MELANOMA SKIN CANCER DETECTION USING IMAGE PROCESSING

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ABSTRACT

Melanoma is the most dangerous type of skin cancer. It originates in the cells (melanocytes) that create melanin, the pigment that gives your skin its color. Melanoma can also develop in the eyes and, in rare cases, inside the body, such as the nose or throat. Melanoma risk can be reduced by limiting your exposure to UV light. We've used image processing with convolutional neural networks (CNN) to detect such cancer. In this paper we've used ISIC dataset to support our research. The skin image is the input to the process and then we apply various image processing techniques in which use of convolutional neural networks is a part to extract the features of the image and thereby detect whether the image is of normal skin or melanoma cancer lesion.

Index Terms— *Melanoma, Lesion, Convolutional neural network, Deep learning.*

1. INTRODUCTION

Melanoma is the most hazardous of the three fundamental kinds of skin cancer, namely Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), and Melanoma, with an extremely low survival rate. Melanoma can be detected early, which may increase the chances of survival [1]. Melanoma can be cured if detected and treated early on; but, if detected later, melanoma can spread deeper into the skin and to other regions of the body. Its spread to other sections of the body, which is difficult to cure, can be dangerous. Melanoma is caused by the presence of Melanocytes in any portion of the body. Melanoma is caused by prolonged exposure to UV light on the skin.

Dermoscopy is a non-invasive skin inspection procedure that uses incident light and oil immersion to allow for a visual examination of the skin's subsurface structures. Though dermoscopy has a better rate of melanoma detection than unaided observation3, its diagnostic accuracy is dependent on the dermatologist's training. Melanoma from melanocytic nevi is difficult to diagnose, especially in the early stages. As a result, physicians require an automatic diagnosing tool. The accuracy of melanoma diagnosis is believed to be 75-84 percent even when skilled dermatologists employ dermoscopy for diagnosis. 4 Computer-assisted diagnostics can help improve the accuracy and speed of diagnosis [2].

In this paper, we use four different phases. Picture preprocessing, which comprises hair removal, de-noise, sharpening, and resizing of the given skin image, and segmentation, which is used to segment out the region of interest from the given image, are the four essential components of skin cancer detection technology. Segmentation can be done in a variety of ways. K-means, threshold in histogram, and other segmentation methods are extensively employed, as are features extraction from the segmented picture and image classification using the features set collected from the segmented image. This can be accomplished using a variety of categorization techniques. The categorization algorithms of modern skin cancer detection technology are based on machine learning and deep learning. Support vector machine (SVM), feed forward artificial neural network, and deep convolutional neural network are the most often used classification techniques [1].

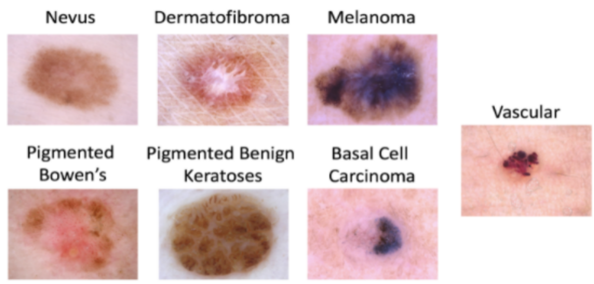

Figure 1: Different types of skin cancer

2. Related Work

Many researches have been done in context of medical imaging. Various algorithms have been implemented using image processing , artificial neural networks and machine learning techniques which involves several steps including its preprocessing, segmentation, classification etc

Sanjay J et al. [8], described various techniques to preprocess the dermatoscopic images, using image resolution, equalizing illumination, and color range normalization. Anitha J et al. [9] segmented image using otsu thresholding, where the focused region is separated by comparing pixels against a threshold value and changing them to 0 or maximum.

Alquran H et al [10] in their studies about skin cancer detection, classified the data using a supervised non-linear machine leaning algorithm called Support Vector Machine. They collected, preprocessed, and segmented the data, and extracted the features using GLCM and ABCD rule. Also, they selected the most expressive features using Principal Component Analysis (PCA) and resulted in classification accuracy of 92.1% with SVM.

Deep learning techniques are considered among the best for solving complex and large datasets. One method is the Kohonen self-organizing map which consists of only two layers. Said et al. [11] suggested a system deployed with a median filter, extracted statistical features and KNN, categorized data as cancerous or noncancerous with accuracy of 98.3%.

Pomponiu V et al [12] suggested another deep learning approach with a Convolutional Neural Network for classifying the image data. CNN architecture involved five convolutional layers, pooling layers and three fully connected layers. It all gave two-class classification of accuracy 93.64%. Therefore, following these studies, we proposed a model which will be discussed in several sections of report.

3. METHODS OF SKIN CANCER DETECTION

Skin cancer detection using image data involves a series of steps which are explained in this section. The implementation of all processes is done using python and various extended machine learning built-in libraries such as TensorFlow, keras, scikit, etc.,

4.1 IMAGE ACQUISITION

Image dataset used for this project is skin cancer data from 'Skin cancer ISIC The International Skin Imaging Collaboration' , which has separate 'Train' and 'Test' dataset.[3] The data has 9 classes, each defining a unique type of skin cancer., namely, 'Actinic keratosis', 'Basal cell carcinoma', 'Dermatofibroma', 'Melanoma', 'Melanotic nevus', 'Pigmented benign keratosis', 'Seborrheic keratosis', 'Squamous cell carcinoma' and 'Vascular lesion'. Among them, melanoma is considered as the deadliest form of skin cancer. The data has been modified and consists of 2310 training images and 250 validation images. ISIC dataset is an international repository which has dermoscopic images for clinical training as well as technical research of cancer detection.

4.2 IMAGE PREPROCESSING

In this section, all the preprocessing techniques applied on bunch of images are described below in detail.

4.2.1. Grayscale Conversion: A technique to convert colored images or RGB data to shades of gray whose values lies between the pixel value of 0 and 1 [5]. It decreases the dimensionality of data which further reduces the computational cost, the complexity and is also supported by many built-in libraries. It can be calculated as,

$$Grayscale = 0.299R + 0.587g + 0.114B$$

Where, R, G and B represents the red, blue and green pixel values.

4.2.2. Image Denoising: A process of retrieving the original and useful information from image data by removing the random noise generated while acquisition and processing of data. There are linear and non-linear spatial filters available for de-noising. A non-linear median filter has been applied in our work . Median filter is a sliding-window filter which replaces the pixel value at center with computed median of all pixel values present in that specific kernel window. [6] It can be computed as,

$$S(i,j) = \text{Median}_{(k,l) \epsilon W_{m,n}}\{D(i+j,k+l)\}$$

Where, $W_{m,n}$ is sliding window size, m×n pixels, i and j are the center coordinates.

4.2.3. Hair/bubble Removal: As, the name depicts those hairs will be removed from the images aslesion identification can be obscured by presence of hair or bubble pattern in the image data. They act as obstacles to segmentation process for computed-based diagnosis. Here, opening operation is used to detect small object on the outer surface of image and remove that noise whereas, closing operation can close small holes or fill those small holes inside the foreground surface. Using these two operations of morphology, hairs has been removed from image.

4.2.4. Contrast Enhancement: This is an essential step to add quality to the image. It visualizes the information that is present in low dynamic range of grayscale image. As it is visible that in previous steps due to application of various filters, the image quality has been compromised which will be improved through contrast enhancement technique. Therefore, adaptive histogram equalization is implemented to improve the image quality. This is digital technique of image processing which enhances the contrast locally by dividing the image into separate sections and then, computing their histogram equalization. It also preserves the edges of different sections of image. The algorithm for AHE is represented in Figure 2. [4]

```
AHE Algorithm

for each (x,y) in image do
{
    rank = 0
    for each (i,j) in contextual region of (x,y) do
    {
        if image[x,y] > image[i,j] then
            rank = rank + 1
    }
    output[x,y] = rank * max_intensity / (# of pixels in contextual region)
}
```

Figure 2: AHE algorithm

4.3. IMAGE SEGMENTATION

In image segmentation, a digital image is divided into various segments . It assigns labels to those segments or pixels which reduces complexity. The pixels of same category will have same label and will be separated from other pixels of different label. In this way, it will display at the shape of particular object in image. For image segmentation, various techniques are used but, in this implementation, Otsu thresholding method is used with certain threshold. This thresholding classifies the image pixels into two categories , one which belongs to object and other that belongs to background of image . [5] **Otsu** algorithm exhaustively looks for the suitable threshold that has minimum intra-class variance , where weighted sum of variance is calculated for both classes.

$$\sigma_{\omega}^2(t) = \omega_0(t) + \omega_1(t)\sigma_1^2(t)$$

$\omega_{0,1}(t)$ can be computed from L bins of histogram as,

$$\omega_0(t) = \sum_{i=0}^{t-1} p(i)$$

$$\omega_1(t) = \sum_{i=t}^{t-1} p(i)$$

As, minimizing and maximizing the intra-class variance are equivalent to each other, therefore, it can be written as,

$$\sigma_b^2(t) = \sigma^2 - \sigma_{\omega}^2$$
$$= \omega_0(t)\left(\mu_0 - \mu_T\right)^2 - \omega_1(t)\left(\mu_1 - \mu_T\right)^2$$
$$= \omega_0(t)\omega_1(t)\left(\mu_0(t) - \mu_1(t)\right)^2$$

Then class means $\mu_0^{(t)}$, $\mu_1^{(t)}$ and μ_T are calculated as follows,

$$\mu_0(t) = \frac{\sum_{i=0}^{t-1} ip(i)}{\omega_0(t)}$$

$$\mu_1(t) = \frac{\sum_{i=t}^{L-1} ip(i)}{\omega_1(t)}$$

$$\mu_T = \sum_{i=0}^{L-1} ip(i)$$

This provides following relation between class means and probabilities which will be computed iteratively until the optimal threshold is achieved.

$$\omega_0\mu_0 + \omega_1\mu_1 = \mu_T$$

$$\omega_0 + \omega_1 = 1$$

So, in Otsu thresholding , the probabilities and histograms are computed at each intensity level. The probabilities and mean are initialized which are iterated till maximum intensity and updated which calculates the intra-class variance.

4.4. FEATURE EXTRTACTION

The features in our implementation are the pixel values of image which are 0 and 1, representing black and white in image processing. Different pixels and their values will help the classification network to identify the image and detect the presence of different cancer lesions. Although, there are different methods used for feature extraction namely, 2D wavelet transform method, Grayscale co-occurrence matrix, etc., but depending upon the type of our data and the previous filters applied, these methods will not provide any useful information. So, the image with their two pixel values at different pixels are fed into image classifier.

4.5. IMAGE CLASSIFICATION

The final step is image classification. This is a supervised machine learning algorithm where input data is classified into different categories depending upon the features of data. It is a task of assigning labels images to two or more classes. Advanced deep neural networks have been a great contributor to image classification which brough various efficient networks providing great accuracy such as CNN, Inception, GoogleNet, Resnet50, etc. Convolutional Neural Network is implemented and will be discussed in this report.

Deep Convolutional neural network is a combination of various convolutional and pooling layers especially, designed for image classification with large dataset. They provide better performance than simple artificial neural network and classifies well. It can work with n-dimensional data. Also, they are able to learn basic filters automatically and combine them hierarchically for pattern recognition. Convolutional neural networks are composed of multiple layers of artificial neurons(mathematical functions that calculate the weighted sum of multiple inputs and outputs with an activation value) .Once image is input into model, each layer generates several activation functions that will be carried on to the next layer, where the first layer usually extracts edges. In these networks, a filter is applied to an input in order to create a feature map which detects features presence in the input. The whole deep Convolutional network consists of various layers of convolution and pooling, which are then flattened and fed to fully connected dense layers.

5. EXPERIMENT

The different phases of skin cancer detection have been implemented in the following manner and their respective results are discussed as well.

5.1. Image Acquisition: The original images of ISIC dataset are shown in Figure 3. It has image of 9 different classes and their respective names.

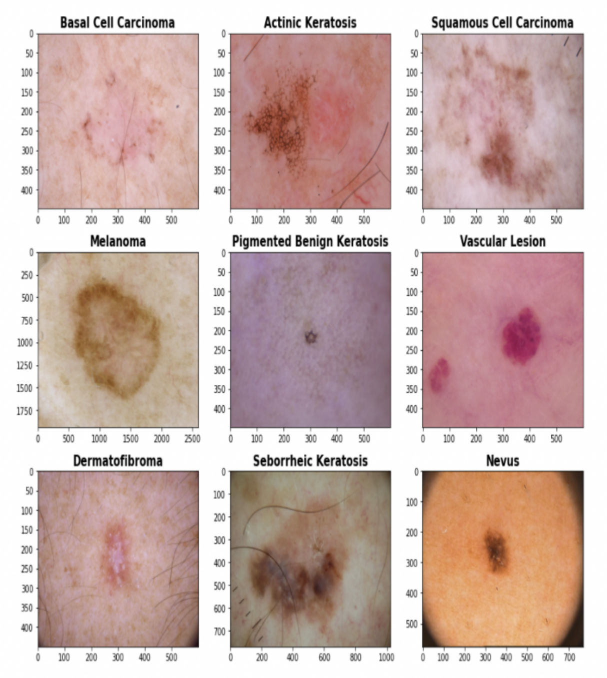

Figure 3: Different classes of images with names

5.2.1. Grayscale conversion: Here, three channeled images with different RGB values has been converted to 1 channeled image. In this implementation, OpenCV library has been used for grayscale conversion and, the image has been then resized to pixel size of . The converted images are displayed in Figure 4.

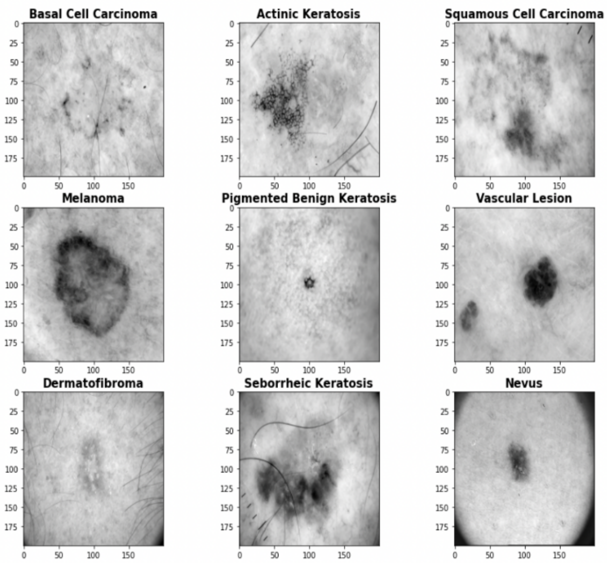

Figure 4: Converted image

5.2.2. Image denoising: The resultant images after applying median filter with function named **cv2.medianBlur()**, are displayed in Figure 5. Here, the excessive noise has been removed and clean image is obtained.

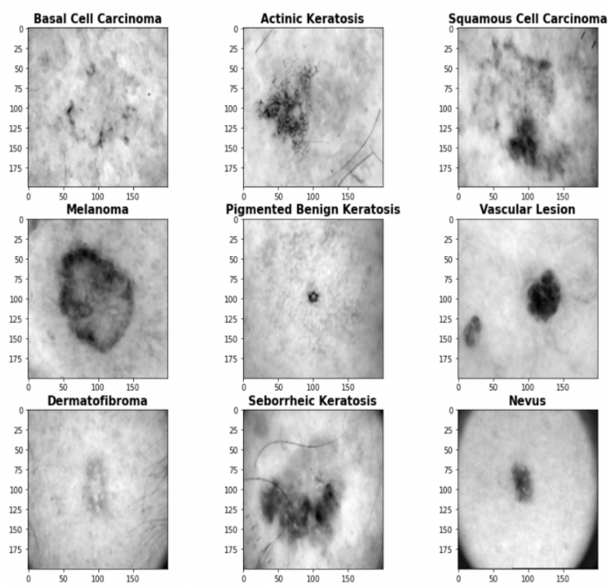

Figure 5: Resultant image after applying median filter

5.2.3. Hair/Bubble Removal: The function called **cv2.morphologyEx(i,cv2.MORPH_CLOSE,kernel, iterations = 2)** is used in our implementation, with kernel size of 3. The image representation after hair removal is shown in Figure 6, which removed unnecessary hair noise from the image.

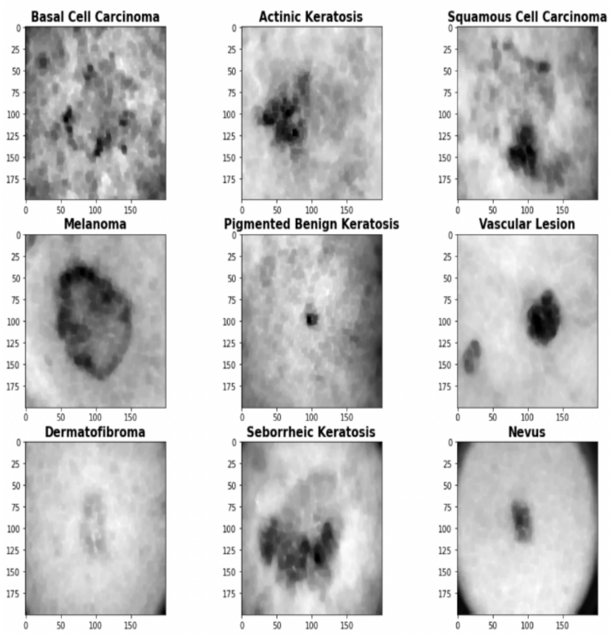

Figure 6: Resultant image after hair removal

5.2.4. Contrast Enhancement: Function used to implement adaptive histogram equalization is **skimage.exposure.equalize_adapthist().** In Figure 7 , the edges are clear in comparison to Figure 6. The hidden structure of image is also visible and image quality is enhanced which will turn out to be effective in segmentation process of image.

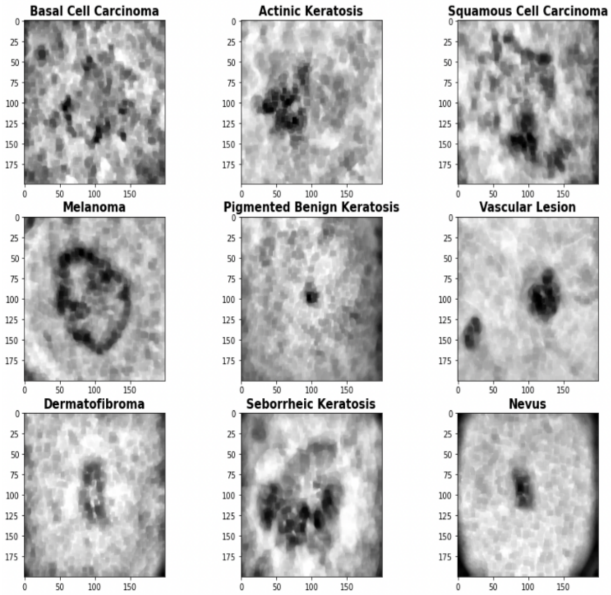

Figure 7: Contrast Enhanced image

5.3. Image Segmentation: In this part, Otsu thresholding method is implemented using function **filters.threshold_otsu(image),** on which certain threshold is applied . The output image is shown in Figure 8, where the useful information of shape and structure for lesion detection is extracted.

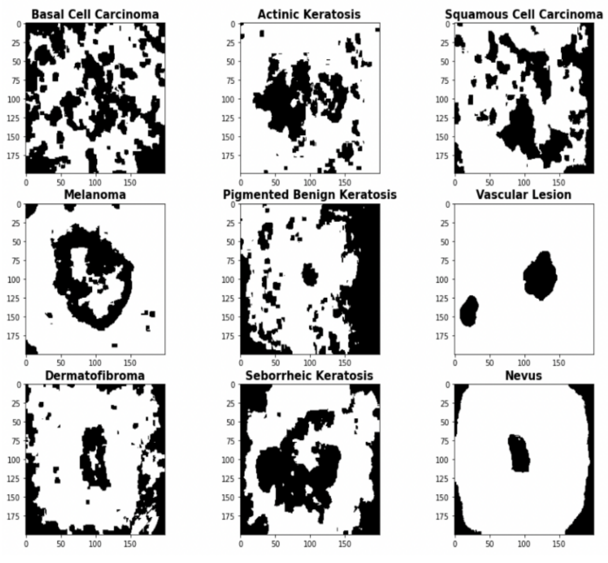

Figure 8: Segmented image

5.4. Feature Extraction: The features used are the pixel values of segmented image which will then be fed into image classifier for predicting lesion class.

5.5. Image Classification: CNN model is implemented which is discussed and explained in detail . Steps to implement deep CNN model:

1. A sequential API from keras is called to create layer to layer model .
2. The first Conv2D layer is applied with input which has 32 filters of shape (3,3), 'same' padding and 'relu' activation function .
3. Dropout layer is added with dropout of 0.4.
4. Second Conv2D layer is applied which has 64 filters of shape (5,5), 'same' padding and 'relu' activation function .
5. Max Pooling layer having pool_size of 2 is applied.
6. Another Dropout layer is added with dropout of 0.4.
7. Third Conv2D layer is applied which has 128 filters of shape (5,5), 'valid' padding and 'relu' activation function .
8. Second Max Pooling layer having pool_size of 2 is applied.
9. Third Dropout layer is added with dropout of 0.4.
10. Final Conv2D layer is applied which has 256 filters of shape (7,7), 'valid' padding and 'relu' activation function .
11. Final Max Pooling layer having pool_size of 2 is applied.
12. Final Dropout layer is added with dropout of 0.4.
13. Now, flatten layer is applied to reshape the output from Convolutional layers and then input them to fully connected dense layers.
14. Dense layer with 300 units will be applied with activation function as 'relu'.
15. This is then followed by Dropout layer of dropout 0.4.
16. Again, one more Dense layer is added with 200 units and activation function as 'relu' .
17. This is then followed by Dropout layer of dropout 0.4.
18. The Fully Connected (Dense) layer reduces its input to the number of classes(i.e.,9)using a SoftMax activation .

Finally, a model is created and compiled with optimizer = 'adam', it merges the best characteristics of the AdaGrad and RMSProp algorithms to provide an optimization algorithm. Thus, it can handle sparse gradients on noisy problems and relatively easy to configure. loss metric is taken as 'sparse_cross_entropy' as our dataset is image and sparse . Also, it a classification problem where there are more than 2 categories. Metric 'accuracy', to get the performance of model and know how efficient model is.

To train the model, fit the parameters into model as, train feature/input 'x_train' and train target 'y_train' . Validation_data is x_test and y_test . here, test set is fed as validation data to show runtime performance and plot of testing data. Runtime performance and accuracy-loss plots of testing set are computed with 100 epochs, in order to avoid or minimize overfitting by early stopping and Batch_size = 128, to get fast computational results, verbose is set to 1

This is how a model is designed. Its architecture is shown if Figure 9.

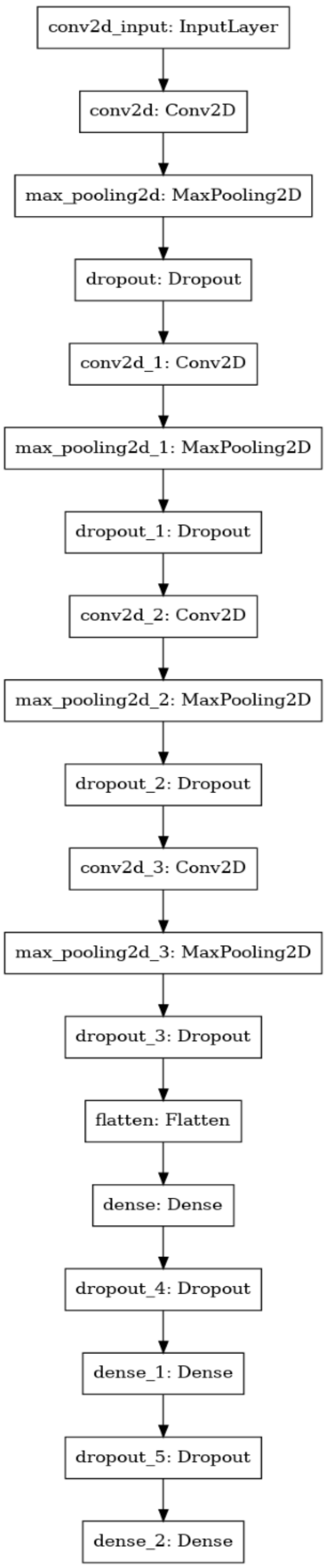

Figure 9: Architecture

6. RESULTS

The previous processes used for lesion detection turned out be quite useful. The training accuracy of 90.09 is achieved with training loss of 0.24 . However, testing accuracy of 79.67 is achieved with loss of 0.705 . Every iteration of implemented give different results but, accuracy of training lies between 86% to 91% whereas accuracy of validation data ranges from 75% to 79%. Similarly, loss of training data varies from 0.1 to 0.3 and loss of validation data lies around 0.6- 0.9. The validation loss is not good. It is visible that model is learning , but due to a smaller number of images in dataset , it is overfitting. The overfitting problem has been handled to maximum extent in our implementation. The best results that are obtained and shown in Figure 10. In this figure, the line graph is plotted for both loss and accuracy metric of training and validation data. From graph representing loss, the loss of validation data started to increase after certain point when models start to memorize the image data rather than learning it. In accuracy plot, the graph shows that model is still learning both the training and test dataset images at a certain pace. More epochs may provide better results and other combinations of CNN parameters can also be implemented to get better results. However, this approach and dataset also proved to be efficient in identifying different classes of lesions.

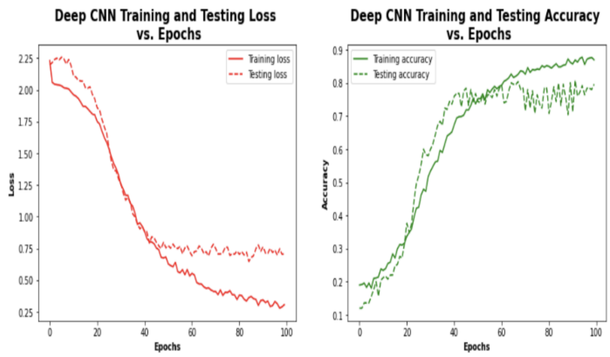

Figure 10: Graph and loss accuracy metrics

7. FUTURE WORK

Melanoma detection using image processing is an area that may be researched further to deliver more reliable and error-free detection. Models are developed to detect and analyze the nature of skin lesions using deep learning techniques. Melanoma detection has been attempted using Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Korhonen Self-Organizing Neural Networks (KNN), and Generative Adversial Networks (GAN), with varied degrees of success [5]. Better neural networks with higher accuracy may be formed with better and more abundant training data as well as more processing capacity. Deep learning algorithms can improve their detection rate if pre-processing stages are improved. Improved image segmentation techniques, for example, can result in greater skin lesion isolation in processed pictures. The most important stage of pre-processing is image segmentation, which separates the melanoma from the rest of the skin.

Making image-based detection algorithms relevant to a broader variety of instances is another field of research. Because melanoma mostly affects people with lighter skin, there isn't much data on how to construct neural networks that can detect skin lesions in those with darker complexion. Furthermore, the created neural networks' ability to evaluate lesions of atypical size, particularly those in early stages and hence likely to be small, is limited. The absence of training data for uncommon skin malignancies and the elderly, as most standard datasets consist of photos of youth, highlights the shortcomings of existing datasets. In addition, because diverse genetic influences on melanoma likelihoods exist, combining image processing techniques with models that incorporate these genetic aspects can improve detection accuracy.

8. CONCLUSION

We explored a computer-aided diagnosis technique for melanoma skin cancer in this research. The findings indicate that the suggested system may be utilised effectively by patients and clinicians to more correctly diagnose skin cancer. This can be further developed to be used in other diagnostic fields as well which can reduce human work and also improve the scope of early diagnosis.

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