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Effect of Image Enhancement on Early Detection of Skin Cancer

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Abstract: *Skin cancer is the out-of-control development of unusual cells in the epidermis, the outermost skin layer, brought about by DNA harm that causes harmful variations. These changes lead the skin cells to duplicate quickly and form dangerous tumours. Despite consistent upgrades in medication, skin cancer is still an issue. According to the insights by the Skin Cancer Foundation, one of every five individuals will develop skin cancer by age seventy. The paper expects to plan a framework that will be adequately proficient to distinguish the occurrences of different sorts of skin malignancy in the body by extracting significant patterns from the dataset.*

Keywords: Skin Cancer, Convolutional Neural Networks, Lesion Classification, Deep Learning, Melanoma Classification.

I. Introduction

In 2018, there were over a million cases of skin cancer worldwide [1]. One of the fastest-growing diseases on the planet is skin cancer. The susceptibility to ultraviolet radiation released by the Sun is the primary cause of skin cancer. Early diagnosis of skin cancer is critical with the scarce services available. In general, for skin cancer prevention strategy, accurate diagnosis and identification viability are crucial. And dermatologists face difficulty in detecting skin cancer in the early stages.

Skin cancer is typically caused by unnecessary sun exposure or because of some toxic radiation. Melanoma is the fifth most common skin malignancy in the world. In twenty percent of the cases, even complex medical procedures like surgery and laser treatment fail to fix it. In overall skin disease related deaths, seventy-five percent of them occur because of melanoma. Knowledge about it, and identifying it in its early phases can help decrease the pace of its casualty worldwide and the number of instances of recently infected personnel [1]. The majority of customary systems out there perform just proper twofold (binary) classification. CNN produces a breathtaking exhibition in image classification problems, yet, the limit of the technique is that it is datahungry and it isn't appropriate for small datasets.

The traditional strategy that has been followed up until this point, by specialists, to identify melanomas in people is the ABCDE approach. It represents Asymmetry, Borders, Color, Diameter, and Evolving [9]. More unevenness or boundary anomalies is the main cautionary symptom, just as strange color of the scar and its size more than 6mm are some of the different alerts

Recently, Convolutional Neural Networks (CNNs) have been used to classify Lesions in skin cancer In the classification of skin cancers, some CNN models have outperformed qualified human specialists. Several approaches, such as transfer learning, are available. The performance of these simulations has increased even further thanks to the use of massive datasets.

Convolutional neural network that has been trained on over a million images. images from the ImageNet collection The framework has 16 layers which can be configured in a variety of ways. Pictures are divided into 1000 different categories, such as console, mouse, pencil, and various animals. As a result, the machine has studied detailed component representations for a variety of objects.a broad range of images The image information scale on the system is 224 by 224 pixels. The definition of the model In ImageNet, a dataset with over a million images, it achieves 92.7 percent top5 test precision. There are 14 million pictures in 1000 schools.

In this paper, we have generated a CNN model that analyses the skin pigment lesions and categorizes them using a publicly available dataset and a variety of methods. techniques for deep learning By using CNN and transfer learning models, we were able to increase classification accuracy. The HAM10000 dataset, which is freely available, was used to validate our model.

II. Literature Survey

CNNs have been widely used in medical image analysis, image recognition, and other fields [2]. In the area of microscopic picture classification, CNNs have already shown impressive results, such as human epithelial 2 cell image classification [3], diabetic retinopathy fundus image classification [4], cervical cell classification [5], and skin cancer identification [6-9].

The first systematic study on classifying skin lesion diseases was proposed by Brinker et al. [10]. The writers concentrate on the use of CNN for skin cancer classification. The study further addresses the difficulties that must be overcome in order to complete the classification process. Han et al. suggested a clinical image-based classifier for 12 related skin disorders in [11]. They used 19,398 training images from the Asan dataset, the MED-NODE dataset, and atlas site imagesto fine-tune a ResNet model. This study does not take into account patients of various ages.

The first comparison of CNN with an international association of 58 dermatologists for skin cancer assessment was proposed by the authors in [12]. The majority of dermatologists The CNN outperformed them. The authors concluded that, regardless of any physicians' opinions, They could benefit from the image classification provided by a CNN. Google's search engine Dermoscopic images were used to train and test the Inception v4 CNN architecture. as well as the corresponding diagnoses Marchetti et al. [13] used 100 randomly chosen dermoscopic photographs in a cross-sectional sample (50 melanomas, 44 nevi, and 6 lentigines)

An international machine vision melanoma challenge dataset (n = 379) was used in this research. For the classification function, the authors constructed a fusion of five approaches. The authors of [14] used 7895 dermoscopic and 5829 close-up photographs of lesions to train a CNN-based classification model. Between January 1, 2008, and July 13, 2017, these photographs were excised at a primary skin cancer center. Furthermore, the model was tested on a sample of 2072 unknown cases and the findings were compared to those of 95 individual raters who were medical professionals. The majority of current research focuses on binary classification, such as whether the cancer is melanoma or not, and only a limited amount of study is done on classification of general images. However, their outcome isn't ideal. Deep learning and neural network architectures are now used in skin cancer disease identification and classification algorithms.

III. System Architecture

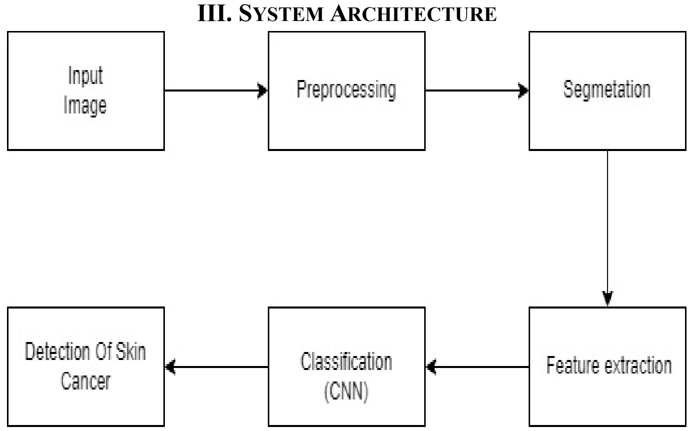

Figure 1: System Architecture of Skin Cancer

3.1 Methodology

This Section will emphasis over the methodology adopted for the classification task. Over all steps of the methodology is shown in figure 1.

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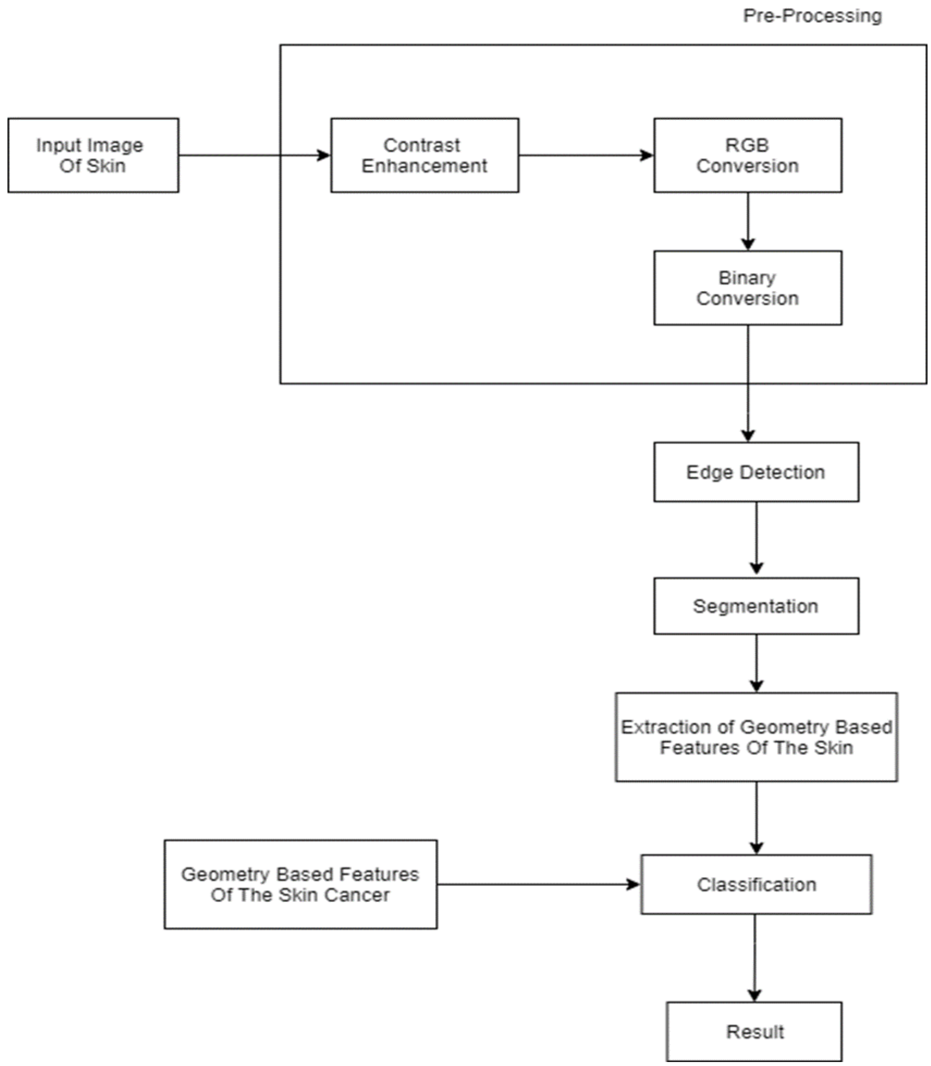

Figure 2: The Flowchart of methodology implemented

3.2 Preprocessing

Before being fed into the model, the data had to be washed and ordered. The data is, however, heavily skewed, with the lesion category 'melanocytic nevi' accounting for more than half of the overall dataset. To improve the learnability of the network, we used many pre-processing networks. We used Data Augmentation to prevent data from being overfit. By varying the translation, rotation, and zooming of the files, we were able to make multiple copies of the existing dataset. In addition, we used Histogram Equalization to improve the contrast of skin lesions in this article.

3.3 Method

For the classification task, Convolutional Neural Networks and Transfer Learning approaches are used. Deep learning models pre-trained on the ImageNet dataset were used for Transfer learning. It contains a little more than 14 million labelled photographs divided into over 20,000 categories. These pre-trained models are then further trained on the HAM10000 dataset by inserting additional layers and freezing some of the initial layers.

To compare the results, we used various learning algorithms such as XGBoost, SVM, and Random Forest Algorithms to perform the classification task in the HAM10000 dataset.

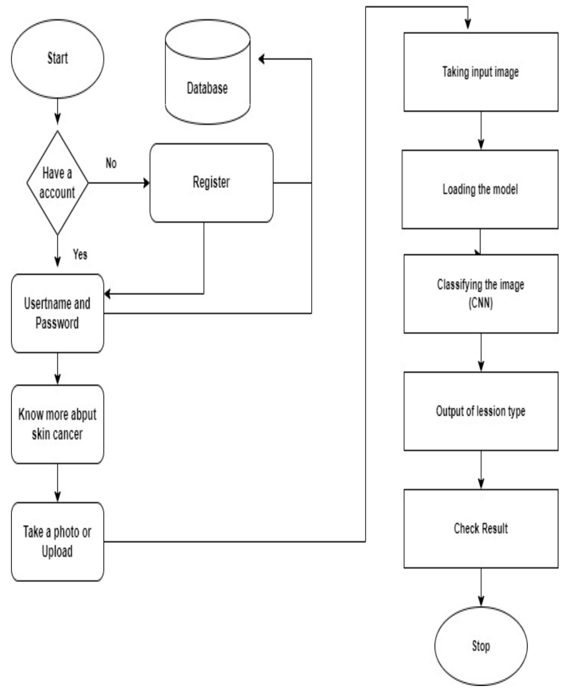

Figure 3: Flowchart of On-screen implementation

3.4 What Is CNN?

[1] Convolutional Neural Network (CNN) is used as classifier in this study due to this is the common method in Dermoscopy Image Analysis (DIA) since 2015 [3], provide higher classification accuracy [4] than the dermatologist efficacy [15], [5]. VGG16 is used in this study as CNN architecture [6]. There are two types of images that are used in this study, the first dataset consists of the original images (without image enhancement) or the original dataset. The second dataset consists of the enhanced image from the first dataset or enhanced dataset.

Biological mechanisms influenced convolutional neural networks. The communication pattern between neurons in these networks parallels the organization of the visual cortex in animals. The receptive field is the response of a single cortical neuron in a limited area of the visual field. Different neurons' receptive fields partly overlap,allowing them to occupy the whole visual field. To assemble its architectures, CNN uses three levels of neural layers: Convolutional, Pooling, and FullyConnected.

The study is implemented using Tensorflow as an end-to-end open-source machine learning platform that is run in a common Personal Computer (PC) equipped with a 2.7 GHz processor and 8 GB of RAM. In the ISIC archive 2019 dataset, there are several image dimensions, i.e. 1024 × 768; 1504 × 1129; 962 × 722; 2592 × 1944; 2018 × 1536; 722 × 1043; and 3024 × 2016; 4288 × 2848; and downsized to 600 × 450 pixels. To increase the computation speed, the dimension of all input images is reduced to the smallest image size of the ISIC 2019 dataset, i.e. 600 × 450 pixels. The assumption is that the image information still remains during the downsizing process. In this study, the number of epochs is set to 50. All the processes in this study are quite simple.

There are no other image processing techniques that are used other than CLAHE and MSRCR. Using these approaches, it is expected that the results of this study can examine the role of image enhancement using CLAHE and MSRCR in the early detection of skin cancer using CNN.

3.5 What Is Melanomas?

Melanomas are cancers that develop from melanocytes, the cells that make the brown pigment that gives skin its color. Melanocytes can also form benign (non-cancerous) growths called moles. (Your doctor might call the mole a nevus.)

Melanomas can occur anywhere on the body, but are more likely to start in certain areas. The trunk (chest and back) is the most common place in men. In women, the legs are the most common site. The neck and face are other common places for melanoma to start.

Melanomas are not as common as basal cell and squamous cell cancers, melanoma can almost always be cured in its early stages. But if left alone, melanoma is much more likely to spread to other parts of the body, where it can be very hard to treat.

Figure 4: Melanomas skin

IV. Conclusion

The recognition of cancer in beginning phases can be of very assistance to fix it. In view of the literature, execution of the different CNN models will assist with understanding which can be the most proficient one compared to others as far as speed and accuracy is concerned. Also, the proposed research work can come handy in situations where human help is not accessible very easily. Consequently, it will be the focal point of the following phase to develop such an application which will be proficient enough for the clinical field to depend on.

The suggested method takes the approach of extracting features first, and using those features to train and validate the transfer learning model. According to the As a result of our observations, we have come to the conclusion that the Transfer Learning process should be used. to the HAM10000 dataset in order to improve skin cancer lesions classification accuracy. We also discovered that the ResNet model, which is pre-trained in the ImageNet Dataset, performs well. The effective classification of cancer lesions in the HAM1000 can be extremely useful.

We have discovered that in the HAM10000 dataset, learning algorithms such as Random Forest, XGBoost, and SVMs are ineffective for classification tasks. As a result of these findings, future research will focus on improving prediction results and classification accuracy.

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