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Skin Disease Classification Using MobileNet Algorithm based CNN

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ABSTRACT: Skin lesions are a severe disease globally. Early detection of melanoma in dermoscopy images significantly increases the survival rate. However, the accurate recognition of melanoma is extremely challenging due to the following reasons: low contrast between lesions and skin, visual similarity between melanoma and non-melanoma lesions, etc. Hence, reliable automatic detection of skin tumors is very useful to increase the accuracy and efficiency of pathologists. In this paper, we proposed two deep learning methods to address three main tasks emerging in the area of skin lesion image processing, i.e., lesion segmentation (task 1), lesion dermoscopic feature extraction (task 2) and lesion classification (task 3). A deep learning framework consisting of two fully convolutional residual networks (FCRN) is proposed to simultaneously produce the segmentation result and the coarse classification result. A lesion index calculation unit (LICU) is developed to refine the coarse classification results by calculating the distance heat-map. A straight-forward CNN is proposed for the dermoscopic feature extraction task. The proposed deep learning frameworks were evaluated on the ISIC 2017 dataset. Experimental results show the promising accuracies of our frameworks, i.e., 0.753 for task 1, 0.848 for task 2 and 0.912 for task 3 were achieved.

KEYWORDS: Privacy, AES, Authentication methods, cloud, security

I. INTRODUCTION

Skin cancer is the unrestrained irregular growing in skin cells. It happened when unrepaired DNA injury to skin cells, (most of the time produced by electromagnetic energy from sunshine or tannings beds) activity changes, or inherited faults. As a result the top of the skin cells grow fast and procedure malignant tumours. Here are 2 main kinds of skin cancer, melanoma and non-melanoma. These are explained in details below Melanoma is a type of skin cancer that begins in your skin's pigment control cells (melanocytes).This illustration shows melanoma cells that extend to the deeper layers of the skin from the surface of the skin. Non-melanoma skin cancer refers to a group of cancers in the upper layers of the skin that grow slowly. The incident rate of skin cancer continues to increase for melanoma and non-melanoma skin cancer; 5.4 million new cases of squamous cell carcinomas have been reported in the U.S each year (Linos et al.,2017). The number of melanoma deaths is predictable to decrease by 22% in 2019(Zengul et al.,2019).

This is the event of uncontrolled organic process of melanocytes that eventually opened up into the encircling layers of the skin. In the United Kingdom11,000 people are diagnosed with skin cancer each year round the ages of 15-34 years (Walters-Davies, 2013). There are four types of skin melanoma, the nodular melanoma, superficial spreading melanoma, acral melanoma and nodular lentigomaligna melanoma. The lentigomaligna skin cancer principally affects older people on the portions of the skin that are over visible to the sun over the years, the acral skin cancer is seen on the feet or palms of the hands and has be determined to be gift in afro Caribbean origin. The risk factors related to skin cancer are; skin sort, reduced immunity and genetic science. There are four stages of melanoma stage 1, 2, 3 and 4.

Melanocytes are cells that create colors on the skin and normally live within the epidermis, in the dermo-epidermal intersection, and in the follicles of the hair. Some benign neoplasm’s are derived from melanocytes and are the consequence of individual oncogenic transformations on a regular basis (Damsky et al.,2017).There are three kinds of melanocytic nevi; inherent melanocytic nevi and other nevi acquired (Sardana et al., 2014).Routine melanocytic sores evaluation, is constantly examined with the decision as to whether an injury is benevolent or threatening (Sardana et al., 2014).There is currently no overall consensus on which criteria should be included in this activity. Melanocytic

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nevi are much encircled, round to ovoid, with periphery defined by normal and all around. Although most are clinically analysed, another characterization framework for nevi was suggested in 2007, taking into account dermo-scopic highlights.

II. RELATED WORKS

Amira Soudani et al. (2019) recommend a segmentation recommender to condense the training time based on crowd sourcing and transfer learning. The two pre-trained architectures such as VGG16 or ResNet50 are implemented and extract features through the convolution parts. The CNN is a classifier comprises of five nodes, each of them represents segmentation methods, and according to that, an output layer is built. The local features are acknowledged from diverse locations through the two dimensional structuring of Dermoscopic images. From the result, it is concluded that the suggested approach suitably predicts segmentation approach for the detection of skin lesions.

Walker et al. (2019) discusses the analysis of CNN architecture which grows further deeper into the convolution layers for the use of inception v2 network to classify the Dermoscopic images as either benign or malignant. For training the inception v2 parameters, an iterative algorithm called stochastic decent gradient is used under the deep learning framework. The evaluation process produces dissimilar kinds of outcome from Dermoscopic images such as visual features and signification. From the study, concludes that the imaging method tele-Dermoscopic attains improved accuracy and highly sensitive malignant detector for both the pigmented and non-pigmented lesions are obtained from the signification output.

Teck Yan Tan et al. (2018) employs Particle Swarm Optimization (PSO) for feature optimization which is essential for skin cancer diagnosis ondermoscopy images. The suggested method defines about a variety of stages such as pre-processing, skin lesion segmentation, feature extraction, PSO Based feature optimization and classification. The original population gets divided into two sub swarms then the leader leads each sub swarm based search for finding the global optima by avoiding worse solutions. This method integrates local and global food and enemy signals, attraction, mutation-based exploitation, and also capable of extenuating premature convergence of PSO model. The sub swarm leaders are enhanced by three random walks such as Gaussian, Cauchy and Levy distributions. Enormous diversity of search is performed by utilizing the dynamic matrix representation and probability distribution. The proposed algorithm shows better improvement in the classification of melanoma and also solves uni-modal and multi-modal benchmark problems. For further superiority of the proposed algorithm adopts Wilcox on rank sum test.

Mohammed, Al-Masni et al. (2018) proposes a segmentation method based on Fully resolution convolution network which has the capability to study full resolution features of every pixel from input Dermoscopic images. The cross entropy loss function is used by CNN for performing pixel wise classification effectively. The proposed approach, extract full resolution features through the convolutional layers with or without the requirement of pre or post processing. The method back propagation is processed on network layers to diminish the training error. The validation is done on two publically available datasets such as ISBI 2017 Challenge and PH2 datasets, then concludes that the method FrCN outperformed on comparing with the latest deep learning segmentation approaches.

Anuj Kumar et al. (2018) compare the analysis of image segmentation techniques. The segmentation is the process of analyzing and determining meaningful features or objects presented inside the image. Edge based segmentation is an important feature for image analysis which represents the discontinuities of the edges in terms of intensity. The canny edge detector is used to remove the broken edges by calculating the threshold value for an image and then comparing that with the pixel value. The higher pixel value concludes that there exists an edge else excluded. The area selected for region based segmentation should be closed. The initial step of watershed transform is pre-processing which reduces noise as well as adjust image intensity by preserving the image information that helps them to obtain well segmented image. Hence, it concludes that the edge detector canny provides finest performance using region growing which makes the segmentation process faster when compared with region splitting-andmerging.

Guotai Wang et al. (2018) develop a Bounding box and Image--tuning-based Segmentation (BIFSeg) for dealing with different - -tuning makes a CNNfor fine tuning the process. Intuitive 2D/3D medical image segmentation is performed through deep learning-based system. The developed method supports both the supervised and un where the image- -tuning is done based on the proposed weighted loss function. The content of bounding box is taken as input by CNN forbinary segmentation of instance, and the CNN is trained in such a way to learn few common structures such as saliency, contrast and hyper-intensity across different objects, which also help for generalizing hidden objects. Hence, the proposed framework BIFSeg achieves higher accuracy, which makes use of fewer user interactions and takes less time rather than the traditional interactive segmentation methods.

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III. PROPOSED WORK

Skin cancer is an emerging global health problem with 123,000 melanoma and 30,00,000 non-melanoma cases worldwide each year. The recent studies have reported excessive exposure to ultraviolet rays as a major factor in developing skin cancer. The most effective solution to control the death rate for skin cancer is a timely diagnosis of skin lesions as the five-year survival rate for melanoma patients is 99 percent when diagnosed and screened at the early stage. Considering an inability of dermatologists for accurate diagnosis of skin cancer, there is a need to develop an automated efficient system for the diagnosis of skin cancer. This study explores an efficient automated method for skin cancer classification with better evaluation metrics as compared to previous studies or expert dermatologists. We utilized a MobileNet model pretrained on approximately 12,80,000 images from 2014 ImageNet Challenge and finetuned on 10015 dermoscopy images of HAM10000 dataset employing transfer learning. The model used in this study achieved an overall accuracy of 83.1% for seven classes in the dataset, whereas top2 and top3 accuracy of 91.36% and 95.34%, respectively. Also, the weighted average of precision, weighted average of recall, and weighted average of f1-score were found to be 89%, 83%, and 83%, respectively. This method has the potential to assist dermatology specialists in decision making at critical stages. 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 easily identify early stage.

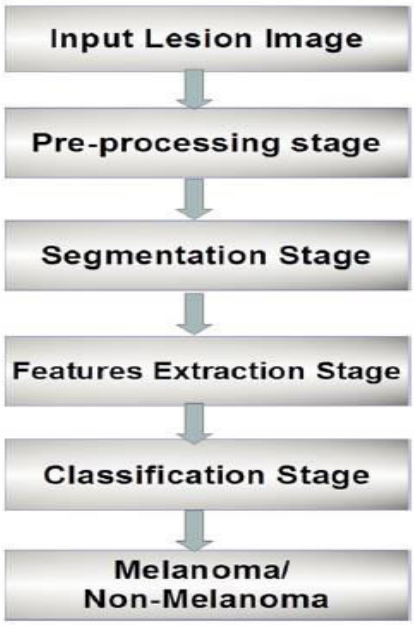

Figure-1 System Architecture

As a first step, create a directory of the images from different sources. In the current dataset, we have 46,466 images which have a size of 224x 224 pixels of RGB images. The dataset is downloaded from Github website .Github is public website and provide free data set for python simulation. The dataset divided by seven classes; each class has around 5,000 images in which 75% for testing and 25 % for validation and after create a validation set using a test because the current work, inside the function, the size (df, test_size=0.20) indicates the percentage of data to be held over for testing and random state is an integer, and then used for a new random state object is seeded (random_state=101).

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Table – 1 Data set

Class	No of Training Images	No of Validation Images	No of testing images
Nv	5,954	1,545	3312
Mel	5,920	1,134	330
Bkl	5,920	1,036	173
Bcc	5,858	1,098	131
Akiec	5,217	1,040	113
Vasc	5,290	1,020	48
Df	4,410	1,024	29
Total	38,569	7,897	4136

HAM10000 dataset has an unbalance distribution of images among the seven classes. Data Augmentation [42] brings an opportunity to rebalance the classes in the dataset, alleviating other minority classes. Data Augmentation is an effective means to expand the size of training data by randomly modifying several parameters of training data images like rotation range, zoom range, horizontal and vertical flip, fill_mode, etc. [42]. We conducted data augmentation of minority classes in the dataset: Melanoma, Benign Keratosis, Basal Cell Carcinoma, Actinic Keratosis, vascular lesion, and dermatofibroma to generate approximately 6000 images in each class giving a total of 38,569 images in the training set.

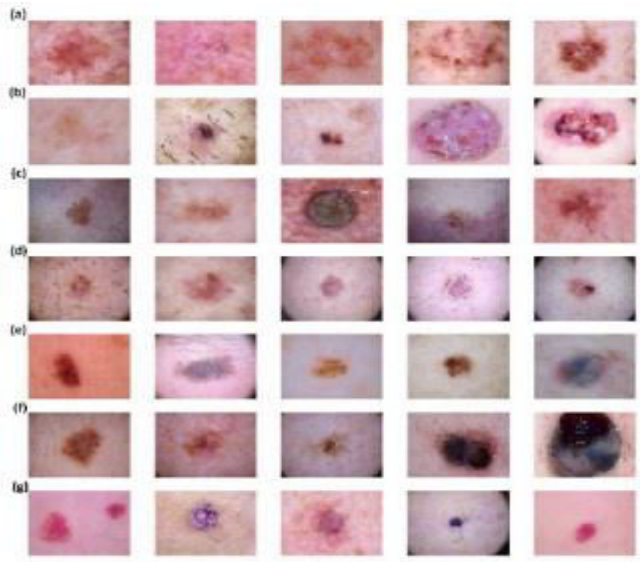

Figure 2 Sample images from HAM10000 dataset for cancer types (a) Actinic Keratosis (b) Basal Cell Carcinoma (c) Benign Keratosis (d) Dermatofibroma (e) Melanocytic nevi (f) Melanoma (g) Vascular Lesions

IMAGE PRE-PROCESSING

The pre-processing of skin lesion images was done by using Keras ImageDataGenerator . The 57 null Age entries in the dataset were filled using the mean filling method. The Dermoscopy images in the dataset were downscaled to 224X224 pixel resolution from 600X450 pixel resolution to make images compatible with the MobileNet model . The 10015 images in the dataset were split into the training set (9077 images) and validation set (938 images). The dataset images with no duplication in training data were selected for the validation set so that the authenticity in the validation process can be maintained.

IMAGE AUGMENTATION

HAM10000 dataset has an unbalance distribution of images among the seven classes. Data Augmentation brings an

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IMAGE SEGMENTATION

Image segmentation is a process of dividing an image into multiple segments that are considerably/perceptually homogeneous in terms of preferred characteristics such as color, texture, etc. Image segmentation is typically used to identify objects, estimate the boundaries of an image, remove unwanted regions on the image, compress and edit images or manipulate and visualize the data with a goal of providing a description or classification of the image. This process is widely used especially in medical image processing.

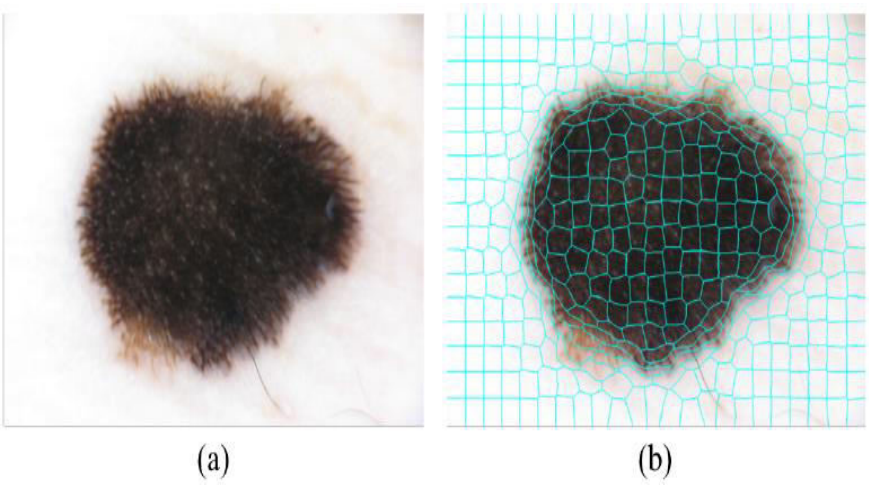

Figure 3 Image segmentation

Skin cancer has seven types and which took from the melanoma and non-melanoma image then made a different class. The current work selected high quality images 224 x224 pixel instead of small pixel because python automatically resize images for simulation. Figure 4 shows the structure of image directory for training and validation. First 224 x 224 input images of the skin cancer are used then MobileNet (CNN) classify our data in different classes. In current work, the network divided input images in seven different classes according to disease. Figure 4.2 illustrates sample 224 by 224 skin cancer images as an input to the CNN. In current work, the input images to the MobileNet(CNN) that passes from different layers.

Input layer: MobileNet has the ability to use multiple input layer sizes consisting of different width factors. The input sizes of the images in MobileNet ranges 224x224 pixel.
Zero padding layer: non zero boundary conditions are used for most image recognition algorithms however MobileNet uses symmetric padding layers for modelling temporal data that should not infringe on the temporal order. The padding layer is used for maintaining the original data of an image.
Conv2D layer: This implies that a convolution process is in three dimensions but the movement of the filters in an image occurs in 2 dimensions across the image. The Conv2D layer uses a convolved layer to create a Tensor Flow of outputs for the convolution Kernel. Keyword arguments should be inputted when the layer is used as a first layer in a model. A filter size of 3x3 was used for convolutional layer.
Batch Normalize layer: this layer is used as a part of the architecture for normalization of every training mini batch of the model. It enables the use of a higher learning rate. This can sometimes eliminate the process of dropout as it can act as a regularize.
ReLu layer: after batch normalization layer the ReLu layer follows. The ReLu activation layer for MobileNet comprises of a ReLu function. The ReLu function is non-linear and it makes computation efficient for fast network convergence. ReLu prevents activation from getting cumbersome.the work used filter size 2x2 for ReLu layer.
Depth wise Cov2D: the depthwise conv2D allows the first step of the model to be performed in a depthwise spatial

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resolve in the convolution upon each input channel independently. In depth wise it uses filter size 1x1.

Global-average: this collects the average of pools from each preceding convolutional layers to prevent over fitting found in fully connected layers. This is also implemented to reduce model size and increase the prediction speed of a model**.**

Dropout: this is a method used in deep learning for regularization. To also avoid over fitting in large networks the drop out technique ignores randomly selected neurons in a model during the training period.

Dense: this layer converts the features in an image into a single prediction for each image. It does not require the use of an activation function due to the raw prediction value used for prediction. Finally, images are classified into different classes.

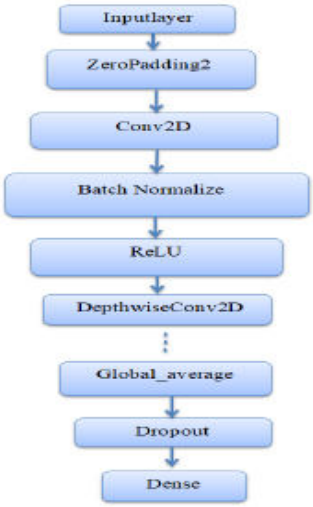

Figure 4: Traditional Block diagram of Mobilenet (CNN) architecture

The structure of MobileNet is built on depth-wise convolutions as mentioned in the previous section except for the first layer that is a full convolution.By defining the network in such simple terms it is easy to explore network topologies to find a good network.All layers are followed by a nonlinearity of batchnorm and ReLU except for the final fully connected layer that has no nonlinearity and feeds for classification into a softmax layer. Figure 4 contrasts a layer with regular convolutions, batchnorm and nonlinearity of ReLU with a factorized layer with convolution, 1 x1 point conversion as well as batch norm and ReLU after each convolution layer. Counting the convolutions in depth and point as separate layers, MobileNet has 93 layers.

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Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 224, 224, 3)	0
conv1_pad (ZeroPadding2D)	(None, 225, 225, 3)	0
conv1 (Conv2D)	(None, 112, 112, 32)	864
conv1_bn (BatchNormalization	(None, 112, 112, 32)	128
conv1_relu (ReLU)	(None, 112, 112, 32)	0
conv_dw_1 (DepthwiseConv2D)	(None, 112, 112, 32)	288
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conv_dw_13 (DepthwiseConv2D)	(None, 7, 7, 1024)	9216
conv_dw_13_bn (BatchNormaliz	(None, 7, 7, 1024)	4096
conv_dw_13_relu (ReLU)	(None, 7, 7, 1024)	0
conv_pw_13 (Conv2D)	(None, 7, 7, 1024)	1048576
conv_pw_13_bn (BatchNormaliz	(None, 7, 7, 1024)	4096
conv_pw_13_relu (ReLU)	(None, 7, 7, 1024)	0
global_average_pooling2d (Gl	(None, 1024)	0
dropout (Dropout)	(None, 1024)	0
dense (Dense)	(None, 7)	7175

Figure 5: Workflow of MobileNet

IV. RESULTS AND DISCUSSION

First, the different CNN architectures are tested in order to find an optimal MobileNet architecture for efficient skin cancer classification. The following sub-sections show the training and validation loss, and training and validation accuracy for different CNN 35 architectures. In the following graphs keep the same CNN layers but the epochs changed for each graph. Some are two layers, some are three layers but the accuracy increase when the number epochs increase.

Mobilenet (CNN) using five epochs with two layers

The following graph shows that the validation accuracy and validation loss of the trained networks. In Figure 6 two convolutional layers were used. Input layer image size 224x224, convolutional layer filter size 3x3, ReLU layer filter size 2x2, and depth convolutional layer filter size 1x1, batch normalization layer, zero padding layers, dropout layer and dense layer. In Figure 6 epochs with two convolutional layers was used and the validation with top 3 accuracy is 94. 43% in figure 4.3 c and our top 2 accuracy is 88.88% figure 4.3(b) and cat accuracy is 77.18% figure 4.3(a). Here Mobilenet use 3x3 size filter for convolutional layer 1x1filter size for deptwise layer.

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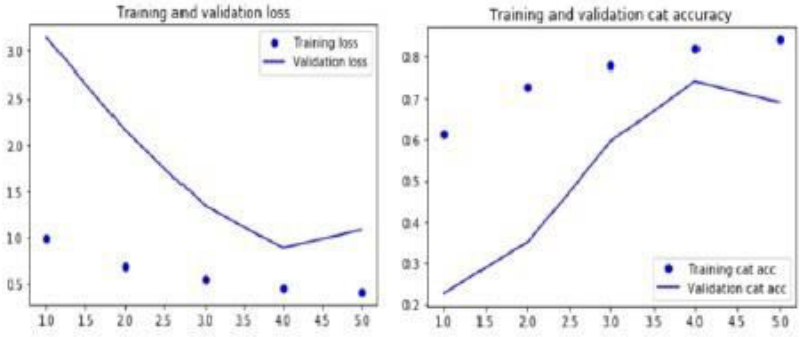
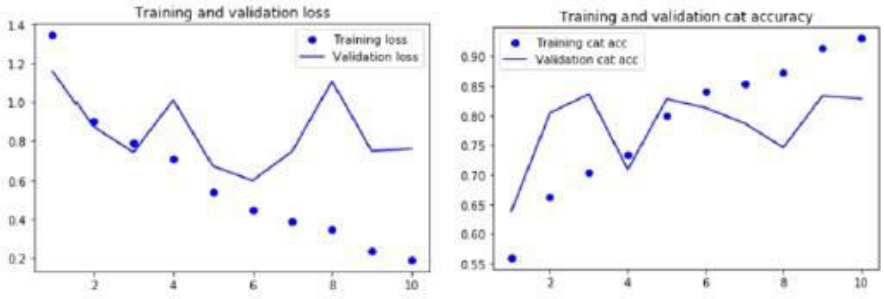


(a): training and validation to loss and cat accuracy

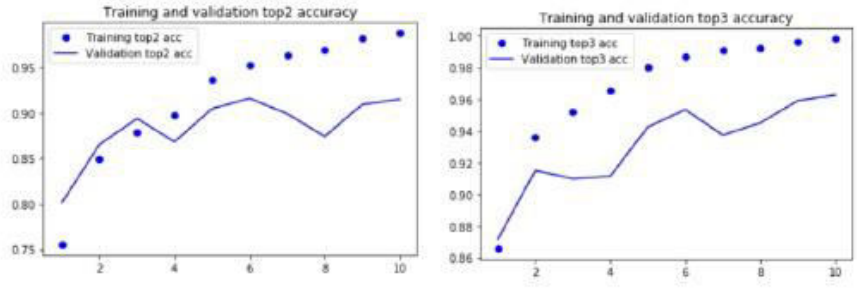
Fig-6 Epochs

MobileNet(CNN) using Three Layers with Ten Epochs

The following graph shows that the validation accuracy and validation loss of the trained networks. In Figure 7 three convolutional layers were used of input layer 224x224 pixel image, convolutional layer filter size 3x3 filter, ReLU layer filter size 2x2, depth convolutional layer filter size 1x1, batch normalization layer, zero padding layers, dropout layer and dense layer. In Figure 7 10 epochs with three convolutional layers were used and the validation with top 3 accuracy is 96. 26% in figure 4.3 c and the top 2 accuracy is 91.50% figure 4.3(b) and cat accuracy is 82.84% figure 4.3(a). Here Mobilenet use 3x3 size filters for convolutional layer 1x1filter size for deptwiselyer.



(a): training and validation to loss and cat accuracy



(b) : Training and validation of top2 (c) :Training and validation of top3

Figure .7: Training and validation loss and cat accuracy for MobileNet architecture with three layers and ten epochs

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V. CONCLUSION

The skin cancer incidences are intensifying over the past decades; the need of an hour is to move towards an efficient and robust automated skin cancer classification system, which can provide highly accurate and speedy predictions. In this study, we demonstrated the effectiveness of deep learning in automated dermoscopic multi-class skin cancer classification with the MobileNet model trained on a total of 38,569 dermoscopy images from HAM10000 dataset. We matched the performance of expert dermatologists across seven diagnostic tasks with an overall accuracy of 83.1% for seven classes in the dataset, whereas top2 and top3 accuracy of 91.36% and 95.34%, respectively. Also, the weighted average of precision, the weighted average of recall, and the weighted average of f1-score were found to be 89%, 83%, and 83%, respectively. We conclude that MobileNet model can be used to develop an efficient real-time computer-aided system for automated medical diagnosis systems. As compared to previously proposed models the MobileNet model has shown accurate and robust performance in addition to its faster and lightweight architecture. The future work may deal with the utilization of patient's personalized data such as genes, age, color in addition to the current study for skin cancer diagnosis. This additional feature can be advantageous to develop personalized computer-aided systems for the diagnosis of skin cancers.

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