National Institute of Technology
Karnataka, Surathkal

Internship Project Report

SKIN CANCER DETECTION

Professor in Charge
Dr.Shyam Lal
Department of Electronics and Communications Engineering
NITK Surathkal

Authors
Abhinav Pavithran 17EC202

October 10 , 2020

DECLARATION

I hereby declare that the Project Report entitled "Skin Cancer Detection" which is being submitted to Dr.Shyam Lal in fulfillment of the requirements of the internship is a bonafide report of the project work carried out by me. The material contained in this report has not been submitted to any University or Institution prior.

Table of Contents

1 ABSTRACT

This paper is about Skin Cancer Detection using a deep learning model. Skin cancer is a dangerous and widespread disease. The global statistics are quite alarming. India alone had 1.16 million cases in 2018. The mortality of this disease is expected to double in the coming years. The average survival rate is less than 14% if diagnosed late. However if the disease is detected early on then the survival rate is 97%. This paper addresses the issue of early diagnosis, with improved accuracy

2 INTRODUCTION

In order to diagnose skin cancer speedily at the earliest stage there has been extensive research in the domain of computer image analysis algorithms.

2.1 Problem Definition

Most of the solutions required the data to be normally distributed. the problem with this is that most real world data cannot be controlled and these methods would not give accurate diagnosis. Non-parametric solutions do not have such constraints. In this paper, an augmented assistance to the dermatologist is provided using deep learning. The essence of the approach is that a computer is trained to determine the problem by analyzing the skin cancer images.

2.2 Previous Work

Mohammed Ali Kadampur and Sulaiman Al Riyaee from the College of Computer and Information sciences have written a paper on skin cancer detection using a deep learning based model driven architecture in the cloud for classifying dermal images. The advantages of this paper were that a model could be constructed by anyone even without prior programming knowledge. Limitations were that the user was limited by the limiations of the software

2.3 Motivation

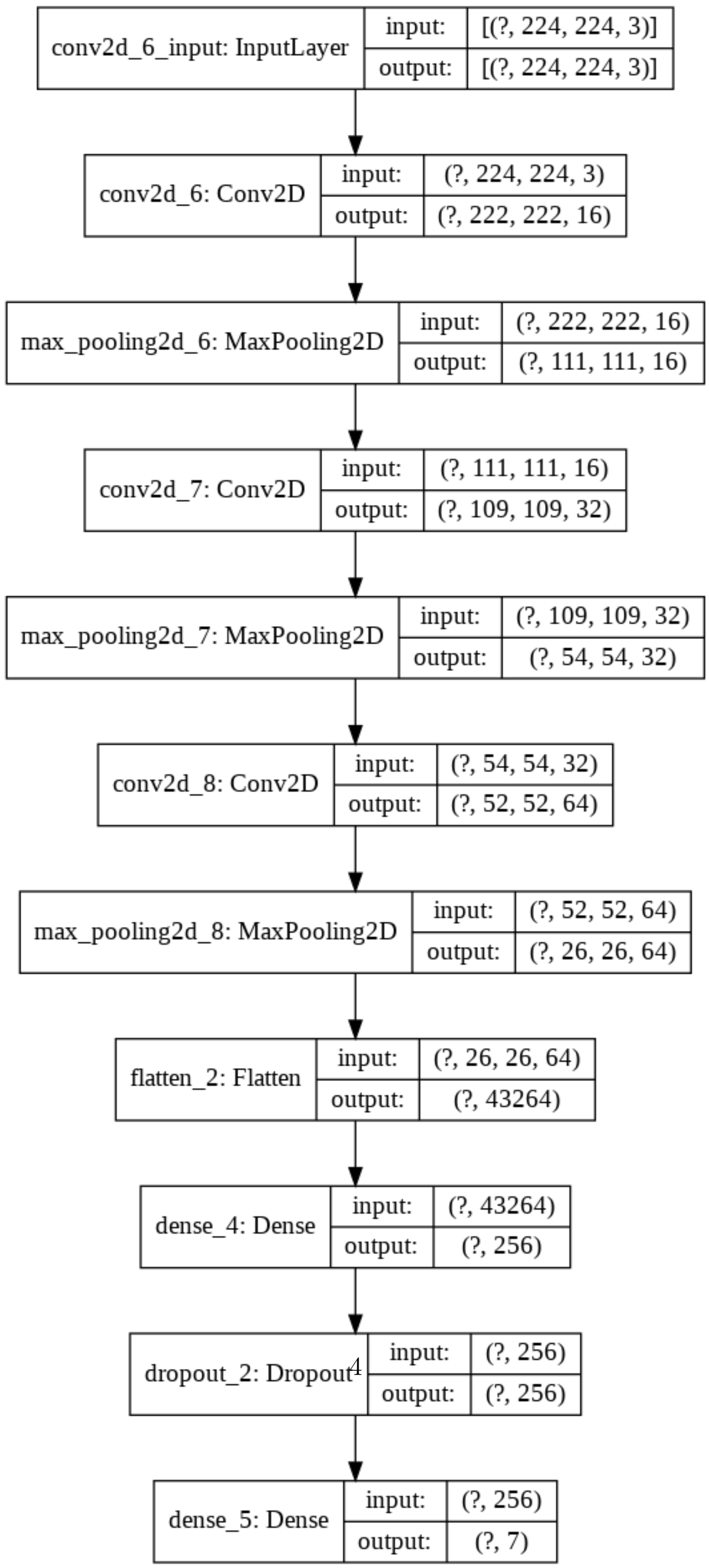
To help people detect cancer in the early stages so that they may get access to the health care they need to treat the disease. Thereby decrease the mortality rate of a disease such as this which can be easily detected using the proper application of already existing algorithms.

2.4 Overview

In this paper the deep learning model will be developed using Python,Tensorflow and Keras API. The problem will be approached using two methods. The first method is a hard coded CNN approach and the second method a transfer learning approach will be used. The dataset that is used to train the models are the HAM10000 dataset

3 CNN IMPLEMENTATION

3.1 Model Diagram



3.2 Model

1. Convolution Layer

First level of convolution of image

2. Convolution Layer

Second level of convolution of image

3. Maxpooling Layer

Compress the image

4. Convolution Layer

Third level of convolution of compressed image

5. Maxpooling Layer

Compress image again

6. Convolution Layer

Fourth Convolution of compressed image

7. Maxpooling Layer

Compress image again

8. Flatten Layer

Flatten the image array into a 1D array to be fed into the network

9. Dense Layer

First hidden layer with 256 neurons

9. Dropout Layer

Drop neurons that do not provide necessary information

10. Dense Layer

Final dense layer which is output

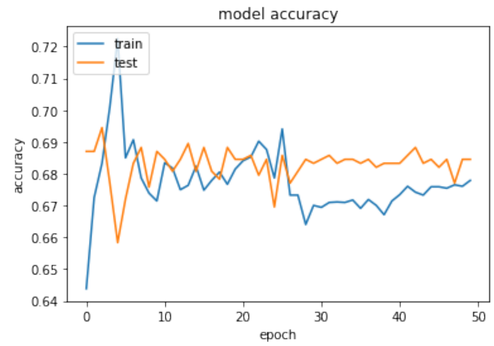
3.3 Training

The model was trained for 50 epochs using Adam optimizer, categorical cross entropy as loss function and accuracy as metric. On training the model it achieved 67.74% on training data, 68.45% on validation data and 67.78% on test data. The table shown below contains scores for various metrics of the model.

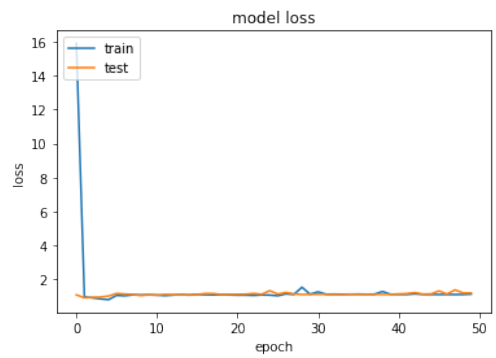
S.No	**Metric**	**Training**	**Validation**	**Testing**
1	Accuracy	67.74%	66.20%	65.46%
2	IoU	46.64%	45.72%	44.83%
3	F1 Score	74.51%	65.32%	64.13%
4	Precision	78.73%	69.03%	69.22%
5	Recall	71.39%	62.53%	59.97%

Table 1: Metric Scores for CNN model

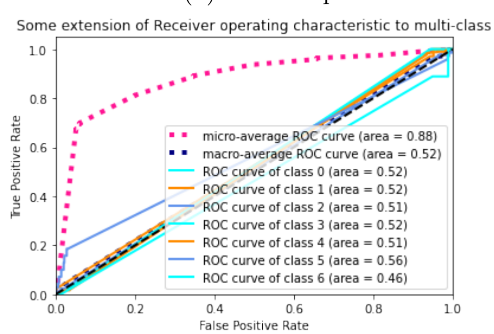
3.4 Graphs



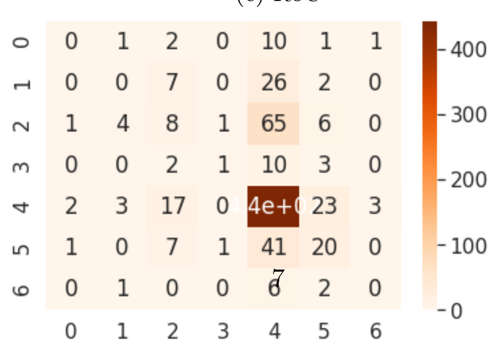
(a) Accuracy V Epoch



(b) Loss V Epoch



(c) RoC

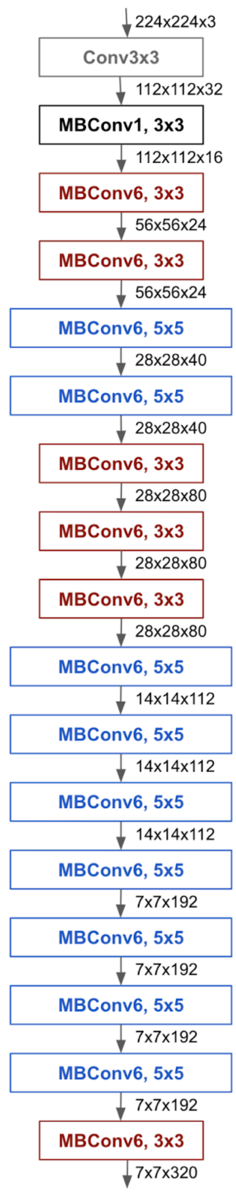


(d) Confusion Matrix

Figure 1: Accuracy,Loss,RoC and Confusion Matrix For CNN model

4 TRANSFER LEARNING IMPLEMENTATION

4.1 Model Diagram



4.2 Model

The EfficientNet-B0 architecture was developed by the neural network itself. They developed this model using a multi-objective neural architecture search that optimizes both accuracy and floating-point operations.

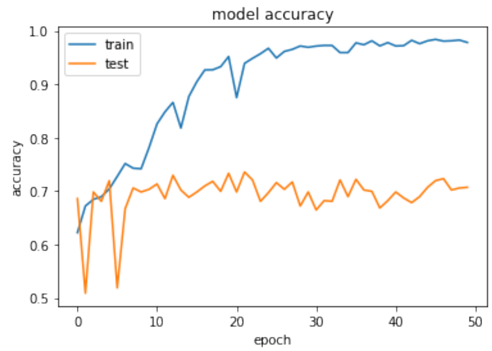
4.3 Training

The model was trained for 50 epochs using Adam optimizer, categorical cross entropy as loss function and accuracy as metric. On training the model it achieved 89.89% on training data, 69.66% on validation data and 72.39% on test data. The table shown below contains scores for various metrics of the model.

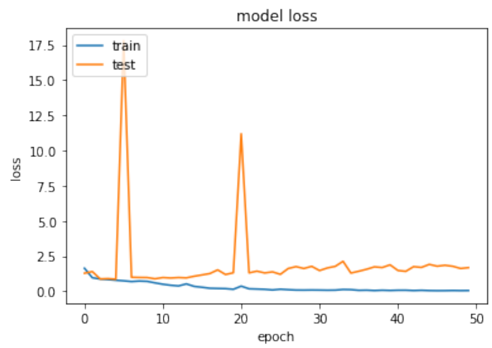
S.No	**Metric**	**Training**	**Validation**	**Testing**
1	Accuracy	89.89%	69.66%	72.39%
2	IoU	47.18%	46.64%	47.94%
3	F1 Score	89.75%	68.97%	68.52%
4	Precision	92.64%	72.35%	73.36%
5	Recall	87.51%	66.66%	67.23%

Table 2: Metric Scores for TL model

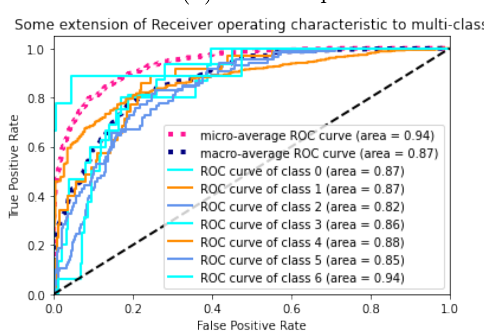
4.4 Graphs



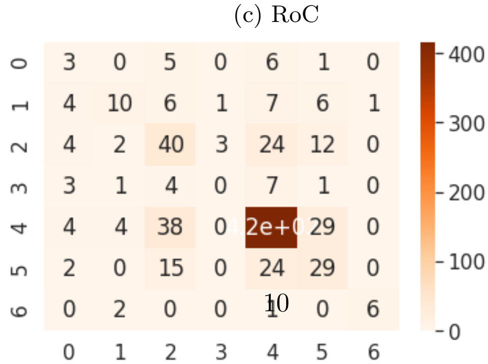
(a) Accuracy V Epoch



(b) Loss V Epoch



(c) RoC



(d) Confusion Matrix

Figure 2: Accuracy,Loss,RoC and Confusion Matrix For TL model

5 CONCLUSIONS

5.1 Analysis

Upon testing both approaches it can be seen that the metrics for Efficient-nets model is better and as seen from the graph the model improves steadily and not erratically like the CNN model. Tables below shows the contrast between scores.

Metric	**Training**		**Validation**		**Testing**	
	CNN	**TL**	**CNN**	**TL**	**CNN**	**TL**
Accuracy	67.74%	89.89%	66.20%	69.66%	65.46%	72.39%
IoU	46.64%	47.18%	45.72%	46.64%	44.83%	47.94%
F1 Score	74.51%	89.75%	65.32%	68.97%	64.13%	68.52%
Precision	78.73%	92.64%	69.03%	72.35%	69.22%	73.36%
Recall	71.39%	87.51%	62.53%	66.66%	59.97%	67.23%

Table 3: CNN v TL

5.2 Conclusion and Future work

The efficient-nets model is preferred as it has better metric scores and accuracy improves steadily. In the future transfer learning approaches using ResNet models can be employed to further improve accuracy and get deeper models.

6 References

[1] Mohammed Ali Kadampur, Sulaiman Al Riyaee (Author), Skin cancer detection: Applying a deep learning based model driven architecture in the cloud for classifying dermal cell images, Department of Information Management, College of Computer Information Sciences, Al-Imam Muhammed Ibn Saud Islamic University, Riyadh, India