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A Competent Algorithm for the Detailed Analysis of Skin Images from Dermoscopy

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Abstract: Melanoma is the dangerous skin cancer. Mostly it caused due to the malignant growth in the melanocytic cells. Diagnosis of Melanoma becomes more dreadful. Since proposed system is based on classification of skin cancer at it early stage to classify whether it is benign and malignant by using a new algorithm deep depth wise separable residual convolution. The stages of this project is first the noise were removed by Non Local Mean Filter(NLM) followed by enhancement process by contrast limited adaptive histogram equalization over discrete Wavelet transform algorithm. Then images are fed to the model as multi channel images matrices with their channels across color spaces based on their ability to optimize their performance of the model. The proposed model achieved an ACC of 99.55% on international skin imaging collaboration (ISIC).

Keywords: Data Duplication, Deduplication, Do not Repeat Yourself (DRY), Database Management System (DBMS), Data Redundancy.

I. Introduction

Today, skin cancer is a public health and economic issues this can be treated with a same methodology by using dermatology field [1]. Based on the survey for the last 30 years the number of cased diagnosed with skin cancer increased significantly [2]. This is most accounted that it is a serious human illness it affects all ages, gender and most probably 30% to 70% of people affected with a skin cancer and among 3, at least one person affected by a skin cancer[4]. Therefore, skin disease is the most serious disease in the global scale and positioned 18th rank in health burden worldwide [5].In an addition, the suggested way to find early skin diseases is depend upon the new or changing skin growths [6].Analysis with a naked eye is the first resource to detect the skin cancer with the ABCDE rule with over time [7]. It has been raised many years. The main caution factors are longer longevity of the population, more people being unsheltered from the sun[8].These type of skin cancer mostly occurs with a population of predominant white skin mostly in Australia and New Zealand [9].Our aim is to classify the melanoma detection in dermoscopic images at any stage of disease by providing a novel and effective algorithm The proposed model has been built by integrating a separable convolution algorithm, which saves the parameter space and enhance the execution of the network while reducing its time complexity. Minimal error and optimal accuracy accomplished by using the residual learning algorithm which ensures suitable transmission of the error throughout the network during the training phase. Addition to obtain the best performance results we merge the Red, Green and Blue (RGB) image with b*channel from the CIELAB (CIE L* for lightness, a* for green-red component and b* for blue-yellow component of the image color space saturation value from the hue saturation and value. The related work proved that many algorithms was there to tackle this problem but there is some difference in this shallow and deep method with that in view, this work will guide its efforts in using deep neural networks to achieve its main objective. The project is explained as follow, the literature survey is explained in chapter 2. The proposed method is described in chapter 3, the result and discussion is expressed in chapter 3. In chapter 5 describes the conclusion and future work.

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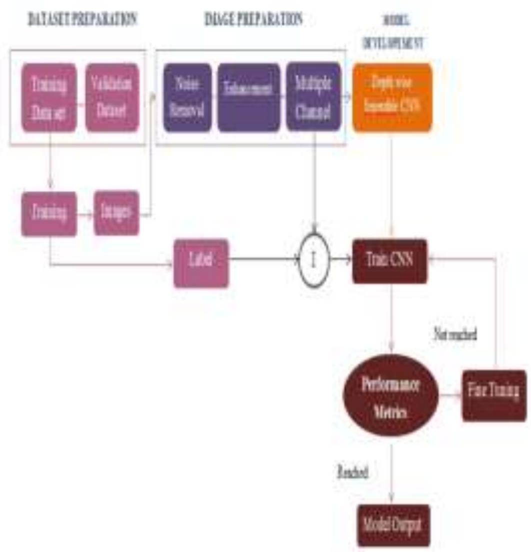
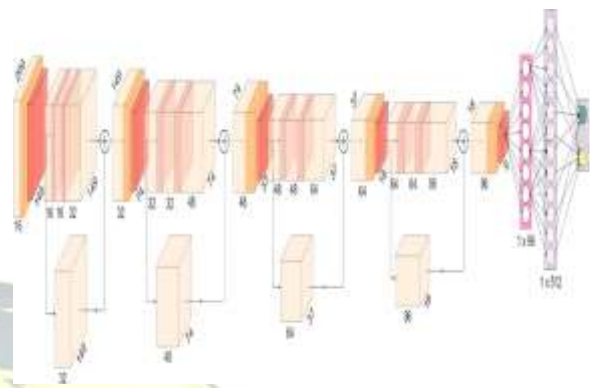


II. Literacy Survey

Here [1] they proposed a method for recognition melanoma by implementing a two kernel based classifier by using support vector machine (SVM).Major advantage is it improves the recognition rate of SVM. It faces major disadvantage that it focuses on melanoma detection alone. Dynamic effectiveness is not verified.[2] He proposed KNN that dependent on texture and color features that get from the skin images. Major disadvantage is that the classification of Actinic Keratosis (AK) and squamous cell carcinoma (SCC) is very low and output is very poor.[3] He proposed the model for screening the melanoma by using two models. It explains the double shot detection model. The advantage is it improves the better performance. Major disadvantage is it limits the number of attributes that used in this model.[4] They explored an innovative idea for melanoma screening by using adaptive fuzzy inference neural network (AFINN). The advantage is that it achieved sensitivity about 81.5% and specificity (SP) of 73.9%.Major disadvantages that due to limited Classification it proved to be inferior when compared to other multi layer neural network or other non-linear nodes. [5] He proposed the techniques that extract the melanoma by its image and genetic data. Important advantage is that explore the disease with low level biological information related to gene expression.[6]He proposed a neural network for detecting human interpretable and tracking of the disease. Major disadvantage is that the data has been trained in with synthetic data and they were tested on real world data so it decreases the validity of this paper. [7] They proposed a residual learning CNN architecture that makes a higher layer to be merging with the lower layers. The advantage is that it improves the optimal performance of images. Major disadvantage is that there is complexity in training the samples and space.



Noise removal algorithm	ACC%	AUROC score
non-local means De-noising	**99.50**	**0.9949**
Gaussian filer	96.67	0.9655
Average filter	93.33	0.9342
Bilateral filter	97.80	0.9731
Median filter	T 95.50	0.9543

III. Proposed Methodology

In this project, the images can be processed and it can be detect and extract the images and classify the lesions from the dermoscopic images. It can be used to classify whether it benign or melanoma. It can be found in further process.

Table 1: After using noise removal algorithm on the images

In table1 it shows the proposed model's performance after applying various noise removal algorithms on the images.

a. *Preprocessing*

Preprocessing is the most consequential part of the project. By employing deep learning algorithm there is no endeavor that can be put into this phase. But in that place the attributes can be extricated from the images automatically. In preprocessing more

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can be done in the original data images to aid the extrication from the images and specify whether it is benign or malignant.

b. Noise removal

After preprocessing the noise can be taken away from the dissimilar noise removal algorithm can be used to take away the noise from the image. Among them non local de-noising algorithm is ideal as it creates the Acc of about 94.61%.Five most common and effective de-noising techniques is used to filter the images they are non local de-noising filter, Gaussian filtering ,average filtering, median filtering, bilateral filtering among the five de-noising filter is best.

The main reason for noise removal is to reduce the influence of body hair that can be large in lesions. Also lesions can be small in size and textures on the surrounding regions. The blurring of images is vital in order to take away the impact of regions.

c. Enhancement of Images

Enhancement used to enrich the contrast of the images and edges of the skin lesions. Enhancement method is done after the noise removal because if enhancement method is done before noise removal then it leads to over blurring of images then it cannot be identifies the information. ABCDE rule cannot be used because it wrongly gives information as malignant but actually it is benign. So for these reasons we implement it by using CLAHE-DWT algorithm in low frequency features on applying. The Haar wavelet transform on the image using CLAHE. It is best than traditional CLAHE algorithm. The algorithm is enhanced in both low frequency and high frequency components by applying DWT. The Inverse DWT is used to achieve the enhanced version in order to transform the image and merge the images.

d. Selecting multiple channels

For the proposed model we merge certain channels using RGB color space. Primarily ten channel image matrix of mixed color space, channels of HSV color space. An optimal space matrix with dimensions (299*299*6) was obtained during the training the several channels can be used for this project.

(i) Residual module

Residual method is used to incorporate the idea of deep learning algorithm it uses the gradient method which induces the back propagation method. During this training phase the network has the weights of its unit modified by propagating the gradient of the error or loss function throughout the network using back propagation. There are six layers.

(ii) Convolution layer

Computing dot product between all filters and image patch provides the output volume. Suppose we use total 12 filters for this we obtain the outcome volume of dimension 32 x 32 x 12.

(iii) Activation Layer

This layer will claim element wise activation function. We bid the function in the outcome of convolution layer. Some common activation functions are Sigmoid: 1/ (1+e^-x). Outcome volume will have dimension 32 x 32 x 12 hence the volume remains unchanged.

Activation	ACC%	AUROC Score
Sigmoid	99.50	0.9949
Leaky Re-Lu	98.49	0.9839
Parametric Re-LU	98.75	0.9865

Table 2: Activation layer function

In the table 2 the bold value signifies the activation function chosen in the residual blocks used to build the model.

(iv)Pooling layer

Max-pooling and average pooling is the two common type of pooling layers. If we use a max pool with 2 x 2 filters and stride 2, the occurring volume will be of dimension 16x16x12. It is used to decrease the size volume and speeder and fall the over-fitting.

(v) Fully connected layer

Fully connected layer that connects the preceding layer to the input of upcoming layer it assemble the output of 1-D array of size.

IV. Results

In this model we discussed about the performance and we used various parametric in order to give best in proposed when compared with existing melanoma algorithm. Here we used about 250 samples were used for validation and 100 images were used for training of the models. We also uses the data form ISIC datasets in terms of contrast, brightness and other features which results in difference in hardware to develop the images.

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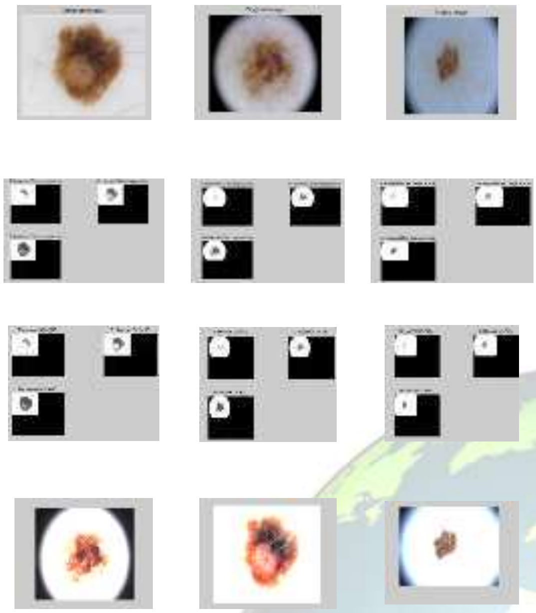

1

this image belongs to ::Maligant:: class

::Maligant::
ROC CURVE DATA

Roc Curve analysis

ROC CURVE DATA

Cut-off point		Sensivity	Specificity
1.0000	0.0000	1.0000	
2.0000	0.0192	1.0000	
3.0000	0.0385	1.0000	
4.0000	0.0577	1.0000	
5.0000	0.0769	1.0000	
6.0000	0.0962	1.0000	
7.0000	0.1154	1.0000	
8.0000	0.1346	1.0000	
9.0000	0.1538	1.0000	
10.0000	0.1731	1.0000	
11.0000	0.1923	1.0000	
12.0000	0.2115	1.0000	
13.0000	0.2308	1.0000	
14.0000	0.2500	1.0000	
15.0000	0.2692	1.0000	
16.0000	0.2885	1.0000	
17.0000	0.3077	1.0000	
18.0000	0.3269	1.0000	
19.0000	0.3462	1.0000	
20.0000	0.3654	1.0000	
21.0000	0.3846	1.0000	
22.0000	0.4038	1.0000	

ROC CURVE ANALYSIS

AUC	S.E.	95% C.I.		Comment
0.98558	0.01195	0.96216	1.00000	Excellent test

Standardized AUC	1-tail p-value	
40.6503	0.000000	The area is statistically greater than 0.5

It classify whether it is benign or malignant.

V. CONCLUSION

It operates cost effective specification and to enlarge the speed and accuracy. However, it is still a problem with several demanding, even more when we study clinical images that may present an extreme diversity due to variables such as cameras and environments. Seeing this, this work presented a model capable of classifying 2 skin lesions, that reached results comparable with state-of-the-art The proposed methodology introduces a concept to increase the performance of the model by building a multiple channel image matrix with six channels selected across different color spaces, which enhances the visibility of the lesion for the network. Optimal blurring and enhancement of the images were performed to reduce the influence of unrelated regions from the images and to enhance the region enclosing the lesion. The model presented here is dynamic in nature and achieves high-performance scores when validated against several benchmark datasets. Melanoma diagnosis carry out by this model is inadequate to only dermoscopic images. In future we plan to diagnosis the image with all the three methods BCC, SCC and actinic keratoses. To upgrade the performance, the images can be specified without the preprocessing stage.

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