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An Automated Approach for the Detection of Melanoma Skin Cancer

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ABSTRACT: Melanoma skin cancer is the most dangerous form of skin cancer and causes most of the deaths related to skin cancer. However, timely medical and clinical interventions can be administered to those diagnosed with melanoma in order to increase their chances of survival. Therefore, it is vital to detect melanoma in the early stages. In this work, we address the problem of detecting melanoma via a web application that uses a trained Convolutional Neural Network. The web application takes the dermoscopic image of a suspected skin lesion as input and outputs the class label i.e., either Benign (Non-Cancerous) or Malignant (Cancerous) of the lesion. The model that is deployed in the web application achieved an accuracy of 0.9588 and a validation loss of 0.3536.

KEYWORDS: Convolutional Neural Network (CNN), melanoma, web application, benign, malignant, dermoscopy, adam optimizer, transfer learning.

I. INTRODUCTION

Melanoma, the most serious type of skin cancer, develops in the cells (melanocytes) that produce melanin - the pigment that gives the skin its color. When some cells develop DNA damage, new cells may begin to grow out of control and can eventually form a mass of cancerous cells. Just what damages DNA in skin cells and how this leads to melanoma isn't clear, but exposure to ultraviolet (UV) radiation from sunlight or tanning lamps and beds increases the risk of developing melanoma. Limiting the exposure to UV radiation can help reduce the risk of melanoma. The risk of melanoma seems to be increasing in people under 40. Knowing the warning signs of skin cancer can help ensure that cancerous changes are detected and treated before the cancer has spread. Melanoma can be treated successfully if it is detected early.

Using traditional Machine Learning (ML) algorithms for classification gives comparatively less accuracy and requires Image Pre-processing and Feature Extraction before applying classification algorithms. But the problem with these traditional ML approaches is that the features selected as the basis for detection are already known and used by the clinicians. There may be some more features that are not yet discovered by humans but on which the melanoma may be detected.

So, the need of the hour is to develop a quick, efficient, robust, and cost-effective method for diagnosing Melanoma Skin Cancer. Our approach aims to build a web application that uses a CNN model at its core that can detect melanoma skin cancer in its early stages. The model used in the web application is built using transfer learning. The main objectives of our web application are:i) To classify cell images and identify skin cancer with a high degree of accuracy using Deep Convolutional Neural Networks ii)To provide an easy-to-use User Interface to input the skin lesion image in the web application.

II. RELATED WORK

In recent years the detection of melanoma skin cancer with the help of machine learning has turned into one of the highly researched topics. Various research papers have attempted to solve this problem through image analysis.

S.S Mane and S.V Shinde in [1] have compared five different techniques for melanoma skin cancer detection based on the different algorithms used for pre-processing, segmentation, feature extraction and classification of the lesion

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image. Adria Romero Lopez et al. in [2] presented a deep-learning based approach to classify an image as benign or malignant. Their solution used Transfer Learning and was built on the VGGNet Convolutional Neural Network architecture which was trained and tested on the ISIC 2016 challenge dataset. Yuexiang Li et al. in [3] proposed two deep-learning frameworks namely Lesion Indexing Network (LIN) and Lesion Feature Network (LFN) to solve three primary problems of skin lesion image processing namely lesion segmentation, dermoscopic feature extraction and lesion classification on the dermoscopic images that were collected from the ISIC archive.

T Yamunarani in [4] presented the ABCD technique for the classification of skin lesions based on four parameters i.e., A – Asymmetry, B – Border, C – Color, D – Diameter. A Total Dermoscopic Score (TDS) was calculated on the above parameters and based on the TDS value the lesion was classified as mole, benign or malignant melanoma. Lakshay Bajaj et al. in [5] presented an automated system for predicting five types of skin diseases namely Eczema, Psoriasis, Impetigo, Scleroderma, and Melanoma. The system amalgamated image processing and machine learning modules. The image processing module employed various filters such as grayscale filter, sharpening filter, median filter, smooth filter and RGB extraction. The machine learning module employed a feed forward Artificial Neural Network (ANN). Titus Joseph Brinker et al. in [6] presented a systematic review on the use of Convolutional Neural Networks (CNN) for the classification of skin lesions. In their study they categorized the use of CNN for lesion classification into two categories namely CNN as feature extractor and End-to-end learning.

L Sai Vineela et al. in [7] presented a methodology for image pre-processing, segmentation, and feature extraction of ABCD parameters to determine Total Dermoscopic Score (TDS) to classify the skin lesion as either benign or malignant. Vijaylakshmi M.M in [8] presented a completely automated system for the detection of melanoma skin cancer using lesion images. The system used a Support Vector Machine (SVM) for the core implementation and amalgamated it with image processing techniques such as hair removal, shading removal and glare removal. Gaana M et al. in [9] presented a machine learning model that classified the input lesion image into one of three categories namely benign, to be melanoma, and melanoma. The core model was built on a supervised machine learning algorithm namely Cubic Regression.

Mohammad Ali Kadampur et al. in [10] experimented with five different Convolutional Neural Network (CNN) models to assist in the prediction of melanoma skin cancer. These models were built using Deep Learning Studio (DLS) which is a model driven architecture tool which can be used to build CNN models by dragging and dropping suitable components from the dashboard. Mahamudul Hasan et al. in [11] proposed an artificial skin cancer detection system using image processing and machine learning. The features were first extracted from segmented dermoscopic images and a convolutional neural network was used for the stratification of the extracted features. K Young et al. in [12] presented two existing local interpretability models GradCAM and Kernel SHAP to analyze the convolutional neural network trained in the context of melanoma detection.

Yasuhiro Fujisawa et al. in [13] explained the approach of traditional machine learning algorithms and deep learning techniques in the context of skin cancer detection. JinenDaghrir et al. in [14] described a method using deep learning and machine learning to assist in the accurate diagnosis of melanoma skin cancer. The methodology consisted of three phases namely image pre-processing, segmentation and lesion classification. SVM classifier, KNN classifier and CNN classifier were used for lesion classification.

III. PROPOSED METHODOLOGY

A. *Data Set:*

In this work, we have used the publicly available dataset from Kaggle Platform titled ‘melanoma’ which are augmented dermoscopic skin lesions from the HAM10k dataset. The original data is the HAM10k images dataset, Human Against Machine with 10,000 Training Images, which is freely available. The dermoscopic images in the HAM10k dataset had been curated and normalized in terms of luminosity, colors, resolution, etc. The actual diagnosis was validated by histopathology (a.k.a. source of truth) in more than 50 percent of the cases, which is twice more than the previously available skin lesion datasets. The rest of the lesion's diagnosis was based on a consensus of dermatologists. Instead of trying to classify seven skin lesions with a highly imbalanced dataset, the task was simplified to the diagnosis of Melanoma vs. Not Melanoma. The dataset contained three directories for training, testing and validation. The training, test and validation directories were further divided into two directories – Melanoma and NotMelanoma, where the training folder contained 5341 images each, test folder contained 1781 images of Melanoma and 1780 images of NotMelanoma and validation folder also contained 1781 images of Melanoma and 1781 images of

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NotMelanoma. All images are of resolution 224 X 224. Since images are already sorted into Melanoma and Not Melanoma, the ground truth or actual class label of every image is pre-known.

B. *Overview of the Proposed Method:*

Figure 1 describes the architecture of the Melanoma Skin Cancer Detection Application. It mainly constitutes two blocks – Image processing and Machine Learning. In the Image processing, the skin lesion is given to the application as an input image, which is then resized to an appropriate size comprising the pre-processing phase. In the machine learning block, the Convolutional Neural Network (CNN) is trained on the HAM10K dataset to build the model and is then saved for later deployment. The pre-processed image is then provided to this model which classifies the image, and predicts it as 'Benign' or 'Malignant'.

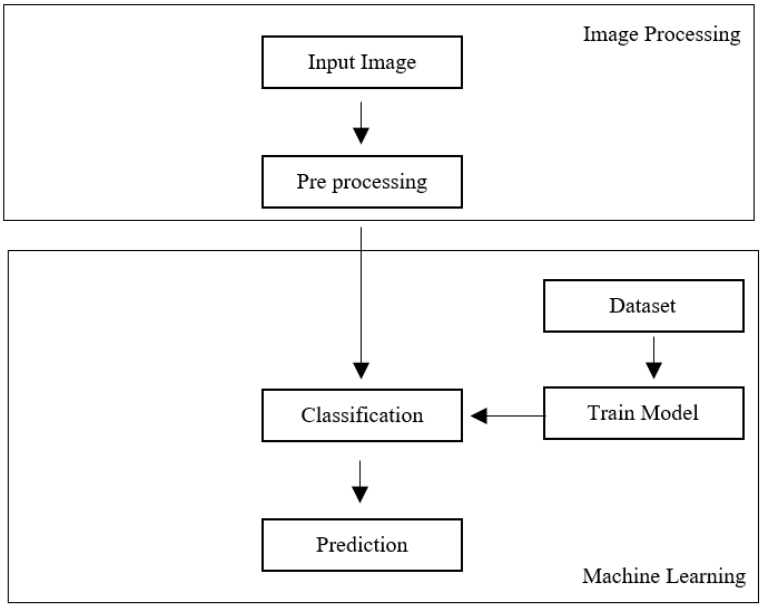

Fig.1.System Architecture

Image Pre-Processing: The skin lesion images are often characterized with noise and images that contain hair, bubbles and other factors that might lead to wrong prediction. Also, for unbalanced datasets, it is highly required to augment the images that are less in number so as to compensate for their fewer contributions to the trained model. Image pre-processing techniques like ColorJitter, Resize, Random Horizontal Flip and Random Rotation transformations are applied to the training set. The test set should not undergo any transformation and hence are left unaltered.

Training Model: The core idea of ResNet is introducing a so-called "identity shortcut connection" that skips one or more layers, as shown in the Figure. 2. The first step on the ResNet before entering the common layer behavior is a block - called here Conv1 - consisting of a convolution + batch normalization + ReLU operation. The next step is the batch normalization, which is an element-wise operation and therefore, it does not change the size of our volume.

The input image is converted to its equivalent Tensor using the transformations functions and then fed to the neural network model, which is ResNet in our case. We have developed one custom ResNet9 architecture and ResNet34 pre-trained model for comparison. The ResNet9 model was trained with 10 epochs. The ResNet34 model had a two step training process – 5 epochs for training the fully-connected layer of the model, and 10 epochs for training the entire model as a whole. The state of learned weights are then saved using PyTorch functions for deploying in the application. Figure 2 shows the ResNet basic block.

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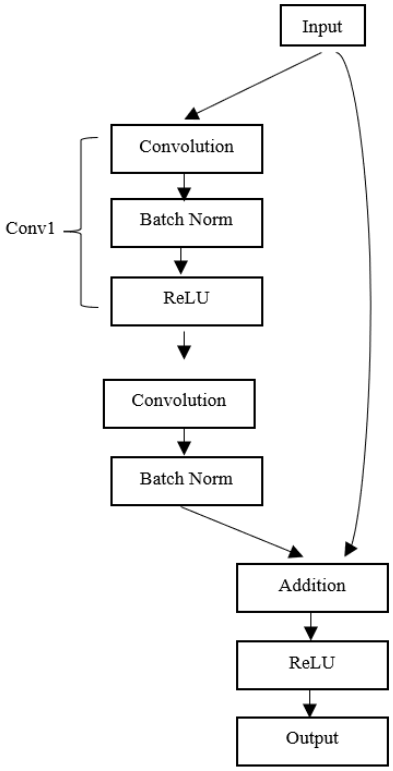

Fig.2.ResNet Basic Block

IV. EXPERIMENTAL RESULTS

We have trained two convolutional neural network models. We defined a custom architecture for ResNet9 by specifying the in features, out features, kernel size and padding to be used in each convolution layer. The other is the pre-trained ResNet34, available at PyTorchtorchvision models machine learning library.

Table 1 shows the values obtained for validation loss and validation accuracy when the pre-trained model ResNet34 was trained for epochs ranging from 1 to 10. The validation accuracy has increased with increasing epochs thereby improving the model performance.

Epochs	Validation Loss	Validation Accuracy
1	0.3594	0.9513
2	0.3608	0.9510
3	0.3629	0.9473
4	0.3634	0.9473
5	0.3637	0.9487
6	0.3656	0.9564
7	0.3571	0.9545
8	0.3591	0.9571
9	0.3539	0.9599
10	0.3536	0.9588

Table 1. Resultant values for the resnet34 model

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Figure 3 shows the variation of validation accuracy for ResNet34 plotted for increasing number of epochs. The graph shows that the accuracy of the model in the first epoch is 0.3594 whereas, its value reaches 0.9588 at the end of 10 epochs.

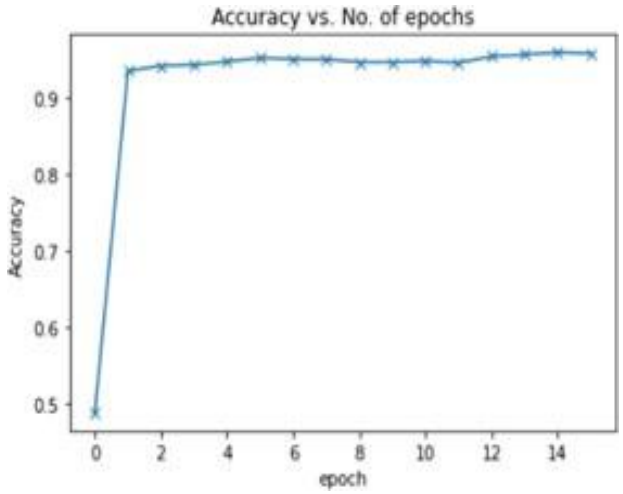

Fig.3. Graph plotted for accuracy v/s number of epochs for resnet34

Figure 4 shows the variation of loss for the train and validation sets with increasing number of epochs for the ResNet34 model.

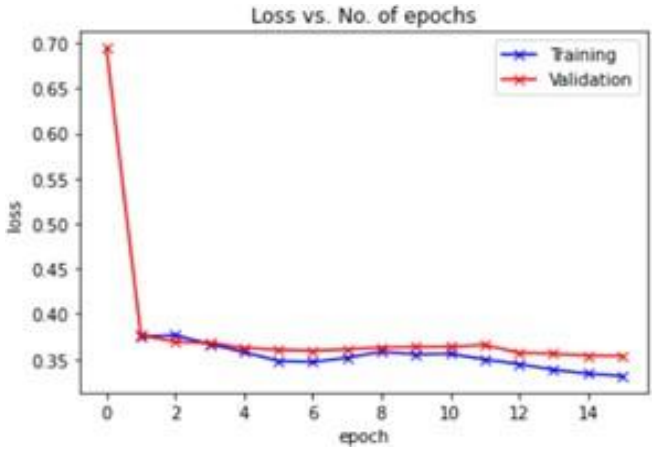

Fig.4. Loss v/s number of epochs for train and validation sets of resnet34

Table 2 shows the values obtained for validation loss and validation accuracy when the custom model resnet9 was trained for epochs ranging from 1 to 10. The validation accuracy has increased with increasing epochs thereby improving the model performance.

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Epochs	Validation Loss	Validation Accuracy
1	0.3210	0.8699
2	0.3476	0.8618
3	0.3671	0.8483
4	0.2143	0.9129
5	0.1479	0.9372
6	0.5406	0.7433
7	0.1497	0.9374
8	0.1444	0.9368
9	0.1355	0.9447
10	0.1328	0.9444

Table 2. Resultant values for the resnet9 custom model

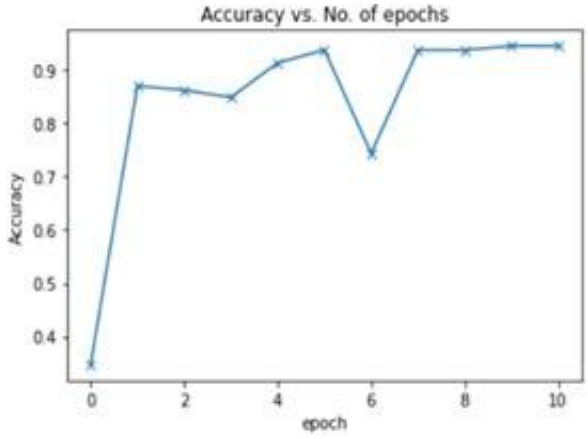

Fig.5. Accuracy v/s number of epochs for resnet9

Training the custom resnet9 model for 10 epochs has also given satisfactory results. At the end of the 10th epoch, the accuracy value has reached 0.9444 which is lesser compared to the pre-trained resnet34 model that had an accuracy value of 0.9588. Figure 5 and figure 6 shows the graphs plotted for accuracy v/s number of epochs and loss v/s number of epochs respectively.

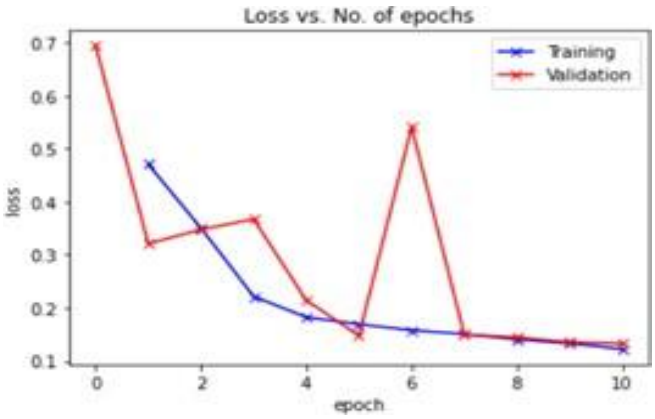

Fig.6. Loss v/s number of epochs for train and validation sets of resnet9

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On analyzing and comparing the results obtained for pre-trained model resnet34 and custom model resnet9, we have used the pre-trained model renet34 in the web application as it has better performance.

V. CONCLUSION AND FUTURE WORK

The system presents a solution for a fully automated melanoma detection application. The application presented shows how convolutional neural networks facilitate classification of skin lesions accurately, sometimes even better than dermatologists. The model implemented is tested and made accurate by considering several other pretrained models and their effective accuracy over the validation set and the best optimal one is selected for deployment. The simple Graphical User Interface (GUI) deployed makes it easier for the end user to work with the application.

The future scope of our work would be to train the CNN model on different publicly available datasets so as to make the model more efficient and robust. Also, our work is concerned with the detection of melanoma skin cancer. However, there are many different types of skin cancer such as Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), Merkel Cell Cancer etc., to name a few. Therefore, a new model could be trained to perform multi-class classification so as to assist the dermatologists to detect other types of skin cancer as well.

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