SKIN CANCER DETECTION USING DEEP LEARNING

A Project Report

Submitted by

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Under the guidance of

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DECLARATION

I undersigned hereby declare that the project report "Skin cancer detection using deep learning", submitted for partial fulfillment of the requirements for the award of degree of Master of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under supervision of Dr. Anzar S M. This submission represents my ideas in my own words and suggestion given by my guide where also taken in account, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other university.

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C E R T I F I C A T E

This is to certify that,this report titled ***SKIN CANCER DETECTION USING DEEP LEARNING*** is a bonafide record of the **Project** presented by **ABHIRAM A P (TKM20MEAI02)**, under our guidance and supervision, in partial fulfillment of the requirements for the award of the degree, **M.Tech Mechanical Engineering (Artificial Intelligence)** in **APJ Abdul Kalam Technological University** .

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ABHIRAM A P

Abstract

In this work, an intelligent system for skin cancer detection is proposed. It is known that skin cancer is one of the deadliest diseases in the world, so it must be detected correctly in the early stages itself for saving human life, for which a fully automatic system using deep learning techniques can be used.In this work, HAM10000 dataset is used for classification which contains classes of skin cancer images. Deep Convolutional Neural Network, AlexNet, VGG-16 and Inception V3 are tested for classification of skin lesions. A dedicated model is proposed for skin cancer classification, Skin Cancer Detection Model, and the model is tested. The same dataset is trained with all the above models and also evaluated the known quantitative measures such as accuracy, precision and recall. Finally, the confusion matrix of the models is plotted. The skin cancer detection model achieved better accuracy than other models. Skin detection model has an accuracy, precision, recall and F1 score of 97.354%, 98%, 97%, 97% respectively.

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Chapter 1

Introduction

The skin is the largest organ of our body and it conveys sensations such as touch, heat, cold, etc. to human beings. So it is clear how important the skin is for the human body. The skin manifests itself in the form of various skin lesions. The skin lesions can appear in the human body due to various reasons, such as birth or sometimes due to the wrong treatment of the skin. Skin lesions are dangerous when they turn out to be cancerous [12]. There are different types of skin cancer. In this paper, skin cancers such as melanocytic nevi, melanoma, benign keratoses, basal cell carcinoma, actinic keratoses, vascular lesions, and dermatofibromas are focused. Melanoma is the most deadly form of skin cancer because it can spread very quickly and even lead to death. Therefore, early detection of skin cancer is very important. The most difficult thing is that the skin lesion is very difficult to see with the naked eye. Therefore, nowadays there are various dermatoscopic imaging techniques that can take pictures of skin lesions. Based on these images, we can easily classify the skin lesion.

The HAM10000 dataset was used to classify skin lesions. This is a universally accepted standard data set consisting of 10015 dermoscopic images of 7 different classes such as melanocytic nevi, melanomas, benign keratoses, basal cell carcinomas, actinic keratoses, vascular lesions, and dermatofibromas.

Recently, several researchers have successfully applied deep learning techniques to object recognition as well as other visual tasks. For example, it has already been shown that deep learning and transfer learning techniques can be efficiently applied to image classification tasks. Codella et al [6] proposed a hybrid model for melanoma classification using SVM, sparse coding and Deep Learning techniques and achieving 93% accuracy. There are also some other great works on skin cancer classification. Ozkan and Koklu [2] proposed a skin lesion classification system. They classified skin lesions into melanoma, abnormal and normal skin lesions using four different models. Among the four models, the artificial neural network achieved a better accuracy of about 92%. Chakravorty et al [8] proposed classification of skin lesions considering the irregular color distribution in the skin lesion using Kullback-Liebier divergence and structural similarity matrix and achieved 83% accuracy. Bi et al. proposed a melanoma classification system that classifies images into melanoma and non-melanoma by using multi-scale lesion-based representation (MLR) and joint reverse classification (GFS) and achieved 92% accuracy.

For faster and more accurate detection of skin cancer, we can use advanced technologies such as artificial intelligence by using deep convolutional networks and transfer learning

techniques. In this work, I used a deep convolutional neural network to classify skin lesions and a pre-trained model called AlexNet to classify skin lesions and compared the results to find the best model for classification.

1.1 Major Contributions

The goal of the proposed method is to find a better solution to the challenges of skin cancer detection. The focus is to develop an algorithm to detect skin cancer on RGB images in the dataset HAM 10000 The proposed approach is based on convolutional neural network and AlexNet. The system should be able to improve the classification accuracy and also reduce the loss. The performance of the proposed system is analyzed in terms of classification accuracy, loss and confusion matrix:

1.1.1 Creation of Convolution Neural Network Model dedicated to skin cancer detection

A model for skin cancer detection using a CNN is developed. It has 7 layers with learnable parameters. RGB images are used as input. The CNN model consists of 4 convolutional layers along with max-pooling layers. It also consists of 3 fully linked layers. "Relu" is the activation function used for the entire model except the output layer. Softmax is used as the activation function for the output layer. 13.4 million, the total number of parameters in the architecture. This CNN model is designed for skin cancer detection.

1.1.2 Pre-processing of HAM10000 Dataset

Due to the small size and lack of diversity of the dataset, preprocessing is performed. Thus, to train the model for automatic detection of a pigmented skin lesion, preprocessing is performed. The dataset contains almost 10015 images of different diagnostic categories. The dataset mainly contains 7 categories: Basal cell carcinoma (bcc), actinic keratoses and intraepithelial carcinomas/Bowen's disease (akiec), benign keratosis-like lesions (solar lentigines/seborrheic keratoses and lichen planus-like keratoses, bkl), melanocytic nevi (nv), dermatofibromas (df), melanomas (mel), and vascular lesions (angiomas, angiokeratomas, pyogenic granulomas, and hemorrhages, vasc). However, the main problem with the dataset is that there is an imbalance between the different classes. To solve this problem, the dataset will be extended and the images in each class will be balanced to achieve a better result and avoid misclassification.

1.1.3 Hyper-Parameter Tuning of AlexNetl

In my work, and compared the proposed CNN model with AlexNet. To achieve better results in AlexNet, hyperparameters of the pre-trained model are adjusted and increased the accuracy of the model. To control the learning process, the value of the hyperparameters is controlled. For learning an algorithm, a set of optimal hyperparameters is selected and their values are controlled, this process is called hyperparameter tuning.

1.2 Organization of Work

The remainder of the work is organized as follows. The following section briefly reviews related works on skin cancer detection. Section 3 explains the background of the work, i.e., a brief outline of the conventional approach to skin cancer classification that motivated the progress of the work. The proposed methodology is explained in Section 4. The results of the experiment are detailed in Section 5 along with the data set and experimental setup. The report ends with a brief conclusion in Section 6.

Chapter 2

Related works

2.1 Literature Review

This section reviews the existing skin cancer detection methods using deep learning techniques. The most challenging part of the detection is the images of different skin cancer looks similar so their classification becomes complicated. These works in literature motivated me to propose novel and give me a better understanding of skin cancer detection.

2.1.1 Skin Cancer Classification using Deep Learning and Transfer Learning [1]

One of the deadliest diseases is skin cancer, particularly melanoma. The great similarity between different skin lesions like melanoma and nevus in color photographs of the skin increases the challenge of detection and diagnosis. To save effort, time, and human life, early detection is very important. So reliable automated system for skin lesion classification is required. An automated skin lesion classification approach is proposed in this paper. Transfer learning and a pre-rained model are used in this method. Transfer learning is used to AlexNet by replacing the last layer with a softmax to categorize three different lesions, in addition to fine-tuning and data augmentation. The ph2 dataset is used to train and evaluate the proposed model. The performance of the suggested technique is evaluated using the well-known quantitative measures of accuracy, sensitivity, specificity, and precision. When the suggested method's performance is compared to that of current techniques, the proposed method's classification rate outperforms that of existing methods.

2.1.2 Melanoma skin cancer detection using deep learning and classical machine learning techniques: A hybrid approach [2]

Melanoma is one of the most fatal cancers in the world, and it can spread to other regions of the body if it's not detected early enough. For early detection, a significant advancement in the medical field has put forward an automated detection model that can help the physician and even common people in determining the kind of the health issue they are facing. In this paper they proposed a hybrid technique for the detection of the skin cancer which can be applied for any doubtful skin lesion. They trained a CNN and two machine learning classifiers using a collection of data representing the boundaries, texture, and color of a skin lesion. The proposed model depends on their predictions. For increasing the performance

of the model majority voting is being used by pooling the result of the models. From this experiment it clearly shows that combination of the 3 models gives maximum accuracy.

2.1.3 The Development of a Skin Cancer Classification System for Pigmented Skin Lesions Using Deep Learning [3]

Recent research has shown that convolutional neural networks (CNNs) categorize melanoma photos with accuracies equivalent to those attained by dermatologists. However, no study has yet been published that compares the performance of a CNN trained with solely clinical photos of a pigmented skin lesion in a clinical image classification task against dermatologists. Retrieved 5846 clinical photos of pigmented skin lesions from 3551 individuals for this investigation. Malignant melanoma and basal cell carcinoma were among the pigmented skin lesions, as were benign tumors (nevus, seborrhoeic keratosis, senile lentigo, and hematoma/hemangioma). The test dataset was constructed by randomly selecting 666 patients and selecting one image per patient, while the training dataset was created by adding bounding-box annotations to the remaining photos. Then used the training dataset to train a faster, region-based CNN (FRCNN) and tested its performance on the test dataset. Furthermore, 10 board-certified dermatologists (BCDs) and ten dermatologic trainees (TRNs) completed the same tests, and their diagnostic accuracy was compared to that of FRCNN.

2.2 Background of Work

One of the most important organ in human body is skin. Skin main function is to protect the human body from external factors like bacteria, chemical,and, temperature. Skin is used for regulating temperature in human body. There are skin lesion in human bodies. Skin lesion refers to part of skin which have different characteristics than the surrounding skin. They are very common and appears as a result of miss treatment of skin. Skin lesion becomes dangerous once they are detected to be cancerous.
Skin cancer is one of the deadliest disease in the world. So that it should be detected as early as possible because they have a high chance of spreading to other parts of the body. The main problem of detecting skin cancer is that it cant be detected through the naked eyes. For solving that the dermetoscopic images was introduced to the field even though it was not possible for the doctor or for common people to identify which type of skin cancer is in the image.
For the faster and accurate detection of the skin cancer automated skin cancer detection models where developed by the researchers. But the problem for them was insufficient data for the classification. So the accuracy is low and since they have only small number of available date, the prediction might be false so that they can't be reliable.
For solving all this problems the HAM10000 dataset which consist of different skin lesion are used. In my work different models are used for the detection purpose and the performance is measured using different quantitative measures.

Chapter 3

Proposed Methodology

The proposed work is to classify the different skin cancer images in the HAM Dataset. The dataset has data imbalance for different classes, for example, the number of images under the class of Actinic keratoses is 301 while the melanoma class has 1074 images for regularizing that data augmentation is done. After that, the augmented dataset is used as the input of the two different models. The models used here are CNN which is dedicated to skin cancer detection and also the pre-trained model AlexNet. Both these results are compared at the conclusion and a better model for skin cancer detection is chosen.

3.1 Pre-processing of dataset

In order to prepare the raw data so that our neural network can process it, the initial step that we carry out before giving it to the model for training is pre-processing of the data. We can resize the images in such a way that it matches the input layer's size and also, and we can do augmentations, and contrast can be increased and decreased these are some examples of pre-processing. In my work, it consists of different artifacts like hair so as to reduce that and also to enhance the desired feature pre-processing can be done. i.e, you can normalize or remove noise from input data.
The major problem when coming into an image dataset is that it might have inaccuracy, or inadequacy (data imbalance). So, in order to solve this problem, we use pre-processing step. In the case of the HAM dataset, it consists of 10015 image data but the problem is that it has an imbalance in the dataset, for solving that data augmentation is done and the dataset is increased to 45756. After solving this problem, the dataset is resized into 28x28x3. Then the image dataset is converted into corresponding NumPy arrays for faster detection.
Here data augmentation like rotation, width shift, height shift, horizontal flip, and vertical flip is done to balance the data. It is done using a package in python called "Image Data Generator" which is a very useful tool in python for data management.

3.2 Convolutional Neural Network

It is a deep learning algorithm that can take in an input image and as assign weight and biases to various aspects of an image and also can differentiate one from the other. The main advantage of CNN is that it requires very less pre-processing when compared to other

algorithms. The connectivity of the CNN is very similar to the connection of the neuron in the human brain.

3.2.1 CNN Architecture

The input layer, hidden layer, and output layer are integral parts of a convolutional neural network. In a feed-forward network, the middle layer is called the hidden layer. The middle layer of convolution neural consist of hidden layer with convolutional function. That means the dot product of the convolution kernel with layer s input matrix. Relu activation function is commonly used in these layers.The figure 3.1 shows the architecture.
In a CNN, the input is a tensor with a shape:

$$(numberofinputs) * (inputheight) * (inputwidth) * (inputchannels) \tag{3.1}$$

.
When the images are passed through the convolution layer they get abstracted to a feature map, also known as an activation map, with shape:
(number of inputs) x (feature map height) x (feature map width) x (feature map channels).

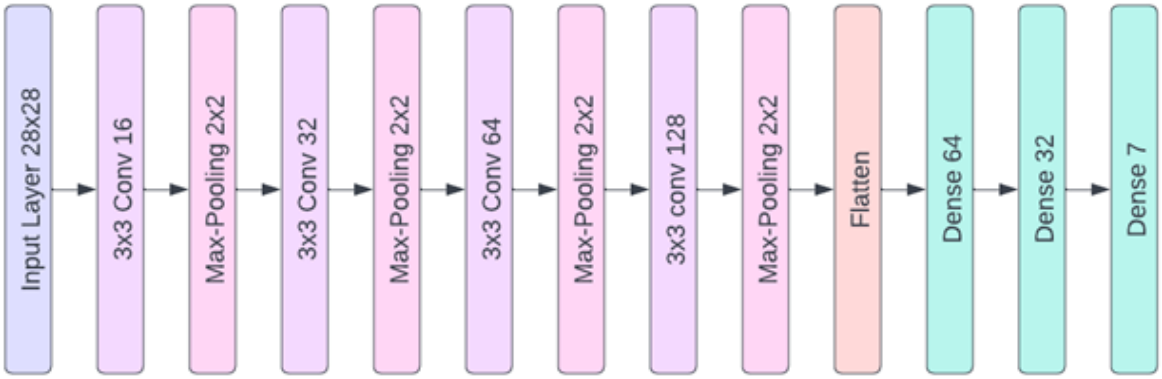

Figure 3.1: CNN Architecture

Convolution neural networks will work with a combination of local or global pooling layers. The pooling layers are mainly used for the dimensionality reduction of the data. It's done by combining the data in the next layer. There are many types of pooling like max-pooling, average-pooling, and sum-pooling. At work, I used max-pooling for dimensionality reduction. For connection, a very neuron in one layer to another layer fully connected layers is used. In a fully connected layer traditional multilayer perceptron neural network (MLP) is used. After passing through the flattened layer the image will be converted into a 1d array then it is passed to the fully connected layer to classify the images.
The proposed CNN (Skin cancer detection model) used for the work will take image input as RGB images. Here, I used the HAM10000 dataset which consists of RGB images of different skin lesions. The proposed model consists of 7 learnable layers which take the skin lesion image as the input. There are 4 convolution layers with max-pooling layers. It has 2 fully connected layers and an output layer. The overall model uses "Relu" as the

activation function except for the output layer. The output layer uses "Softmax" as the activation function. This model is dedicated to skin cancer detection. A total of 13.4 million parameters are there in the above architecture.

3.3 AlexNet

AlexNet has eight layers with learnable parameters. The model consists of five convolution layers with a combination of max-pooling followed by 3 fully connected layers all the layers use Relu as an activation function except the output layer. AlexNet famously won the 2012 ImageNet LSVRC-2012 competition by a large margin (15.3% vs 26.2%(second place) error rates).

3.3.1 AlexNet Architecture

It is a deep learning architecture; drastic padding was introduced to avoid the size of feature maps. The figure 3.2 shows the architecture of AlexNet.The model takes a 28x28x3 sized image as the input. The convolution layer will have a size of 11x11 with 96 filters and stride 4. "Relu" activation is used in this layer.

$$Output = \frac{(Input - filtersize)}{(stride)} + 1 \tag{3.2}$$

After the first convolution layer pooling layers will be introduced. Here a max-pooling layer is used for pooling. The max-pooling layer will have a size of 3x3 and stride. After the max-pooling, the second convolution layer will be added. Now the filter size is reduced to 5x5 and has a filter of 256.
The stride and padding of the layer are 1 and 2 respectively. The activation function used on the layer is "Relu". Again, this pattern or combination is continued. A max-pooling layer of size 3x3 with stride. The third convolution layer is added with a filter 384 of size 3x3 padding and the stride used here is 2 and 1 respectively. Similar to all the above combinations here also "Relu" is used as the activation function.

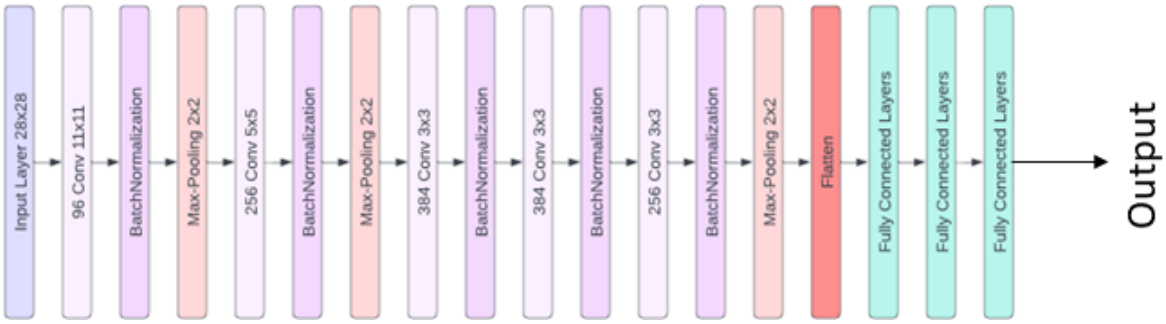

Figure 3.2: AlexNet Architecture

Then the next convolution layer is added it operates with 384 filters of size 3x3. In this layer, both stride and padding are 1. The activation function used here is "Relu". Here the

output sizes will remain the same.
Now comes the final convolution layer of 3x3 with 256 filters added. Here the padding and stride are set to be 1. The activation used here is similar to all the above layers i.e "Relu" is used as the activation function. The final max-pooling layer is also added size 3x3 and stride 2.
After this, a dropout layer is added at the rate of 0.5. there are basically 3 fully connected layers in which the last layer act as an output layer. Then the first and second fully connected layer with 4096 neurons was added. And both have "Relu" as an activation function. The final fully connected layer or output layer will have 7 output neurons because here we are classifying the dataset into 7 classes. There are 63.7 million parameters in an AlexNet model.

3.4 VGG-16

VGG-16 is a 16 layer convolutional neural network architecture which is used for ImageNet dataset which is a large visual database used in visual object recognition. In the year 2014 Karen Simonyan and Andrew Zisserman from the University of Oxford has developed and introduced the architecture of vgg16 through their article "Very Deep Convolutional Networks for Large-Scale Image Recognition"[6]. The main peculiarity of the vgg16 is its unchanged filter size. Compare to other convolutional models vgg16 has a fixed filter size of 3x3. The optimizer of output dense layer is softmax.

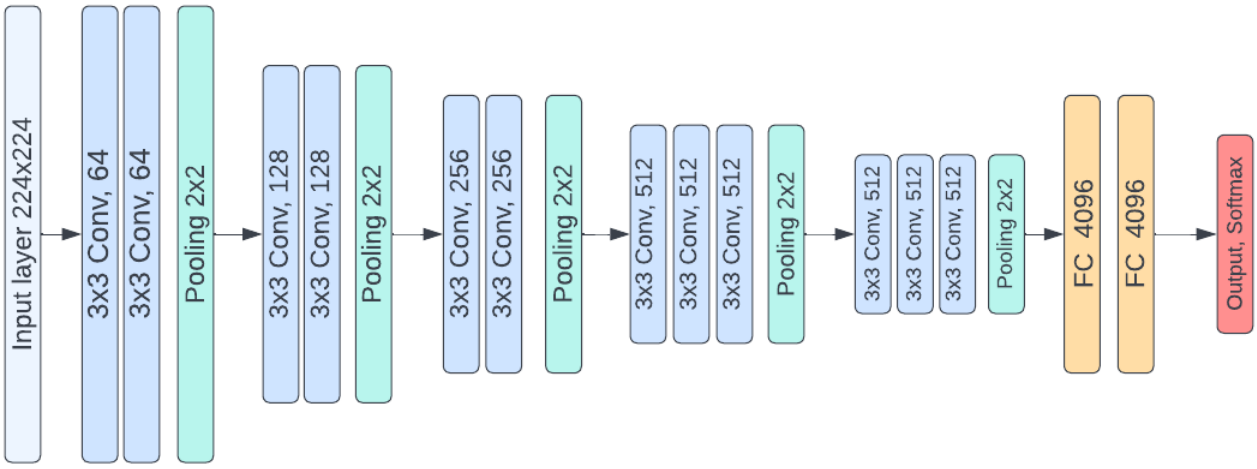

Figure 3.3: VGG-16 Architecture

3.4.1 VGG-16 Architecture

The 16 in VGG16 refers to 16 layers that have weights.The architecture of the VGG-16 is shown in the figure 3.3. In VGG16 there are thirteen convolutional layers, five Max Pooling layers, and three Dense layers which sum up to 21 layers but it has only sixteen weight layers i.e., learnable parameters layer.VGG16 takes input tensor size as 224, 244 with 3 RGB channel Most unique thing about VGG16 is that instead of having a large number of hyper-parameters they focused on having convolution layers of 3x3 filter with stride 1 and

always used the same padding and maxpool layer of 2x2 filter of stride 2.
The convolution and max pool layers are consistently arranged throughout the whole architecture Conv-1 Layer has 64 number of filters, Conv-2 has 128 filters, Conv-3 has 256 filters, Conv 4 and Conv 5 has 512 filters. Three Fully-Connected (FC) layers follow a stack of convolutional layers: the first two have 4096 channels each, the third performs 1000-way ILSVRC classification and thus contains 1000 channels (one for each class). The final layer is the soft-max layer.

3.5 Inception V3

Inception v3 is an image recognition model that has been shown to attain greater than 78.1% accuracy on the ImageNet dataset. The model is the culmination of many ideas developed by multiple researchers over the years. It is based on the original paper: "Rethinking the Inception Architecture for Computer Vision" by Szegedy, et. al. The model itself is made up of symmetric and asymmetric building blocks, including convolutions, average pooling, max pooling, concatenations, dropouts, and fully connected layers. Batch normalization is used extensively throughout the model and applied to activation inputs. Loss is computed using Softmax.

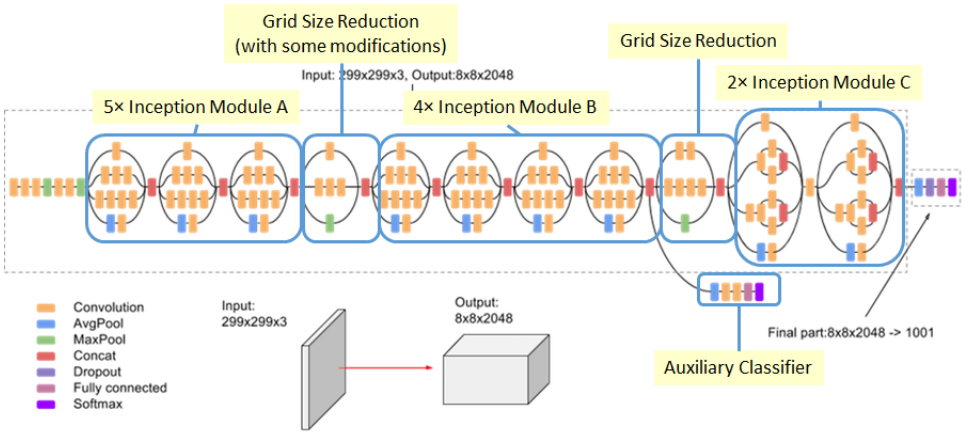

Figure 3.4: Inception V3 Architecture

3.5.1 Inception V3 Architecture

The architecture of an Inception v3 network is progressively built, step-by-step, as explained.The figure 3.4 shows the basic architecture of the model. Factorized Convolutions: this helps to reduce the computational efficiency as it reduces the number of parameters involved in a network. It also keeps a check on the network efficiency. Smaller convolutions: replacing bigger convolutions with smaller convolutions definitely leads to faster training. Say a 5×5 filter has 25 parameters; two 3×3 filters replacing a 5×5 convolution has only 18 (3*3 + 3*3) parameters instead.
Asymmetric convolutions: A 3×3 convolution could be replaced by a 1×3 convolution

followed by a 3×1 convolution. If a 3×3 convolution is replaced by a 2×2 convolution, the number of parameters would be slightly higher than the asymmetric convolution proposed.

Auxiliary classifier: an auxiliary classifier is a small CNN inserted between layers during training, and the loss incurred is added to the main network loss. In GoogLeNet auxiliary classifiers were used for a deeper network, whereas in Inception v3 an auxiliary classifier acts as a regularizer.

Grid size reduction: Grid size reduction is usually done by pooling operations. However, to combat the bottlenecks of computational cost, a more efficient technique is proposed.

Chapter 4

Results and Discussions

4.1 Dataset and Experimental Setup

HAM 10000 dataset has been used for the performance analysis of the proposed method with skin cancer images. The training of neural network for detection of pigmented lesions is hampered by small size and lack of diversity in the dataset of dermatoscopic images. This problem is solved by the release of the HAM10000 dataset. The full form of HAM is "Human Against Machine". The dermatoscopic images are collected from different populations, acquired, and stored by different modalities. The dataset consists of dermatoscopic images of 10015 of 7 different categories. They include Melanocytic nevi, Melanoma, Benign keratosis, Basal cell carcinoma, Actinic keratoses, Vascular lesions, and Dermatofibroma. The dataset includes lesions with multiple images, which can be tracked by the lesion id-column within the HAM10000 metadata file. Using this meta-data the mixed image dataset of different classes is grouped into the corresponding classes.

Table 4.1: Images in different classes of the dataset

Categories	Number of images
Melanocytic nevi	6705 images
Melanoma	1113 images
Benign keratosis	1099 images
Basal cell carcinoma	514 images
Actinic keratoses	327 images
Vascular lesions	142 images
Dermatofibroma	115 images

The skin cancer detection is done using the HAM dataset. The HAM dataset is provided as the input for 2 models. The models are the CNN model which is dedicated to skin cancer detection and also in AlexNet which is a pre-trained model. The experiment is done Intel i5

processor with an 8GB ram. Jupyter Notebook is the platform used for skin cancer detection. The complete coding is done on the above experimental step.
In the work, I used the "Nadam" optimizer for optimization, the loss function used for the work is "sparse categorical cross-entropy". I have also used "ReduceLROnPlateau" which is used for reducing the learning rate when there is no improvement in metric. Models often benefit from reducing the learning rate by a factor of 2-10 once learning stagnates. This callback monitors a quantity and if no improvement is seen for a 'patience' number of epochs, the learning rate is reduced. Early stopping is also applied to stop the training if there is no improvement in the accuracy. The batch size taken for the work is 64, validation split is 0.2 and the epochs are set to be 50.

4.2 Performance with the Convolutional neural network approach

The skin cancer detection system based on the convolutional neural network approach has been implemented and performance is noted. The images for training and testing are taken from HAM 10000 dataset. The performance is analyzed in terms of accuracy, precision, recall, F1 score, and confusion matrix. The training accuracy of the model is 100% while the validation and testing accuracy of the model is 97.92% and 97.34% respectively. Precision and recall of the model are shown in the classification summary image table 4.2. The accuracy curve,loss curve, and confusion matrix are plotted for the CNN model and shown in the figure 4.1(i), figure 4.1(ii), figure 4.2 respectively.

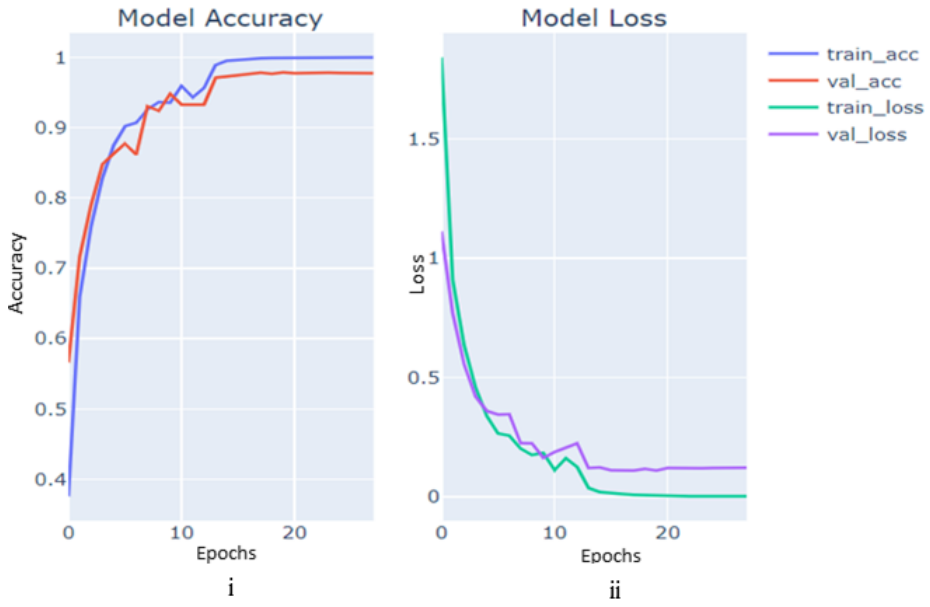

Figure 4.1: (i)Training and Validation Accuracy of CNN Model(ii)Training and Validation Loss of CNN Model

Figure 4.1(i) shows the accuracy curve of the CNN model. As we can see the training accuracy starts from 0.32 and increases approximately to 1.0 at the fourteenth epoch and gets stable. The validation curve starts from 0.6 and increases up to 0.97354 at 16 epoch and become constant. From the above graph, the model has a training accuracy of 1.0 and

a validation accuracy of 0.97354. Figure 4.1(ii) shows the loss curve of the CNN model. As we can see the training loss starts from 1.85 and decreases approximately to 0.0 at the fourteenth epoch and gets stable. The validation curve starts from 1.2 and decreases up to 0.15 at the fourteenth epoch and becomes constant. From the above graph, the model has a training accuracy of 0.0 and a validation accuracy of 0.15.

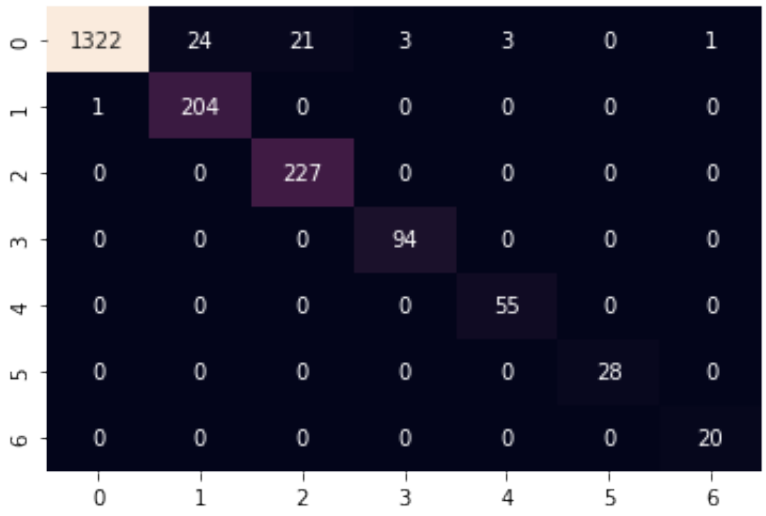

Figure 4.2: Confusion Matrix of CNN Model

Figure 4.2 shows the confusion matrix of the CNN model, a total of 2003 images are taken for testing from different classes. 0 'nv' ,1 'mel', 2 'bkl',3 'bcc', 4 'akiec', 5 'vasc', 6 'df' this are the class labels of different classes in the dataset. In apart from class 0 and class 1 all are predicted accurately. Class 0 is true predicted 1322 images and the false prediction of class 0 is inferenced in the figure. Similarly, class 1 also has a false prediction as shown in the figure.

Table 4.2: Classification Summary of CNN model

Classes	Precision	Recall	F1 Score	Support
Melanocytic nevi	1.00	0.96	0.98	1374
Melanoma	0.89	1.00	0.94	205
Benign keratosis	0.92	1.00	0.96	227
Basal cell carcinoma	0.97	1.00	0.98	94
Actinic keratoses	0.95	1.00	0.97	55
Vascular lesions	1.00	1.00	1.00	28
Dermatofibroma	0.95	1.00	0.98	20

4.3 Performance with the AlexNet model

The skin cancer detection system based on the AlexNet model has been implemented and performance is noted. The images for training and testing are taken from HAM 10000 dataset. The performance is analyzed in terms of accuracy, precision, recall, F1 score, and confusion matrix. The training accuracy of the model is 99.54% while the validation and testining accuracy of the model is 97.55% and 96.605% respectively. Precision and recall of the model are shown in the classification summary image table 4.3. The accuracy curve, loss curve and confusion matrix are plotted for the CNN model and shown in the figure 4.3(i), figure 4.3(ii) and figure 4.4 respectively.

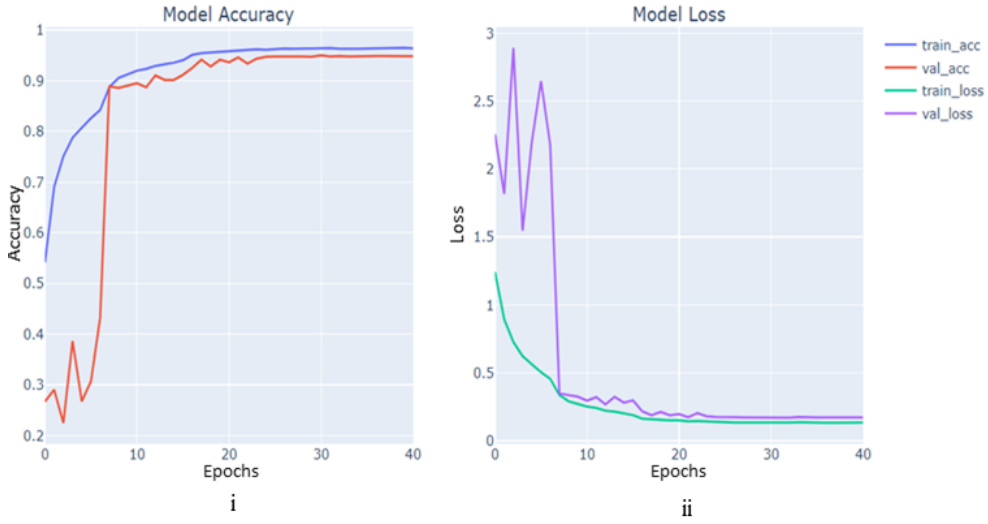

Figure 4.3: (i)Training and Validation Accuracy of AlexNet (ii)Training and Validation Loss of AlexNet

Figure 4.3(i) shows the accuracy curve of the AlexNet model. As we can see the training accuracy starts from 0.55 and increases approximately to 0.989 at the fourteenth epoch and gets stable. The validation curve starts from 0.29 and increases up to 0.9604 at 16 epoch and become constant. From the above graph, the model has a training accuracy of 0.989 and a validation accuracy of 0.9604. Figure 4.3(ii) shows the loss curve of the AlexNet model. As we can see the training loss starts from 1.25 and decreases approximately to 0.12 at the fourteenth epoch and gets stable. The validation curve starts from 2.45 and decreases up to 0.145 at the fourteenth epoch and becomes constant. From the above graph, the model has a training accuracy of 0.12 and a validation accuracy of 0.145.
Figure 4.4 shows the confusion matrix of the AlexNet model, a total of 2003 images are taken for testing from different classes. 0 ‘nv’ ,1 ’mel’, 2 ’bkl’,3 ’bcc’, 4 ’akiec’, 5 ’vasc’, 6 ’df’ this are the class labels of different classes in the dataset.This class are predicted and the confusion matrix is plotted. Apart from class 0 and class 1 all are predicted accurately. Class 0 is true predicted 1303 images and the false prediction of class 0 is inferenced in the figure. Similarly, class 1 also has a false prediction as shown in the figure.

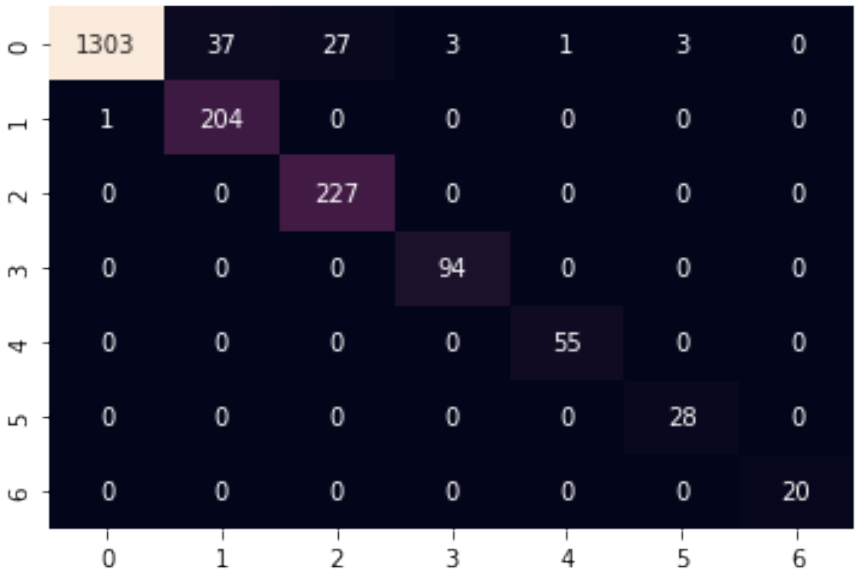

Figure 4.4: Confusion Matrix of AlexNet

Table 4.3: Classification Summary of AlexNet

Classes	Precision	Recall	F1 Score	Support
Melanocytic nevi	1.00	0.95	0.98	1374
Melanoma	0.89	0.99	0.94	205
Benign keratosis	0.87	1.00	0.93	227
Basal cell carcinoma	0.95	1.00	0.97	94
Actinic keratoses	0.95	1.00	0.97	55
Vascular lesions	0.97	1.00	0.98	28
Dermatofibroma	0.95	1.00	0.98	20

4.4 Performance with the VGG-16 model

The skin cancer detection system based on the VGG-16 model has been implemented and performance is noted. The images for training and testing are taken from HAM 10000 dataset. The performance is analyzed in terms of accuracy, precision, recall, and F1 score . The training accuracy of the model is 99.49% while the validation and testing accuracy of the model is 86.35% and 83.605% respectively. The accuracy curve, and loss curve are plotted for the CNN model and shown in the figure 4.5(i), and figure 4.5(ii) respectively. Figure

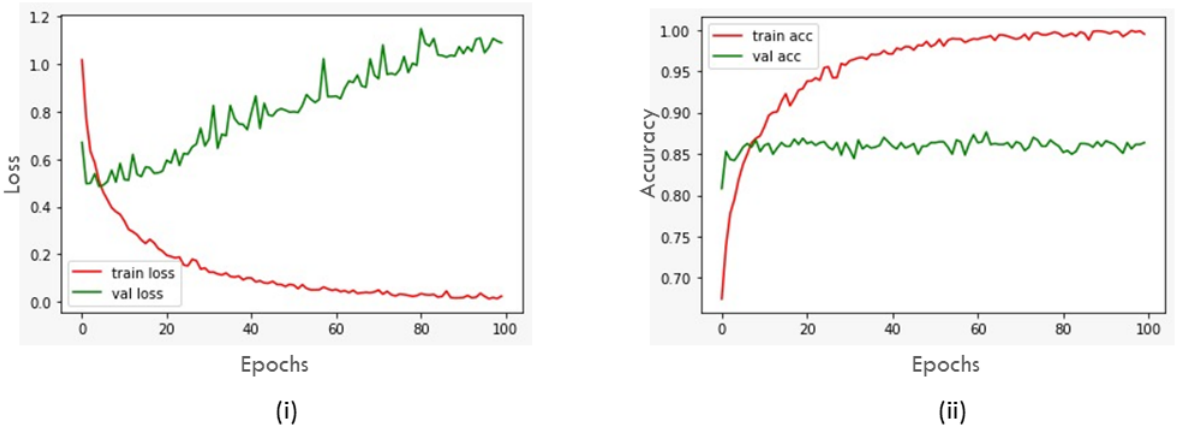

Figure 4.5: (i)Training and Validation Loss of VGG-16 (ii)Training and Validation Accuracy of VGG-16

4.5(i) shows the loss curve of the VGG-16 model. As we can see the training loss starts from 1.0 and decreases approximately to 0.01 at the 85th epoch and gets stable. The validation curve starts from 0.6 and increases up to 1.2 at the 60th epoch and goes on fluctuating. From the above graph, the model has a training loss of 0.01 and a validation loss of 1.2. Figure 4.5(ii) shows the accuracy curve of the VGG-16 model. As we can see the training accuracy starts from 0.65 and increases approximately to 1.0 at the 40th epoch and gets stable. The validation curve starts from 0.82 and increases up to 0.85 at the 10th epoch and keeps fluctuating between 0.80 and 0.85. From the above graph, the model has a training accuracy of 1.0 and a validation accuracy of 0.85.

4.5 Performance with the Inception V3 model

The skin cancer detection system based on the Inception V3 model has been implemented and performance is noted. The images for training and testing are taken from HAM 10000 dataset. The performance is analyzed in terms of accuracy, precision, recall,and F1 score. The training accuracy of the model is 99.25% while the validation and testing accuracy of the model is 86.25% and 79.605% respectively. The accuracy curve, loss curve are plotted for the CNN model and shown in the figure 4.6(i), and figure 4.6(ii) respectively. Figure 4.6(i) shows the loss curve of the Inception V3 model. As we can see the training loss starts from 3.5 and decreases approximately to 0.05 at the 12th epoch and gets fluctuates. The validation curve starts from 1.5 and increases up to 4.0 at the 45th epoch and goes on fluctuating. From the

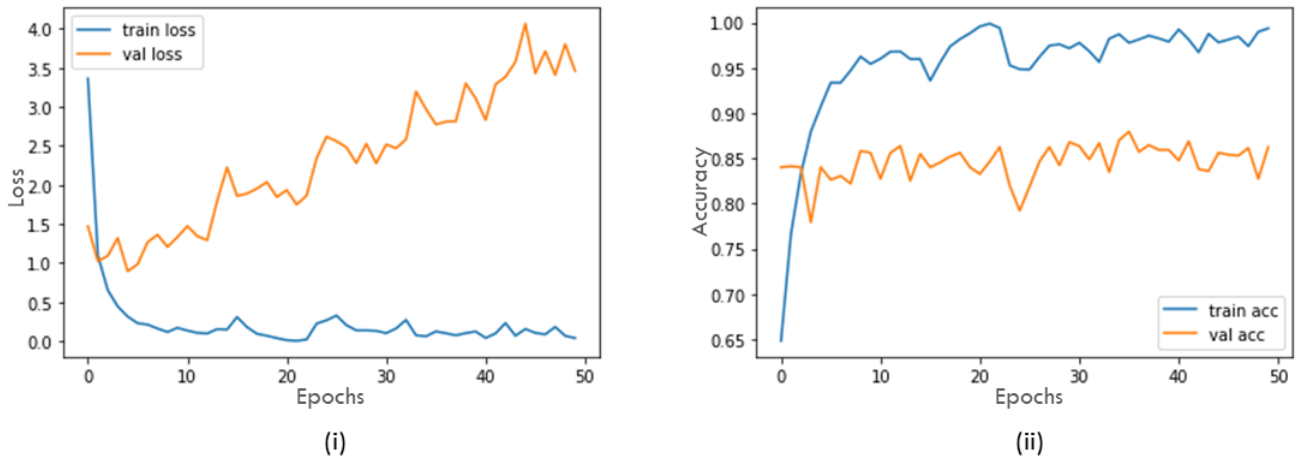

Figure 4.6: (i)Training and Validation Loss of Inception V3 (ii)Training and Validation Accuracy of Inception V3

above graph, the model has a training loss of 0.05 and a validation loss of 3.2. Figure 4.6(ii) shows the accuracy curve of the Inception V3 model. As we can see the training accuracy starts from 0.65 and increases approximately to 1.0 at the 20th epoch and gets fluctuated. The validation curve starts

Table 4.4: Comparison of Skin Cancer Detection on HAM Dataset on differnet models

Model	Accuracy	Loss	Precision	Recall	F1 Score
CNN(Skin Cancer detection model)with Nadam optimizer	**0.9735**	**0.09**	**0.98**	**0.97**	**0.97**
Alex Net with Nadam optimizer	0.96605	0.259	0.97	0.97	0.97
CNN(Skin Cancer detection model)with Adam Optimizer	0.97004	0.225	0.97	0.97	0.97
Alex Net with Adam optimizer	0.88717	0.293	0.92	0.89	0.90
VGG-16	0.8635	0.1001	0.8688	0.8603	0.8645
Inception V3	0.8625	0.3458	0.8625	0.8425	0.8524

The results are formatted and presented in Table 4.4.These results clearly shows that the Skin Cancer Detection is promising using deep learning techniques and more research and work is needed to be done so as to improve the reliability and efficiency of the work.

Chapter 5

Conclusions

Skin cancer is one of the deadliest diseases in the world, which should be detected at an early stage. Therefore, the detection of skin cancer must be done very quickly, which brings the advantage of automatic detection. The main challenge in skin cancer detection has been the availability of a large, reliable dataset. This task is solved by the dataset HAM 10000, which consists of 10015 images from 7 different classes. In the initial studies, researchers used a small dataset for skin cancer classification.
In this work, skin cancer detection detection model. The CNN with 4 convolutional layers and another model is AlexNet with 5 convolutional layers and a combination of max-pooling. The performance of the models is analyzed based on accuracy, precision, detection and confusion matrix. For these two models, CNN performs slightly better than AlexNet. The training accuracy, validation accuracy, and test accuracy of the CNN model are 100%, 97.92%, and 97.34%, respectively. The training accuracy, validation accuracy, and test accuracy of the AlexNet model are 99.54%, 97.55%, and 96.605%, respectively. The same dataset with the same notebook configuration is used for some of the pre-trained models such as VGG-16 and Inception V3, and the conclusion that can be drawn from this result is that CNN shows the best result among all the deep learning models.

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