A novel approach to classify skin malignancy through deep convolutional neural network and image preprocessing approaches

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Abstract---Melanoma is a malignant skin disease that kills roughly one million people per year, as per WHO records. The proposed work's major goal is to create and develop an enhanced deep neural network model that can evaluate, recognize, and predict cutaneous skin disease in its early stages with more accuracy, lowering the chance of death. The dataset, which was gathered from dermatologists and the public domain, contains roughly 3606 images of various types of skin lesions; some of the images were distorted. Gaussian and bilateral filters were used to decrease the noise in the images. After cleaning the data, the proposed six Convolutional layered Deep-CNN networks deployed to identify and predict skin cancer. The proposed CNN network was able to recognize skin diseases such Malignant Melanoma, Squamous cellcarcinoma, and Basal cellcarcinoma with an optimal error rate and good accuracy of 98.07 percent.

Keywords---Melanoma, Skin malignancy, Deep Neural Network, Convolutional Neural Network (CNN).

Introduction

The researchers were able to create an intelligent machine that can replicate the organic human brain thanks for the advancements in machine learning. These cognitive smart machines may be able to assist in the resolution of complicated problems in domains such as health care, audio translation, robotics, and self-driving cars. In modern environment [16], computer-aided diagnoses can help in analyzing and interpreting medical information to diagnose and predict many

hazardous conditions that, if not caught early enough, might lead to death. As per a recent study, there's been a growth in the count of cases of epidermis tumorigenesis due to weather extremes, particular aptitudes for living person [9] such like diet, cigarettes, alcoholic beverage use, and solar radiation, and people under the age of 25-40 years are having a lot of trouble with skin blemishes, with skin disease, the most well-known kind of malignant development is cancer and the most prevalent form of cancer is melanoma of the skin.

The three kinds of skin cancer shown in Figure 2 will be diagnosed in this study: Basalcellcarcinoma (BCC), Squamouscellcarcinoma (SCC), and malignant Melanoma (Mel). Tumors that are detected early are less likely to transmit to certain other portions of the body, but late detection makes treatments challenging and, in certain cases, catastrophic, along with affecting people's social lives. Different Machine Learning methods [19], Computer vision [17], neural network organization [21], and classification [22][23] approaches have been used to help recognize, segment, and define skin cancerous growths. The different kinds of cancerous lesions described in this study are listed in Table 1.

Table1. Skin Cancer Categories [Source 2]

Skin Cancer	Key Points
Basal CellCarcinoma	Carcinomas of the epidermis's epidermal cells, grow locally(neck, head, and trunk),metastasizes rarely
Squamous CellCarcinoma	Creates serious medical problems, the risk of metastatic, or cancer spreading to certain other areas of the human body, the sight of a blister that does not recover, leading the injury area to bleed.
Malignant Melanoma	Melanomas are malignancies of the skin tissues or keratinocytes in the epidermis which prone to grow to lymphoid tissue, the chest, and the skull, for men, the most prevalent location is the back, whereas for women, it's the lower legs.

These epidermal irregularities are routinely assessed visually by specialist doctors, who then conduct a biopsy and a careful examination. The visual assessment approach is widely employed for determination if a dermatologist relates the appearance with any skin injuries is problematic; nevertheless, not all dangerous melanoma sores are perceived by visual examination. Dermatologists require a technology that can reliably diagnose, discover, and forecast skin problems [24]. Dermatologists can use the recommended methodology shown in Figure 1 to support in the classification and detection of skin disease.
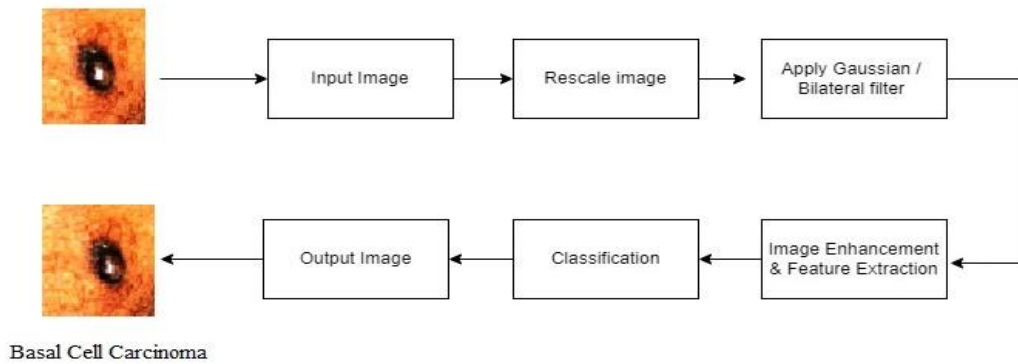
Basal Cell Carcinoma

Figure 1: The suggested model's block diagram

Our study's primary contributions are as follows:
- Use filters to eliminate noise and blurriness and boost picture composition [25].
- Design a efficient model that predict the diverse skin diseases with a better accuracy and lowest possible error rate
- Adapt deep neural network and transfer learning techniques to identify the malignant skin disease portion.

The remaining portion of this article is structured as follows: the literature study is offered in Section 2, Section 3 covers how to generate a dataset, data preprocessing techniques, Section 4 explains the approach that will be utilized, the results are depicted in Section 5, and Section 6 outlines the suggestions for future studies.

a. Basal cell carcinoma   b. Squamous cell carcinoma   c .Malignant Melanoma
Figure 2 Sample images of Skin Cancer [Source 19]

State-of-Art: Overview

CNNs' performance in detecting skin disorders has recently increased dramatically in terms of classification, detecting, and localization. On two - dimensional multi-view pictures of a 3D respiratory system structure, with an accuracy measuring 88.6percent on grayscale snapshots, Du et al [14] diagnosed respiratory illness chronicobstructive pulmonary disease (COPD) and non-chronicobstructive pulmonary disease (non-COPD) samples using CNN models. Using object recognition criteria on biomechanical, volume, and texture feature sets, the author of the paper [15] investigated efficacy of supervised machine learning in distinguishing COPD and NONCOPD patients.

The log-linearized Gaussianmixed neural network [12] a support system presented by Zakeri and Soukhtesaraie that is constructed in two stages: first, artifacts are removed, and then the Otsu thresholding technique is used to locate lesions. Muralikrishna et al. explored the deep learning in medical image analysis, also discussed about diverse fields of deep learning and their theory [3]. To reduce the noise and inappropriate backgrounds, Li-sheng et al. used filtration and transforming preprocessing strategies. The skin illness image was then segregated using the grey-level cooccurrence-matrix (GLCM) methodology, and also the three categories of skin disease were recognised by using support vector machine classifier [1].

A reliable and robust deep neural network model [4] developed by Md Shahin Ali et al., with an average accuracy of 93.16 percent and 91.33 percent of testing, the author made a comparative study with existing transfer learning architectures such as the DenseNet, VGG-16, AlexNet, MobileNet, and ResNet. In [5] author proposed Support Vector Machine to classify the features that are extracted from images using pre-trained CNN with a good accuracy. Soft-Attention approach was introduced by Datta et al. to suppress the features that generate noise while highlighting the important features. The performance of the InceptionVGG, ResNet, and DenseNet networks for diagnosing skin problems was then tested with and without the Soft-Attention methodology. [6].

SaraNasiri et al employed a DePicT Melanoma model [7] case-based reasoning (CBR) upgraded CNN model to provide people with more precise advice regarding their skin problems. In [8] Hosny KM proposed DCNN model that achieved a good accuracy of 95.19 % , 96.86% and 97.70% for the dataset ISIC, MED-NODE, and Derm (IS & Quest). The GrabCut [9] method is being used to isolate lesions of interest. The chosen feature categories are contour, pigment, and shape. Mustafa and Kimura have used SVM-RBF model to discriminate among non-cancerous and cancerous mole lesions.

In order to categorize high-resolution dermoscopic pictures, a patch-based attention technique has been proposed by Gessert et al., that could give global contextual information to boost classification accuracy. A new weighting loss was also proposed to improve the data classes imbalance [10]. Capdehourat et al. [11] employed a hair removal approach to preprocess the photos, then used a segmentation method to partition each image, and later deployed descriptors comprising shape and color information to train the AdaBoost classifier.
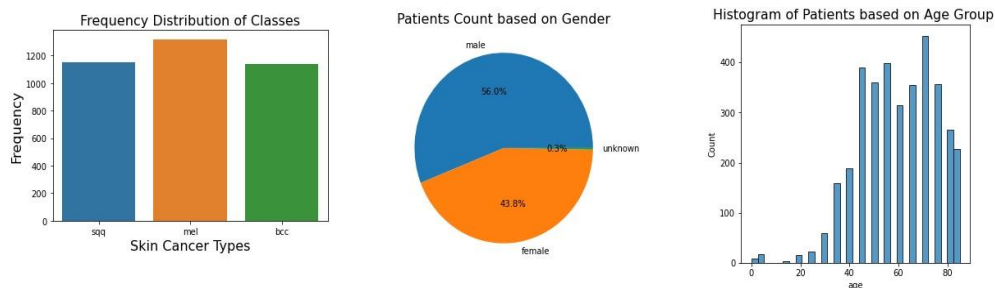

Figure 3. Displays data distribution based on skin cancer type, gender, age wise

Data set creation

Skin infection is the mainly prominent disease on the world; clinicians must encompass a high level of proficiency and exactness while diagnosing it; thus, an automated computer aided skin disease diagnostic approach is considered as a reliable tool. We collected photos from the public domain ISIC dataset [18][20], which has 22900 images, of which 2726 are relevant to our work and the rest are deleted. We also collected roughly 880 images from local hospitals (Telangana) relating to SCC, BCC, and Mel type of skin diseases. Table 2 presents the descriptive statistics that was used for training and testing, and we are using an 80:20 ratio for training and testing. 2885 images were used to train the model, which included skin cancers such as BCC, SCC and Malignant Melanoma, while 721 pictures were utilized to validate the model. Figure 3 demonstrates the distribution of data based on sex, type of skin cancer and age group.

Table. 2 Dataset description

Label	Skin Cancer Category	Train size	Test size	Total Count
1	Basalcell carcinoma	911	228	1139
2	Squamouscell carcinoma	919	230	1149
3	Malignant Melanoma	1054	264	1318
Total		2885	721	3606

Methodology

An accurate automated computer diagnosed health care system is essential in detection of deadliest disease that causes death to humans in early stage. Deep-learning-based [26] technologies have recently acquired appeal in medicine because to their power and flexibility in utilizing accessible dataset. A Deep-CNN is a multi layered deep learning technique for extracting features from data automatically. The performance of picture categorization and detection has substantially improved thanks to advances in CNNs. Handcrafted feature design, retrieval, and choosing are no longer required because a CNN can acquire appropriate features from raw data at multiple levels of abstraction. [13]

Gaussian filter and Bilateral filter

To reduce noise and blurring portions of an image, we can use a Gaussian low pass filter. A kernel Odd sized symmetric applied on every pixel of the picture to get the desired effect on a designated location.

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

The Gaussian function, which is as follows, is used to compute the values inside the kernel, to sharpen the images apply a advanced version of Gaussian filter known as bilateral filter which is a non-linear, edge preserves, noise-reduces, smoothing filter, and sharpen the pictures. It transforms every pixel's intensity

with a weighted sum using intensity data from surrounding pixels. A Gaussian distribution can be implemented to determine this weight. To reduce the noise and sharpen the image filters are applied as shown in figure 4.

Figure 4. Filters applied to sharpen the image

Proposed Deep-CNN architecture

We built a basic architecture for computational economy without sacrificing accuracy, taking into account two-dimensional processing, the quantity of our training data, and available CPU resources. The network was created using framework of deep learning, Keras, and the input pictures were analysed using a free multi-dimensional image analysis tool. There are 19 layers in our suggested deep CNN (see Fig. 5), six convolutional layers to extract the features, six batch normalization layers to normalize the output of previous layers, three max-pooling layers applied on ConvLayer2, ConvLayer4 and ConvLayer6 and GlobalMaxPooling layer applied before flatten layer. By using linear interpolation method, the datasets were resampled to $32 \times 32 \times 32$. The attribute volumes subsequently down-sampled via a maxpooling window dimension is $2 \times 2 \times 2$ and for Convolutional layer the kernel dimension is $2 \times 2 \times 2$. Furthermore, the classification layer was preceded by two dense layers (256 neurons in one and 3 neurons in the other). In each fully - connected and Convolutional layer, the activation function was indeed a rectified linear unit (ReLU). (see Table 3) and to avoid overfitting of model we applied a dropout of 0.2 where ever possible.

Table 3. Represents layers used in proposed model

Layer (type)	Output Shape	Param #
input_3 (Input Layer)	[(None, 28, 28, 3)]	0
conv2d_12 (Conv2D)	(None, 28, 28, 32)	896
batch_normalization_12	(None, 28, 28, 32)	128
conv2d_13 (Conv2D)	(None, 28, 28, 32)	9248
batch_normalization_13	(None, 28, 28, 32)	128
max_pooling2d_6 (MaxPooling2)	(None, 14, 14, 32)	0
dropout_10 (Dropout)	(None, 14, 14, 32)	0
conv2d_14 (Conv2D)	(None, 14, 14, 64)	18496
batch_normalization_14	(None, 14, 14, 64)	256
conv2d_15 (Conv2D)	(None, 14, 14, 64)	36928
batch_normalization_15	(None, 14, 14, 64)	256
max_pooling2d_7 (MaxPooling2)	(None, 7, 7, 64)	0
dropout_11 (Dropout)	(None, 7, 7, 64)	0
conv2d_16 (Conv2D)	(None, 7, 7, 128)	73856
batch_normalization_16	(None, 7, 7, 128)	512
conv2d_17 (Conv2D)	(None, 7, 7, 128)	147584
batch_normalization_17	(None, 7, 7, 128)	512
max_pooling2d_8 (MaxPooling2)	(None, 3, 3, 128)	0
dropout_12 (Dropout)	(None, 3, 3, 128)	0
global_max_pooling2d_2	(None, 128)	0
flatten_2 (Flatten)	(None, 128)	0
dropout_13 (Dropout)	(None, 128)	0
dense_4 (Dense)	(None, 256)	33024
dropout_14 (Dropout)	(None, 256)	0
dense_5 (Dense)	(None, 3)	1799

The suggested network is trained from scratch using an image of size 28x28, with the number of filters determined as 32, 64, and 128 based on past observations. A Softmax function was applied to discriminate between squamouscell carcinoma, basalcell carcinoma, and melanoma labels. An Adam optimizer was deployed to optimize the convolution network structure using the usual learning rate

(0.0001). The CNN models were implemented over 50 epochs on a batch size of 128 observations. To validate the maximum number of iterations, Figure illustrates both iterative accuracy results and loss on the training and testing datasets.
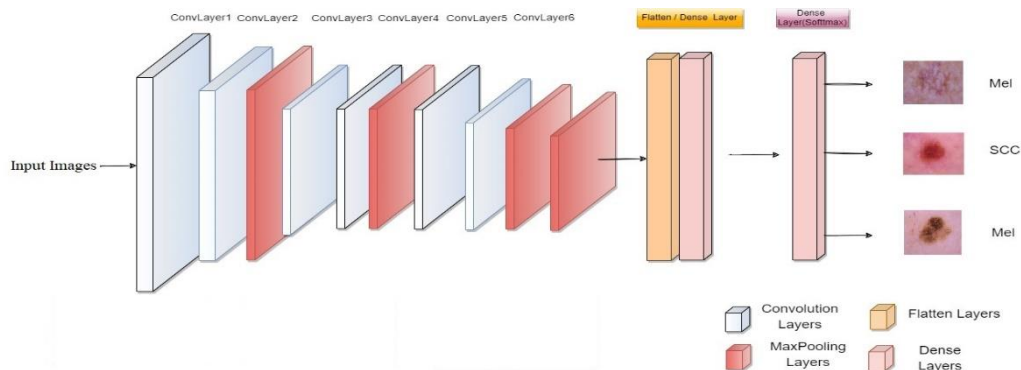

Figure 5. 19 layered DeepCNN architecture

Results and Discussions

The proposed DeepCNN network is being used to recognize epidermis cancer at an early stage levels. The classifier is constructed with 3 distinct types of skin malignancy : Basal CellCarcinoma (BCC), SquamousCell Carcinoma (SCC), and Melanoma, the network is capable of generating very precise results, even model able to identify the portion of infected part of skin.
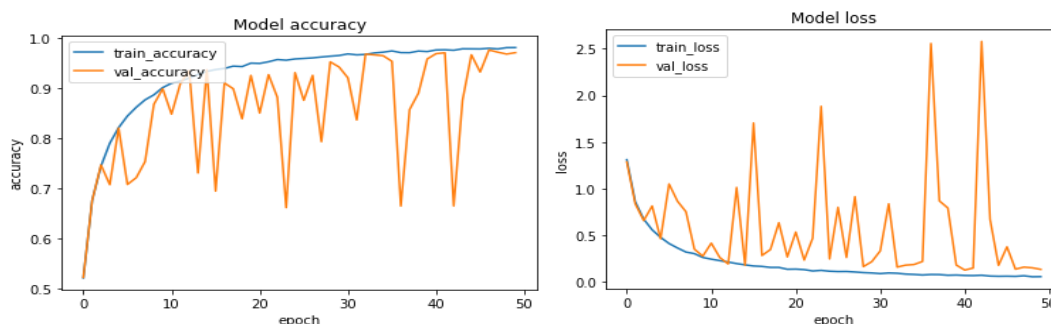

Figure 6. The loss and accuracy generated by the proposed DeepCNN method are displayed.

Initially model trained for 20 epochs, to generate better results number of epochs improved to 50 epochs ,and DeepCNN network achieved an precision of 98.07% of training data whereas it achieved 97.06% accuracy on validation data after applying ReLu activation function, Figure 6 shows that the model had a achieved train loss 0.0576 and a validation loss 0.1352. As demonstrated in Figure 7, the suggested model outperformed for the provided dataset and was able to effectively recognize skin lesions.

Figure 7. Demonstrate prediction result

Conclusion and Future Scope

The suggested technique would mostly help in early identification of cutaneous diseases, minimizing casualty rate and allowing for healing of skin diseases. To diagnose malignant skin cancer in patients, we devised a DeepCNN classifier. The suggested model has six convolution layers, with a varying number of maxpool. The customized dataset compromises of 3603 images, which are collected from the various sources, and the DeepCNN network was able to generate an accuracy of 98.07 percent on, implying that the presented approach could be valuable to dermatologists and individuals suffering with skin infections by detecting infections earlier and precisely.. In future research, we may try to revamp the architecture and increase the count of images used to train the model in order to produce a high-accuracy and to identify the erroneous area of proposed model Grad-CAM technique may be adopted

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