Skin Lesion Analysis Towards Melanoma Detection And Classification Using Machine Learning

A project report submitted in partial fulfilment of the Requirements for the award of the degree of

Bachelor Of Technology

In

Information Technology

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Working on this project helped me in doing a lot of Research and I come to know about so many things.

Lastly, I thank almighty, my parents and friends for their constant encouragement without which this project would not be possible.

Yash Mudgal

Self Declaration

I hereby declare that work contained in this project report titled **“Skin Lesion Analysis Towards Melanoma Detection And Classification Using Machine Learning’’** is original. I have followed the standards of project ethics to the best of my abilities. I have acknowledged all source of information which I have used in the project.

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Certificate

This is to certify that **Mr. Yash Mudgal** has worked on the project entitled **"Skin Lesion Analysis Towards Melanoma Detection And Classification Using Machine Learning''** under my supervision and guidance.

The content of the project, being submitted to the **Department of Information Technology, IIIT Sonepat,** for the award of the degree of **Bachelor of technology** in **Information Technology,** are original and have been carried out by the candidate himself.

This project is not submitted in the full or part for the award of any other degree or diploma to this or any university.

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Abstract

Name of the student **Yash Mudgal**, Roll No. **11912080** Degree for which submitted

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Project Title: **Skin Lesion Analysis Towards Melanoma Detection And Classification Using Machine Learning**

Name of the thesis supervisor: **Dr. Mukesh Mann**

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Skin cancer is a typical common cancer. Melanoma is also known as malignant melanoma which is the most lethal form of skin cancer and responsible for 75% of skin cancer deaths, despite being the least common skin cancer. The best way to combat from this - is trying to identify it as early as possible and treat it with minor surgery.

During this paper, I systematically study about melanoma and how can we detect melanoma in early stages using Machine learning and deep learning techniques and try to optimize previous works based in these areas. Previous researches are done this detection near accuracy of 80% and I will try to optimize this accuracy and try to increase to near 90%. I will also compare different machine learning and deep learning techniques during this research.

Keywords—skin cancer, melanoma, convolutional neural network, classification, machine learning algorithms, transfer learning algorithms.

List Of Abbreviations

ML	Machine Learning
DL	Deep Learning
CNN	Convolutional Neural Network

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Chapter – 1

Introduction

Skin cancer is the most prevalent cancer worldwide. It turns out that survival is very high if you can diagnose it at an early stage and choose the ideal treatment. Therefore, it is essential to find out as soon as possible whether a patient's symptoms correspond to cancer. Traditionally, doctors detected skin cancer with the naked eye. However, this often leads to results that are not so accurate that humans make mistakes. Even experts have a hard time saying that, especially when the cancer is in its very early stages. This is where machine learning can help automate the entire process or pipeline. Deep neural networks can process thousands of images in both categories - Benign and malignant.

By learning the non-linear interactions, the model can tell whether a new image corresponds to a malignant or benign class. This automation could not only have a higher efficiency in avoiding both false positives and false negatives but also reduce time and manual spent on more productive work. Our model can be deployed on locations which lack professional docs. This work could dramatically change the healthcare and well being of humans in developing countries of Africa and Asia.

1.1 Objectives

1. Analysis of previous implemented research papers related to project.
2. Gathering Data Set and Feature Engineering
3. Training different Machine Learning and deep learning Models on Dataset.
4. Comparison of different methods to implement Melanoma Detection.

1.2 Novelty

1. To my best knowledge, I will be the first to apply InceptionV3, ResNet-50 and EfficientNet for melanoma detection.

2. Achieved greater than 90% accuracy on testing by DenseNet-121 model.

1.3 Problem Statement

Implementing a novel model for detection and classification of melanoma cancer through skin lesion analysis. Implementing a model which provides high accuracy and finding the dataset which is suitable and large enough to increase model accuracy.

1.4 Methodology

I will use the concept of transfer learning for the classification. With transfer learning, instead of starting the learning process from scratch, our model starts from patterns that have been learned when solving a different problem. In this way the model leverages previous learnings and avoids starting from scratch. Transfer learning is usually expressed through the use of pre-trained models in image classification. A model which was trained on a large benchmark dataset to solve problem similar to our problem that we want to solve is known as pre-trained model.

1.5 Dataset

I am using Kaggle dataset – Skin Cancer: Malignant or benign dataset which contains total of 3297 images. This dataset includes balanced data of images of benign skin moles and malignant skin moles. I am using 660 images for testing the model and for training I am using 2637 images for training the model. Data is split into 2 folders – train and test. Both folders contain 2 separate folders for benign and malignant(cancerous) images. This dataset is preprocessed from ISIC. The data consists of two folders with each 1800 pictures (224x244) of the two types of moles.

The pictures have all been resized to low resolution (224x224x3) RGB.

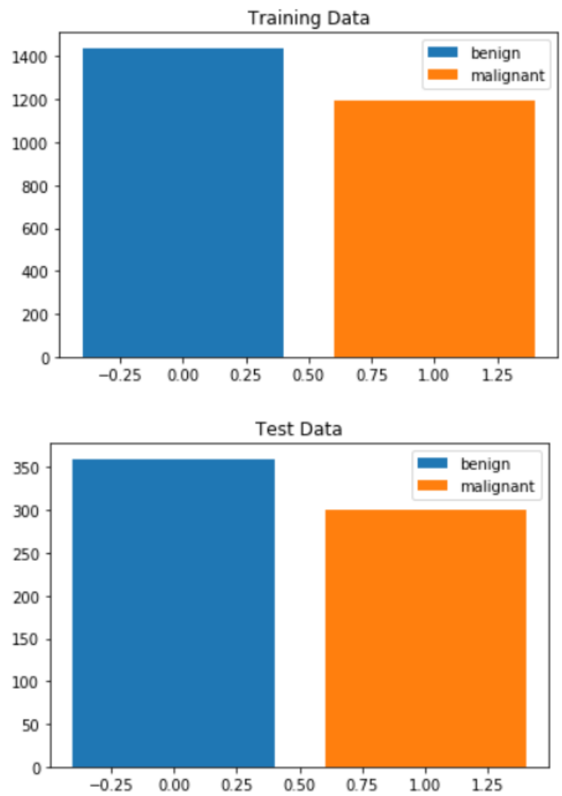

Fig 1.1 Dataset Visualization

Chapter - 2

Literature Review

Lot of researches has been published in the area of skin cancer classification using deep learning and computer vision techniques. Various approaches have been used in these works, including classification only, segmentation and detection, and image processing with different kinds of filters.

(Mahbod A, Schaefer G, Wang C, et al.,2019) used CNN but they have included popular AlxNet, VGG16, ResNet18. I will use the novel models for ResNet50, Inception V3, MobileNet, EfficientNet and DenseNet. EfficientNet uses a baseline network created by neural architecture search to scale all dimensions of depth, width, image resolution using a simple yet highly effective method called compound coefficient. This greatly enhances the ability to capture richer and much more complex features for melanoma recognition.

(Jinen Daghrir, Lotfi Tlig, Moez Bouchouicha, Mounir Sayadi, et al., 2020) used hybrid approach to achieve this classification. They used deep learning and classical machine learning algorithms and at last fuse them. But they have not very efficient ml model. Even after fusion of 3 models – KNN, SVM and CNN. They have got the accuracy of 88.4%.

(Esteva et al., 2017) separately used AdaBoost to classify the skin lesions. (Xu et al., 2014) used various sets of features including type of texture, lesions, colour etc and neural networks for the making of a robust diagnosis system. The examples so far have only shown algorithms using traditional machine learning techniques, but recently deep learning has proven to be more accurate. The reason for that it automates the feature extraction process completely. It is upto the algorithms to find the better features and train the model accordingly. (Lopez et al., 2017) used a pre-trained GoogleNet Inception v3 CNN model to classify 129,450 clinical skin cancer images, including 3,374 dermatoscopic images, for skin cancer classification. This was the breakthrough that has been achieved. (Dorj et al., 2018) developed a convolutional neural network with over 50 layers on ISBI 2016 challenge dataset for the classification of malignant melanoma. In 2018, (Brinker et al., 2018) utilized a deep convolutional neural network to classify 2 a binary class problem of dermoscopy images. (Rezvantalab et al., 2018) developed an algorithm that uses a support vector machine combined with a deep convolutional neural network approach to classify four diagnostic categories of clinical skin cancer images. (Codella et al., 2017) used a deep convolutional neural network to classify the clinical images of 12 skin diseases.

In this paper I will tackling skin cancer classification which is of binary type i.e., there are 2 classes present in the dataset benign and malignant.

2.1 Comparative Study of Research Papers

Paper Title	Researchers Name	Year Of Publish	Classification Algorithm	Performance Measure
Multi-resolution-tract cnn with hybrid pretrained and skin-lesion trained layers.	Kawahara and G. Hamarneh	2016	Multi-tract CNN	79.5%
Skin lesion classification from dermoscopic images using deep learning techniques	R. Lopez, X. Giro-i Nieto, J. Burdick, and O. Marques	2017	CNN	81.33%
Melanoma detection by analysis of clinical images	Nasr-Esfahani, S. Samavi, N. Karimi, S. M. R. Soroushmehr,	2016 (IEEE)	ConvNet	81%

using convolutional neural network.				
Melanoma Skin Cancer Detection using Deep learning techniques: A hybrid approach	Jinen Daghrir, Lotfi Tlig, Moez Bouchouicha, Mounir Sayadi	2020	Hybrid(KNN,SVM,CNN)	88.4%
Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists	A. Haenssle, C. Fink, R. Schneiderbauer, F. Toberer, T. Buhl, A. Blum, A. Kalloo, A. B. H. Hassen, L. Thomas, Enk, et al.	2018		86%
Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm.	S. Han, M. S. Kim, W. Lim, G. H. Park, I. Park, and S. E. Chang	2018	ResNet-152	83%

Multi-Class Skin Diseases Classification Using Deep Convolutional Neural Network and Support Vector Machine	Nazia Hameed et.al.	2019	ECOC SVM	86.21%
An On-device Inference App for Skin Cancer Detection	Irena Spasić, Bradley Meyer, Xiangfeng Dai, Bradley Meyer	2019	CNN(MaxPool2D)	75.2%

Table 1. Comparative Study of Previous Research Papers

Chapter - 3

Implementation

2.1 Technologies Used

2.1.1 Python

It is a class-based, object-oriented programming language (OOP) that is designed to have as few implementation dependencies as possible. Due to OOP, it is in demand continuously. It's popularity is increasing day by day. Python was designed for readability, and has some similarities to the English language with influence from mathematics. Python uses new lines to complete a command, as opposed to other programming languages which often use semicolons or parentheses. Python relies on indentation, using whitespace, to define scope; such as the scope of loops, functions and classes. Other programming languages often use curly-brackets for this purpose.

I use python as our main programming language in this project. We do full code in python in anaconda navigator. We develop melanoma disease classification using python programming language.

2.1.2 Keras

Keras is an open-source high-level Neural Network library, which is written in Python is capable enough to run on Theano, TensorFlow, or CNTK. It was developed by one of the Google engineers, Francois Chollet. It is made user-friendly, extensible, and modular for facilitating faster experimentation with deep neural networks. It not only supports Convolutional Networks and Recurrent Networks individually but also their combination.

I used keras for preprocessing and other machine learning tasks.

2.1.3 Tensorflow

TensorFlow is a free, open-source machine learning and artificial intelligence software library. It can be used for many tasks, with a particular focus on deep neural network training and inference. A platform like TensorFlow helps you implement best practices for model tracking, data automation, performance monitoring, and model retraining. Using production-level tools to automate and track model training over the life of a product, service, or business process is critical to success.

Tensorflow pre-trained models were used.

2.1.4 Kaggle

Kaggle is an online community platform for data scientists and machine learning enthusiasts. Kaggle allows users to collaborate with others, discover and publish datasets, use GPU-integrated notebooks, and compete with other data scientists to solve data science challenges. I can do it.

I used a Kaggle preprocessed data set for this problem.

2.1.5 Image Classification

There are various image classification approaches which can be categorized under two heads - First one uses traditional machine learning algorithms like Decision Tree, Support Vector Machines, Fuzzy Measures etc and the other is based on deep learning like convolutional neural networks, autoencoders etc. Other than Artificial Neural Networks (ANNs), methods Decision Trees, Support Vector Machines, and Fuzzy Measures have been used.

Decision Trees is a machine learning method that works by calculating a class membership, which is done by partitioning a dataset into subsets repeatedly. This hierarchical classification permits approval and elimination of class labels at each stage. This method as a whole, has 3 major steps: Partition the nodes using the dataset, find all the terminal nodes, and allocate class labels to each terminal node. Support Vector Machines are used for a variety of machine learning applications. They work by building a hyper-plane or a set of hyper-planes, in a high-dimensional space. Good separation and classification is achieved when a hyper-plane has the largest distance to the nearest point of any class. Fuzzy measures another classification technique used. Multiple varied stochastic associations are determined in order to describe the image characteristics. The difference stochastic associations are then combined to form a set of properties.

2.1.6 Deep Learning

Deep learning is a set of machine learning methods that was inspired by information processing and distributed communication in networks of biological neurons. Deep learning predominantly involves development, training and utilization of artificial neural networks (ANNs). ANNs are networks of artificial neurons that are based on biological neurons. Every ANN has at least 3 layers: an input layer that takes the input, a hidden layer that trains on the dataset fed to the input layer, and an output layer that gives an output depending on the application. Deep learning has been gaining wide acclaim because of the results it achieves that have never been seen in any other machine learning method. Convolutional Neural Networks (a type of ANNs), are extensively used for image-based applications, and have achieved better results than humans in object detection and classification.

2.1.7 Convolutional Neural Network

CNNs are a kind of neural network which have proven to be very powerful in areas such as image recognition and classification. CNNs can identify faces, pedestrians, traffic signs and other objects better than humans and therefore are used in real time applications like robots and self-driving cars. CNNs are a supervised learning method and are trained using labeled data given with the respective classes. CNNs learn the relationship between the input objects and the class labels and comprise two components: the hidden layers in which the features are extracted and, at the end of the processing, the fully connected layers that are used for the actual classification task. The hidden layers of CNN have a specific architecture consisting of convolutional layers, pooling layers and activation functions for switching the neurons either on or off. In a typical neural network, each layer is formed by a set of neurons and one neuron of a layer is connected to each neuron of the preceding layer while the architecture of hidden layers in CNN is slightly different. The neurons in a layer are not connected to all neurons of the preceding layer; rather, they are connected to only a small number of neurons from the previous layer. This restriction to local connections and additional pooling layers summarizing local neuron outputs into one value results in translation-invariant features. This results in a simpler training procedure due to less parameters and a lower model complexity.

2.2 Development Methodology:

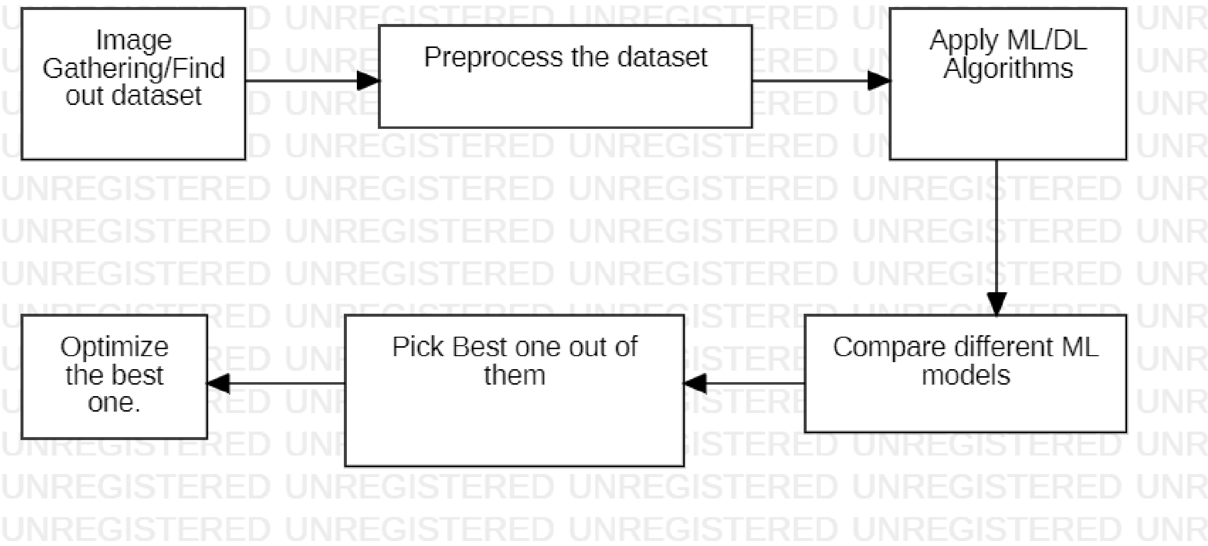

Fig 3.1 Flowchart Diagram

Firstly, I gather dataset which I have taken from Kaggle then I preprocess it then I apply different ML and DL algorithms then I will compare them and pick best one out of them and try to optimize the best one.

2.3 Proposed Solution

My proposed is that I should try all the best classifiers models and pick best one of them or compare between them and suggest best model for this problem. So, I am able to find best model – DenseNet-121 with 90.90%.

I have implemented these model which are as follows:-

1. Support Vector Classifier (SVC)
2. InceptionV3
3. MobileNet.
4. Logistic Regression
5. DenseNet-121
6. ResNet-50
7. VGG16
8. VGG19
9. ResNet-152
10. DenseNet-201
11. Efficient-B6

The dataset is taken from the International Skin Image Collaboration (ISIC) Archive. It includes 1800 pictures of benign moles and 1497 pictures of malignant classified moles. The pictures have all been resized to low resolution - 224x224x3 RGB. The task of this kernel is to create a model, which can classify a mole visually into benign and malignant.

As the dataset is pretty balanced, the model will be tested on the accuracy score, thus (TP + TN)/(ALL).

This has 2 different classes of skin cancer which are mentioned below:-

1. Benign

2. Malignant

In this, I will try to detect 2 different classes of moles using Transfer Learning and classical ML algorithms with keras, tensorflow and pytorch in backend and then analyse the result to see how the model can be useful in practical scenario.

I have used the concept of transfer learning and simple machine learning for the classification. With transfer learning, instead of starting the learning process from scratch, the model starts from patterns that have been learned when solving a different problem. This way the model uses previous knowledge and avoids starting from scratch. In image classification, transfer learning is usually represented using pretrained models. A pretrained model is a model trained on a large benchmark dataset to solve a problem similar to the one you want to solve. Three pre-trained models (InceptionV3) were used as pre-trained weights. So far I have used SVC, InceptionV3

2.4 Support Vector Classifier

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning.

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

2.5 InceptionV3

Google's Inception v3 architecture works by fine-tuning all layers, replacing the upper layer with an average pooling layer, two fully connected layers and finally a softmax layer that allows classification of two diagnostic categories. , was retrained on the dataset. The input image has been resized to (224, 224) to be compatible with this model. The learning rate was set to 0.0001 and Adam was used as the optimizer.

2.6 MobileNet

A fundamental part of MobileNet is a depthwise separable filter called depthwise separable convolution. These convolution layers are a variant of factored convolution, which decomposes standard convolutions into depthwise convolutions called point-wise convolutions. In MobileNet, depth convolution applies one filter to each input channel. Convolution by points applies a convolution operation to combine the outputs of convolution by depth.

2.7 Logistic Regression

Logistic regression is a statistical model used for binary classification tasks. It estimates the probability of an event occurring based on input features and assigns a class label. It's a popular and interpretable algorithm widely used in various fields for its simplicity and effectiveness.

2.8 ResNet-50/152

ResNet-50 and ResNet-152 are deep convolutional neural network architectures that have significantly advanced image recognition tasks. They are part of the ResNet family, known for their skip connections, which alleviate the vanishing gradient problem. ResNet-50 consists of 50 layers, while ResNet-152 has 152 layers, making it deeper and more powerful. These models employ residual learning, where each layer learns the residual mapping instead of directly estimating the desired output. This enables them to handle more complex features and achieve higher accuracy on large-scale image classification benchmarks, making them popular choices for deep learning-based computer vision applications.

2.9 VGG16/19

The VGG (Visual Geometry Group) family includes VGG16 and VGG19, which are popular convolutional neural network architectures for image classification tasks. They are known for their simplicity and uniformity, comprising stacked convolutional layers with small filter sizes (3x3) and max pooling layers. VGG16 has 16 layers, while VGG19 has 19 layers. These models demonstrate impressive performance by capturing intricate patterns through deep feature extraction. However, their increased depth makes them computationally expensive. Despite being surpassed by newer architectures like ResNet, the VGG family remains influential in research and serves as a benchmark for evaluating the performance and generalization of newer deep learning models.

2.10 DenseNet-121/201

DenseNet201 and DenseNet121 are deep convolutional neural network architectures that belong to the DenseNet family. These models introduce the concept of dense connections, where each layer receives direct input from all preceding layers. DenseNet201 has 201 layers, while DenseNet121 has 121 layers. This dense connectivity fosters feature reuse, alleviating the vanishing gradient problem and promoting information flow throughout the network. By combining feature maps from different depths, DenseNets can effectively extract complex features, enhance feature propagation, and achieve impressive performance on image classification tasks. They have demonstrated state-of-the-art results and are widely used in various computer vision applications.

2.11 Efficient-B6

Efficient-B6 is a variant of the EfficientNet family, a series of neural network architectures that aim to achieve excellent performance while minimizing computational resources. Efficient-B6 is specifically designed to balance accuracy and efficiency, making it suitable for a wide range of computer vision tasks. It has a moderate number of layers and parameters, striking a balance between accuracy and computational complexity. By employing advanced techniques like efficient channel and spatial attention modules, Efficient-B6 effectively captures intricate features in images. It has shown competitive performance on various benchmarks, making it a popular choice for applications where a good trade-off between accuracy and efficiency is required.

2.12 Transfer Learning

Transfer learning is a common technique in computer vision that can produce accurate models more quickly. Transfer learning does not start the learning process from scratch, but from patterns learned while solving another problem. The advantages of using transfer learning are: Very easy to integrate. Achieves the same or better performance quickly (depending on dataset model performance). I don't need so much labeled data. Diverse use cases such as transfer learning, prediction, and feature extraction. The proposed method can be summarized in the following three points.

1. Split the data set into two parts. The training and test sets have 80% and 20% images respectively.

2. I tried pre-trained models such as Inception v3, MobileNet by fine-tuning the last layer of the network. We also used traditional machine learning approaches such as SVC and logistic regression.

3. I trained a model with stack size 32 and 20 epochs by varying hyperparameters such as learning rate, stack size, optimizer, and pretrained weights.

Chapter - 4

Experimental Results

In this section, I shown my findings. I plotted the accuracy vs epochs, loss vs epochs and table for comparison of different used models. And I am able to achieve greater accuracy then my base papers. I have got DenseNet-121 as best performing model. This is transfer based learning model. I am able to achieve 90.90% accuracy during testing.

Model Name	**Accuracy Achieved During Testing (%)**
Support Vector Classifier	83.48
InceptionV3	81.36
MobileNet	53.60
Logistic Regression	78
ResNet-50	81.32
VGG16	88.94
DenseNet-121	90.90
ResNet-152	88.18
Efficient-B6	86.36
DenseNet201	89.24
VGG19	88.40

Table 2. Experimental Results

4.1 InceptionV3

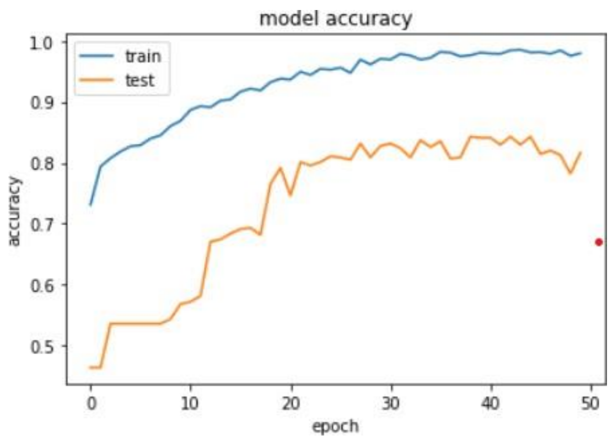

Fig 4.1 Accuracy vs epoch for InceptionV3

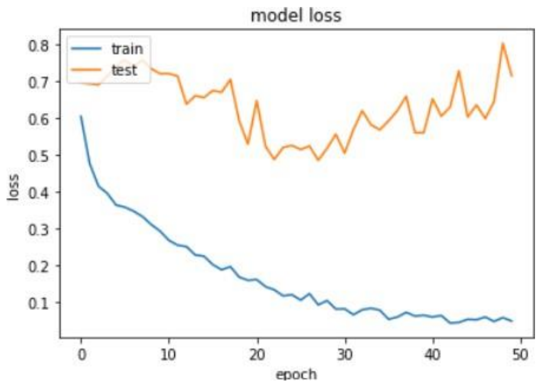

Fig 4.2 loss vs epoch for InceptionV3

4.2MobileNet V2:

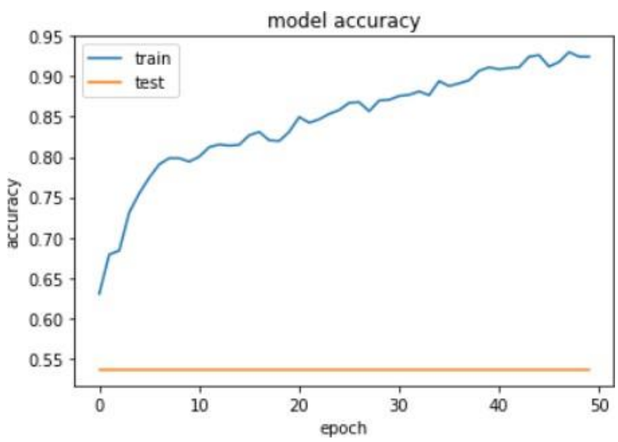

Fig 4.3 Accuracy vs epoch for MobileNetV2

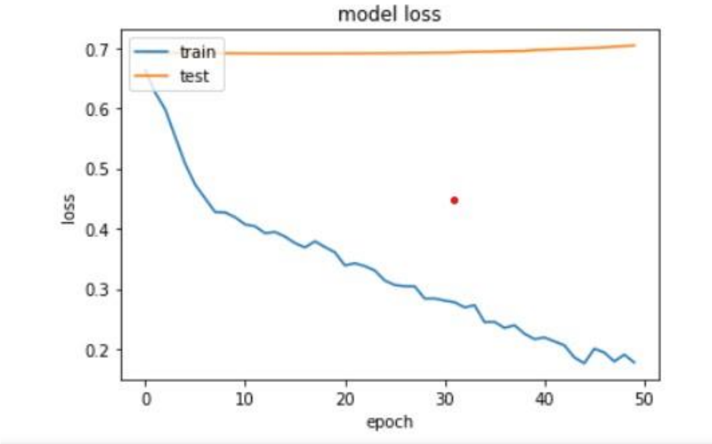

Fig 4.4 loss vs epoch for MobileNetV2

4.3ResNet-50

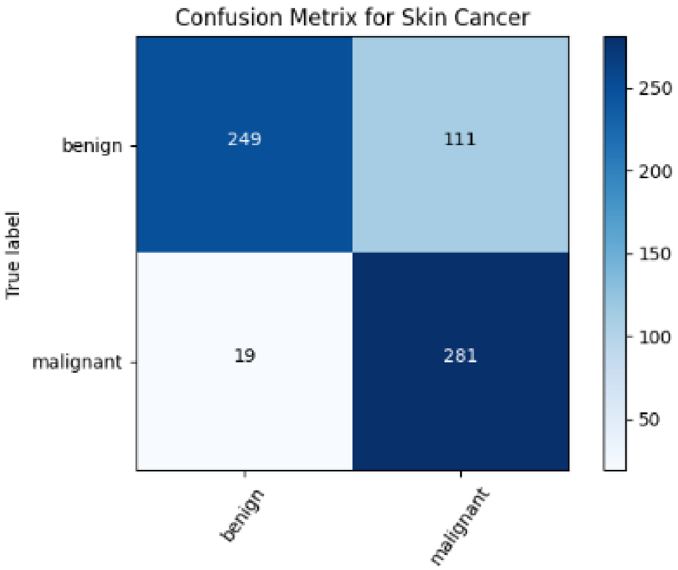

Fig 4.5 Confusion Metric for ResNet-50 model

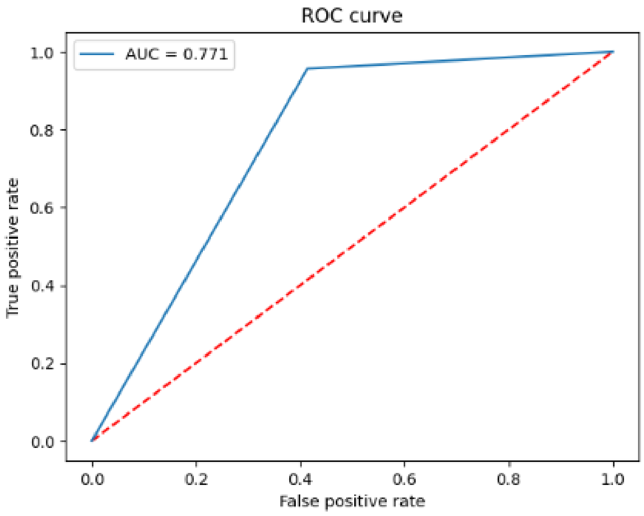

Fig 4.6 ROC Curve for ResNet-50 model

4.4DenseNet-121(Best Model)

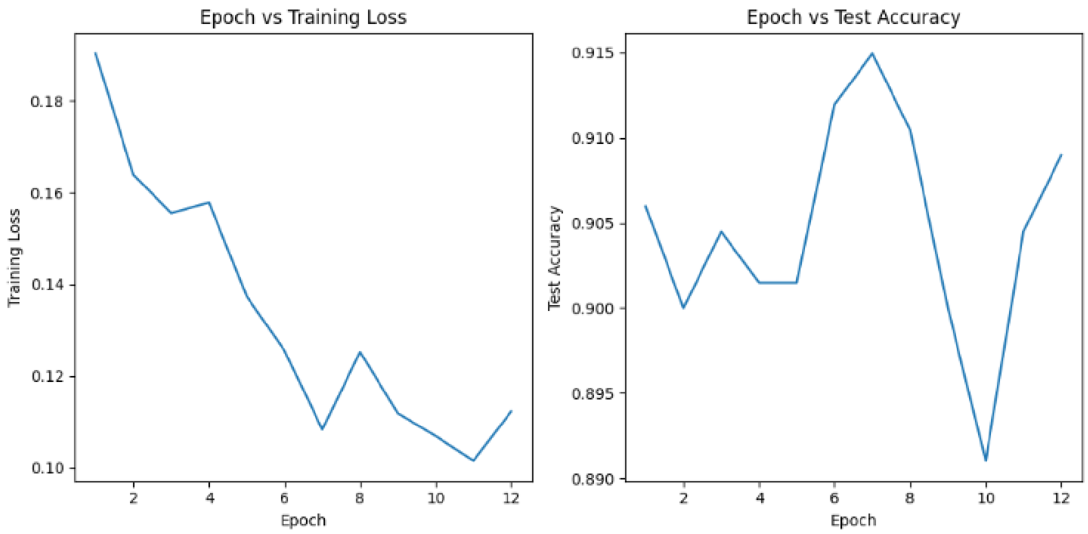

Fig 4.7 Epoch vs Training Loss & Test Accuracy for DenseNet-121

4.6 Testing

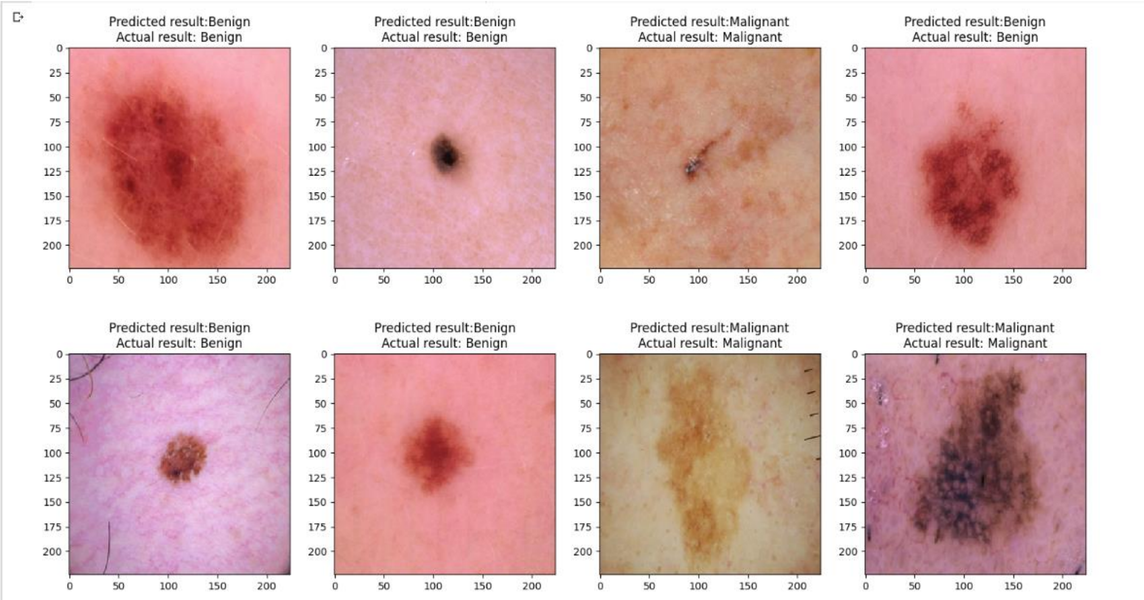

Fig 4.8 Testing of Image classification

Chapter - 5

Conclusions

In summary, this study investigated the ability of deep convolutional neural networks in classifying benign and malignant skin cancers. My results show that state-of-the-art Deep learning architecture trained on dermoscopy images (a total of 3297, consisting of 2637 training sessions and 660 tests) outperforms base papers models. I have shown that by using very deep convolutional neural networks with transfer learning and fine-tuning them with dermoscopy images, we can achieve better diagnostic accuracy compared to experienced physicians and clinicians. These models can be easily implemented in dermatoscopy systems and smartphones to support dermatologists. Further improvements require a more diverse dataset (different categories, different ages) with more dermoscopy images and balanced samples per class.

I am able to surpass base papers accuracy. I am getting 90.90% accuracy on testing. I have compared different classical ML algorithms with newly transfer based learning algorithms. The best performed model in this comparison is DenseNet-121.

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