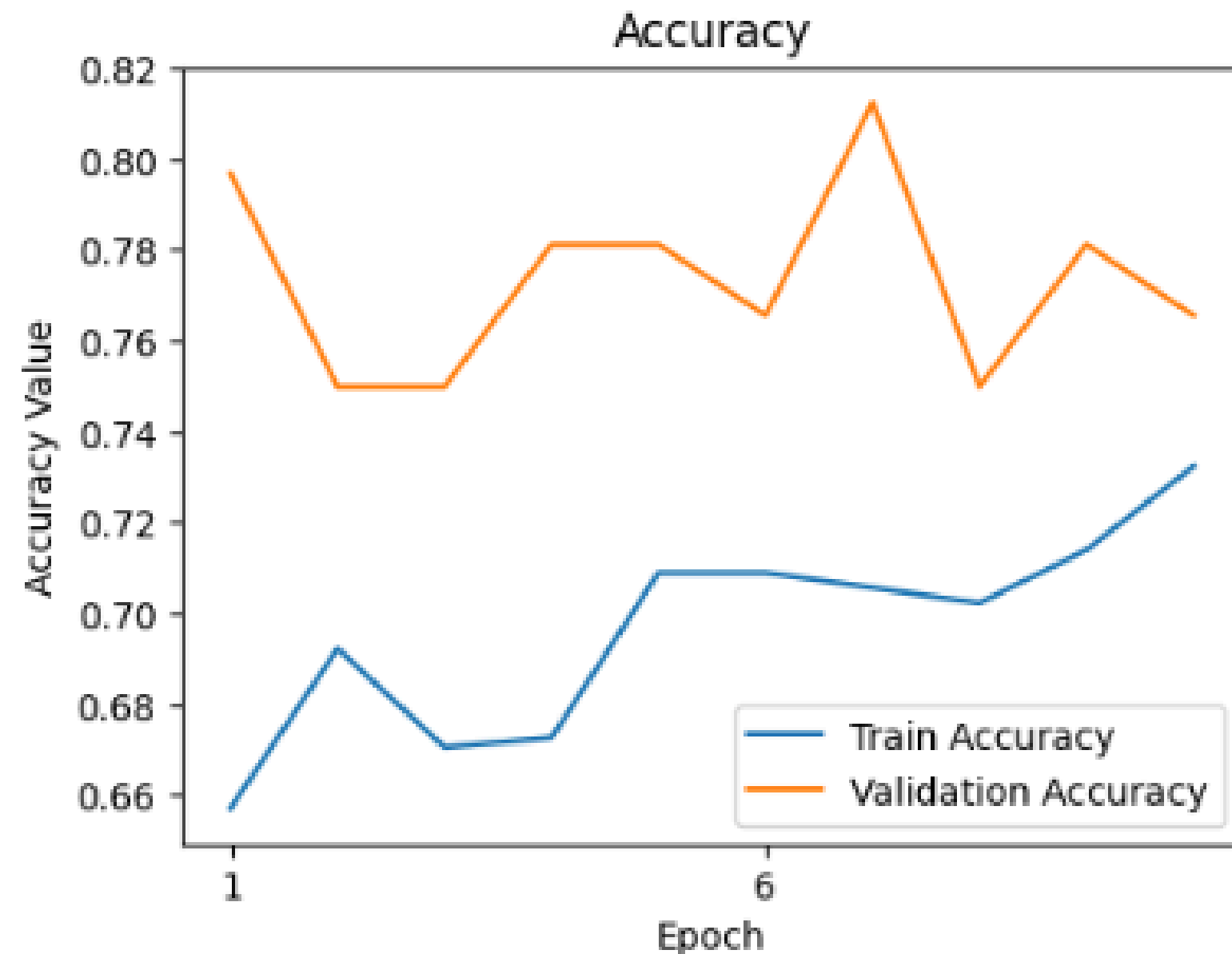
ResNet-50 using Softmax activation

Performance of ResNet-50 with softmax



ResNet-50 using sigmoid activation

Performance of ResNet-50 with sigmoid



TRAINING PERFORMANCE

Models	Training accuracy	Training Loss	Validation Accuracy	Validation Loss
Basic CNN	0.8984	0.2873	0.7857	0.4566
ResNet-50 using Softmax	0.9013	0.2772	0.8906	0.2393
ResNet-50 using Sigmoid	0.9030	0.2544	0.8750	0.2526


MODEL PERFORMANCE

Model	Accuracy	Precision	Recall	F1 measure
Basic CNN	0.8000	0.8008	0.8000	0.8001
ResNet-50 Softmax activation	0.8967	0.8977	0.8967	0.8967
ResNet-50 Sigmoid activation	0.9367	0.9377	0.9367	0.9367

We can see that we got better training accuracy and less training loss for ResNet-50 model with sigmoid activation. While we got better validation accuracy and less validation loss for ResNet-50 using Softmax activation.




Conclusion

- In this research, we experimented with end-to-end deep learning neural networks to improve malaria diagnosis classification performance.
 - Methods like data augmentation showed positive results by increasing the performance of the models.
 - We also compared the ResNet-50 Basic CNN model, ResNet-50 using different softmax and sigmoid activation functions and their performances.
 - ResNet-50 using sigmoid activation outperformed all the other models by achieving an accuracy of 93.67%.
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Reference

1. Rajaraman S, Antani SK, Poostchi M, Silamut K, Hossain MA, Maude RJ, Jaeger S, Thoma GR. 2018. Pre-trained Convolutional neural networks as feature extractors toward improved malaria parasite detection in thin blood smear images.
 2. World Health Organization (2012) malaria fact sheet no. 94. Geneva:WHO.
 3. WHO. World malaria report 2016. World Health Organization; 2016.
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 5. Ersoy I, Bunyak F, Higgins J, Palaniappan K. 2012. Coupled edge profile geodesic active contours for red blood cell flow analysis. In: Proceedings of the 9th IEEE international symposium biomedical imaging. 2-5 May. Barcelona. Spain. Piscataway. IEEE. 748-751.
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Thank you !!!!

