Melanoma Detection using CNN

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Abstract* – Skin is the largest organ of the body. It is exposed to a lot of harmful environmental threats. This leads to so many diseases one among then is the lethal skin cancer. Skin cancer is the abnormal growth of skin cells which turns into black coloured lesions. Melanoma is the most serious type of skin cancer which produces the melanin, this results into black lesions. These lesions can be detected by our naked eyes but for more medical efficiency the doctors use a device called dermoscope. Dermoscope is a non-invasive, in vivo technique primarily used for examination of lesions. In this project, we have developed a model which identifies melanoma automatically using the Convolutional Neural Network (CNN). This CNN model will be developed in Python using Keras and Tensorflow in the backend. The model is developed and tested with different network architectures by varying the type of layers used to train the network including Convolutional layers, Pooling layers. The model will be tested and trained on the dataset collected from the International Skin Imaging Collaboration (ISIC) challenge archives. The proposed system gives 89% accuracy for multiclass classification model using a custom convolutional neural network model in tesnerflow.

***Keywords* – Deep learning, CNN, Rel-U.**

I. INTRODUCTION

Melanoma is one of the deadliest type of skin cancer that exists. There are so many factors which leads to Melanoma, the primary ones include exposure to UV rays, poor immune system, rare genetic conditions, a history of affected family member and others. Melanoma develops in our skin cells called melanocytes. It starts when the healthy cells begin to grow out of control, creating a cancerous tumor. It can affect any area of the human body as the entire body is covered with skin. It usually appears on the areas exposed to sun, such as on the hands, face, neck, lips, etc. If this is not diagnosed in the early stages the mortality rate reduces to less than 20% where as in early detection the mortality rate is 95%. Melanoma can be cured if diagnosed early, else they spread to other body parts and leads to death.

Dermatoscopy is a non-invasive device which is used for early detection of melanoma. It has higher accuracy than the naked eyes. But is not possible to totally rely on the perception and vision to detect melanoma lesions, even if an experienced dermatologist performs dermoscopy. So computer aided analysis is used which improves the efficiency and objectivity of dermoscopy images. However, due to insufficient training samples and blurred images and their blurry boundaries of the lesions, the lesions of different subjects show significant difference in shapes, location of the lesion and also color interference with segmentation task. Along with these a large number pf artifacts which include inherent characters of skin such as blood vessels, hair, birthmarks and burn marks and artificial artifacts such as uneven lighting, ruler marks, air bubbles, incomplete lesions, etc. makes the task of

In recent years, convolutional neural network is widely used in medical image processing, especially for medical image segmentation. Convolutional Neural Network (CNN) is used for image classification tasks which is a feed-forward neural network. CNNs can recognize a wide variety of objects even when they are presented in a different ways, as it understands translation invariance. This is the main advantage of CNN over feed-forward neural networks which does not understand translation invariance.

The Convolutional Neural Network mimics the brain in the recognition of images. The effective type of image classification can be done by feature extraction according to machine learning tasks. Before the implementation of CNN, the experts used a hand-crafted feature-extraction tools for the digitalized image processing. The CNN model now performs the task of feature extraction automatically during the training phase with multilayers of convolutional layer and pooling which are sandwiched. In the convolution layer, different types of dynamic alters are used that train according to the classification that is done during the training phase. In the same manner, pooling layers retains both the size and shape of invariant features by reducing the dimension of the input image. This is achieved by down sampling the neighboring pixels into a single pixel. When we compared CNN to the feed-forward network, a CNN is less denser and can easily be trained.

II. LITERATURE SURVEY

The paper [2] throws a light on attaining highly segregated and potentially general tasks against the finely grained object categorized, deep convolutional neural networks (CNNs) are used. In this paper, they propose anew prediction model that classifies skin lesions into benign or malignant lesions based on a novel regularizer technique. Hence, this is a binary classifier that discriminates between benign or malignant lesions. The proposed model achieved an average accuracy of 97.49%, which in turns showed its superiority over other state-of-the-art methods. The performance of CNN in terms of AUC-ROC with an embedded novel regularizer is tested on multiple use cases. The area under the curve (AUC) achieved for nevus against melanoma lesion, seborrheic keratosis versus basal cell carcinoma lesion, seborrheic keratosis versus melanoma lesion, solar lentigo versus melanoma lesion is 0.77, 0.93, 0.85, and 0.86, respectively. The results showed that the proposed learning model outperformed the existing algorithm and can be used to assist medical practitioners in classifying various skin lesions.

In research paper [4], using the ISIC dataset for the conditions of skin cancer and skin benign tumors, an automatic skin disease classification system was developed based on deep learning with PNASNet-5-Large architecture which gives the best performance accuracy of 76%. Furthermore, other studies using CNN for the detection of skin diseases the CNN method with random regulators gave performance accuracy of 97.49% to distinguish some lesions of skin disorders such as nevus lesions, carcinomas, and melanomas.

In paper [3] analyzing the primary research questions remains important for a systematic review. The analysis procedure involves designing the search strategies to find and extract relevant studies after defining the research questions. The answers to these questions fetched through the published literature, according to the methodology suggested by Kitchenham. The fundamental purpose of this study was to summarize the current, state of the art techniques for melanoma detection in the context of CNN-based models. The research questions were formulated to evaluate the importance of the study.

In paper [6], the method of segmentation before recognition can make the model make better decisions based on the lesion area, but the good recognition effect depends largely on the accuracy of the segmentation network, and due to the classification network has certain requirements on the resolution of input image, result in the input image size of segmentation network is too large, which also puts forward higher computing resources and unsuitable for mobile end design requirements. Furthermore, with limited training data, it is difficult for us to fully excavate the discriminative ability of the lightweight deep learning network.

In paper [1], Convolutional Neural Network (CNN) is a development of the Multilayer Perceptron (MLP) which is designed to process two-dimensional data. CNN is included in the type of Deep Neural Network because it has a high network depth and has been widely applied to image data.

The purpose of this paper [7] is to present an automatic skin lesions classification system with higher classification rate using the theory of transfer learning and the pre-trained deep neural network. The transfer learning has been applied to the Alex-net in different ways, including fine-tuning the weights of the architecture, replacing the classification layer with a SoftMax layer that works with two or three kinds of skin lesions, and augmenting dataset by fixed and random rotation angles. The new SoftMax layer has the ability to classify the segmented color image lesions into melanoma and nevus or into melanoma, seborrheic keratosis, and nevus. The performance of the proposed method has outperformed the performance of the existing.

In paper [10], Computer Aided Diagnosis and Detection Systems have been developed in the past for this task. They have been limited in performance due to the complex visual characteristics of the skin lesion images which consists of inhomogeneous features and fuzzy boundaries. In this paper, they propose a deep learning-based method that overcomes these limitations for automatic melanoma lesion detection and segmentation. An enhanced encoder-decoder network with encoder and decoder sub-networks connected through a series of skip pathways which brings the semantic level of the encoder feature maps closer to that of the decoder feature maps is proposed for efficient learning and feature extraction. The system employs multi-stage and multi-scale approach and utilizes SoftMax classifier for pixel-wise classification of melanoma lesions.

In paper [9] deep neural networks play a significant role in skin cancer detection. They consist of a set of interconnected nodes. Their structure is similar to the human brain in terms of neuronal interconnectedness. Their nodes work cooperatively to solve particular problems. Neural networks are trained for certain tasks; subsequently, the networks work as experts in the domains in which they were trained. In our study, neural networks were trained to classify images and to distinguish between various types of skin cancer. Different types of skin lesion from International Skin Imaging Collaboration (ISIC) dataset are presented.

In paper [5], Artificial intelligence (AI) algorithms focus primarily on the injury image for which they were designed. Although the evaluation of the surrounding tissue is not necessarily a predictor of the disease, it is key when making a diagnosis and, in some cases, establishing a prognosis. In the case of act in keratosis, chronic exposure to ultraviolet light causes damage to the tissue surrounding the main lesion, however, a human inspector still focuses on the main lesion, leaving aside this peripheral damage, which would improve the frequency of correct diagnoses by 32.5%. In the case of melanoma, there may be involvement of the surrounding tissue, manifesting with metastatic lesions in transit, which are of poor prognosis or with satellite lesions that are locoregional cutaneous manifestations of dissemination because of embolization of tumor cells between the primary tumor and the regional lymph node; therefore, these lesions are highly predictive of lymphatic invasion and predict the development of disseminated disease.

In paper [8], The proposed dermoscopy image lesion area segmentation method includes three steps: image pre-processing, model construction and model training, and model fusion. Image pre-processing is mainly to augment the original training set to alleviate the overfitting of the model; model construction and model training mainly includes build a lightweight encoder, standard decoder, pre-training weight loading under the U-Net architecture, and model training based on mixed loss function, it is mainly used to reduce the number of parameters of the model while maintaining a high model segmentation accuracy, the related flowchart.

III. OBJECTIVES

- To build a Multiclass classification model using a custom convolution neural network in Tensorflow.
- To create a new technology in the field of melanoma diagnosis.
- To predict melanoma in early stages.

IV. METHODOLOGY

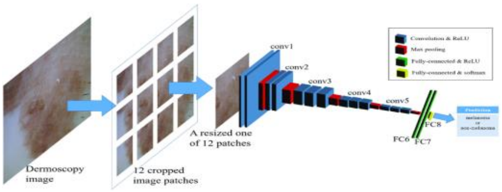

Figure 1: Architecture of the system

A dataset of about 2357 images of skin cancer types are taken from the ISCI dataset. The dataset contains 9 sub-directories in each train and test sub-directories. The sub-directories contain the images of 9 skin cancer types respectively. We use 80% of the images for training and 20% for validation. Using seed=123 while creating our dataset using keras preprocessing. Now resizing our images to a designated height and width.

The image_batch is a tensor (32, 180, 180, 3). This is a batch of 32 images of shapes 180x180x3 (RGB color channels). The label_batch is a tensor of the shape (32), these are corresponding label to the 32 images.

Creating a CNN model, which can accurately detect the 9 classes present in the dataset. We choose an appropriate optimizer and loss function for model training. We created three models in CNN and improvised each model to give better accuracy than the previous one. In the first model there was a problem of over-fitting with the accuracy of 81%. The training and validation accuracy for first model, training accuracy of 92% and validation accuracy of 54% after 20 epochs.

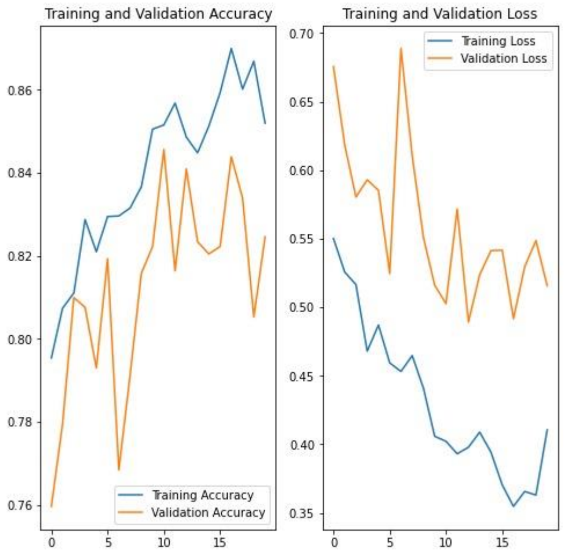

Figure 2: The graph showing the training accuracy and validation accuracy of model 1

In real life datasets can have class imbalance, one class can have proportionately higher number of samples compared to the others. Class imbalance can have a detrimental effect on the final model quality. Hence as a sanity check it become important to check what is the distribution of classes in the data. To overcome this situation we started working on our second model using a python package known as Augmentor to add more samples across all classes so that none of the classes have very few samples. Augmentor has stored the augmented images in the output sub-directory of each of the sub-directories of skin cancer types. Let us take a look at total count of augmented images. Training the model on the data created using Augmentor. The training and validation accuracy for second model, training accuracy of 57% and validation accuracy of 55% after 20 epochs. This shows we have come over the overfitting now.

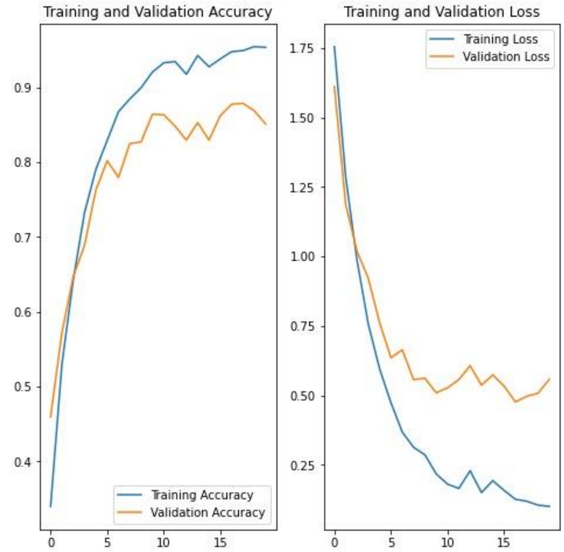

Figure 3: The graph showing the training accuracy and validation accuracy of model 2

We constructed a third model where we improved the accuracy. It contains the convolutional layer and max-pooling techniques. We also used a dropout layer. After the execution of this model, we got the accuracy of over 89% and also there were no chances of overfitting. Hence we finalized this model as it gave all the desirable solution for our problem and also covered the objectives which are stated.

Design of the system

The following are the techniques used in our project:

Skin Lesion Segmentation

The purpose of skin lesion segmentation is to find the borders or the boundaries of the lesion. One of the major risks faced in Melanoma detection is performing the accurate segmentation of skin because many skin features imposes faulty detection of the cancerous melanoma cells which is based on the border detection. We have found an approach to find the lesion border in a texture distinctiveness-based manner.

Convolution layer

In this layer, the convolution process occurs which is the main underline for the CNN. It is the first layer that processes the image as an input system model. Feature map is the extraction of the features from the input image, this is possible because of a convolution with a filter to extract it.
Figure 4 shows the convolution process.

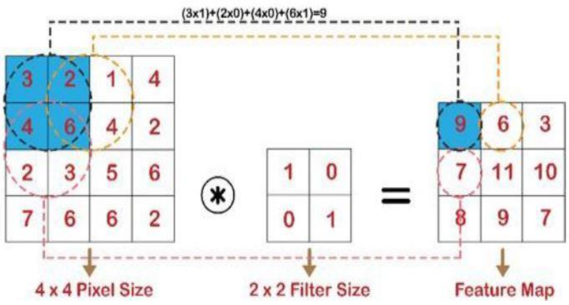

Figure 4: Illustration of convolution process

Pooling

Pooling layers in this method is put right after convolutional layers, the major advantage of using the pooling layer is it can progressively reduce the size of the output volume on the Feature Map so that it can control over-fitting. There are two types of pooling, max-pooling and mean-pooling. The max-pooling selects the max value from the confusion matrix whereas the mean-pooling takes the average value of the confusion matrix. Figure 5 shows the pooling process both max-pooling and mean-pooling.

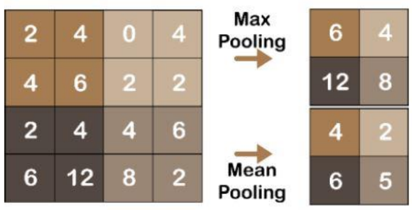

Figure 5: Pooling Process

Max pooling is a discretization process. It applies NxN max filter over the image, it selects the highest pixel value in each stride and it builds the feature map. Figure 6 shows the max-pooling process.

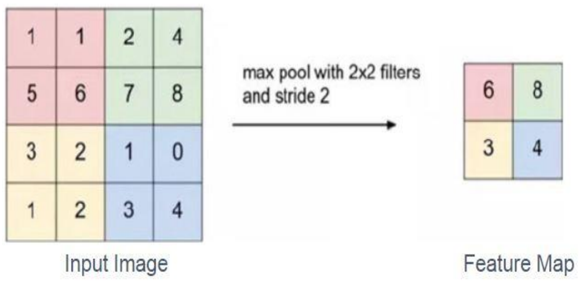

Figure 6: Illustration of Max polling

Rectified Linear Unit

ReL-U (Rectified Linear Unit) is an activation layer used in CNN which minimizes the errors and also increase the training stage on neural network. ReL-U is used as an activation which makes all pixel values to zero when a pixel image has a value runs in negative values.

Flattening

The flattening is a technique where the obtained feature map is feed into the neural network. For processing the images we consider a single column vector of image pixels.
The feature maps are flatten into columns like vector. Figure 5 shows the flattening technique.

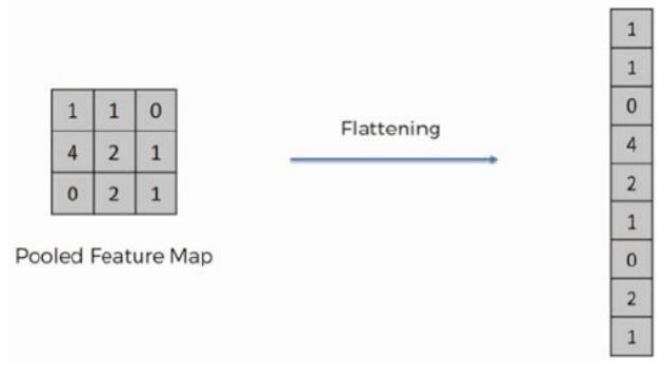

Figure 5: Flattening operation

Fully Connected Layer

The Fully Connected Layer is the layer which was used at the end of the architecture. It uses the multi-layer perceptron. This layer connects all the neurons of that were used in the previous activation layer. The flatten process takes place in this layer. All the neurons in the input layer are converted into one-dimensional data.

IV. RESULTS

We made a model which helps in effectively separates other malignant growth cells .The datasets which we considered contained various sort of dermoscopy images which are ordered as melanoma cells after the proposed model is applied.

We have also proposed three different computer-based models for melanoma cancer diseases determination. Accessing their validation , training accuracy and diagnostic performance results requires a strong and dependable assortment of dermoscopic images. Different skin cancer datasets have lacked size and variety other than for pictures of nevi or melanoma lesions. Training of convolutional neural networks for skin lesion classification is hampered by the small size of the datasets and a lack of diverse data. In spite of the fact that patients commonly suffer from a variety of nonmelanocytic lesions, past exploration for automated skin malignant growth finding principally centered around diagnosing melanocytic lesions,resulting in a limited number of diagnoses in the available datasets .Hence , the accessibility of a norm , solid dataset of dermoscopic images is exceptionally significant. Real-world datasets for the evaluation of proposed skin malignant growth discovery procedures.

CONCLUSION

The results achieved with the proposed model suggests a significant improvement over the results obtained in the state of the art as far as perfoemance of skin lesion classifiers is concered , the proposed model is promising to use as an current apparatus for clinical staff in deciding the diagnosis of skin cancer which is melanoma.The frameworks can be created for characterize the melanoma type of skin cancer.

Skin cancer detection requires multiple stages , such as pre-processing and image segmentation , followed by feature extraction and classification. We propose a detection method to naturally preceives skin cancer and segmentation skin lesion area present in dermoscopy images, simultaneously, we have completed a wide range of examinations to testing the viability of the proposed strategy.

In this study, a programmed framework was designed to characterize the states of actinic keratosis, basal cell carcinoma, dermatofibroma, nevus, pigmented benign keratosis, seborrheic keratosis, squamous cell carcinoma, vascular lesion and melanoma based on dermoscope image processing. CNN gives better results than othe rtypes of neural networks whuThe CNN model used in this study consists of 3 hidden layer and ReLU activation function , which can accurately detect 9 classes present in the datasets.

To restate, this process was conducted with the aim of developing a deep convolutional neural based architecture for robust detection and segementation of melanoma lesions.This architecture adopts an enhanced deep convolutional network that is interconnected with series of skip pathway.We also investigated data augmentation techniques as a pre-processing step to improve the reliability of CNN pattern classification.
In this approach , the whole network is divided into stages, with each stages handling different section of features learning and extraction.

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