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SkNet: A Convolutional Neural Networks Based Classification Approach for Skin Cancer Classes

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***Abstract*— Skin Cancer is one of the most common types of cancer. A solution for this globally recognized health problem is much required. Machine Learning techniques have brought revolutionary changes in the field of biomedical researches. Previously, It took a significant amount of time and much effort in detecting skin cancers. In recent years, many works have been done with Deep Learning which made the process a lot faster and much more accurate. In this paper, We have proposed a novel Convolutional Neural Networks (CNN) based approach that can classify four different types of Skin Cancer. We have developed our model SkNet consisting of 19 convolution layers. In previous works, the highest accuracy gained on 1000 images was 80.52%. Our proposed model exceeded that previous performance and achieved an accuracy of 95.26% on a dataset of 4800 images which is the highest acquired accuracy.**

***Index Terms*—Skin Cancer Classes, Classification, Artificial Intelligence, CNN, Deep Learning.**

I. Introduction

The largest organ in the human body is skin and skin cancer is known as the most common global health problem [1], [2]. Skin is a big shade in our human body and it helps to regulate our body temperature. In general, Human skin creates connection with other organs such as muscle, tissue, bones of the body and protects ourselves from heat, high levels of ultraviolet rays and several infections which are injurious to our health [2]. Skin cancer is totally unpredictable because it changes its character according to the weather. Cancer occurs when an abnormal cell develops in the human body in an uncontrolled manner [3].

Skin cancer happens due to the overexposure of sunlight. The one which is most commonly seen and deadly is women breast cancer and prostate malignancy which has high death rates for men [4]. Some major skin cancer types are Basal cell carcinoma (BCC), Actinic Keratosis, Squamous cell carcinoma (SCC) and Melanoma. Among them, Melanoma is widely recognized as the most common type of skin cancer and it is deadly for all ages. It is usually different from other types of cancer because of its mortality rates. On the other hand, BCC and SCC usually occur from the ultra-violet ray of the sun and prone to grow slowly into the skin and spread into other portions of the body such as face, ears, neck, lips respectively [5]. Melanoma diagnosis from melanocytic nevi is hard to identify particularly in early stage [10].

Skin cancer is a major health problem throughout the world. As a result of the great extent of ultra-violet ray emission from the sun, people's skin doesn't suit due to the harsh condition [6]. In Australia, a Large number of malignant cancers are identified every year. In 2016, Approximately 13,280 new cases of melanoma have been diagnosed and around 1770 people died from this cancer [7]. Males proportion of new cases (7850) were higher than women's (5440) having 59% and 41% respectively. But, in 2019, Australian women were expected to have a 1 in 21 possibility of being diagnosed with melanoma before the age of 85, whereas men were estimated to have a 1 in 14 risks. Digital dermoscopy is one of the most generally used non-invasive, cost-effective imaging tools to recognize melanomas in patients [8].

Due to a lack of medical knowledge, sometimes doctors become confused to identify the skin disease. So, it is badly needed to detect automatic skin disease problems for patients and doctors. Our proposed model will provide a better solution than any other model in detecting skin cancer.

In this paper, we proposed a method to identify 4 serious types of skin cancer. Our main goal is to develop a proper system for doctors and patients to communicate easily. We will use Deep Learning methods such as Convolutional Neural Network, Deep residual Neural Network.

The rest of the paper is arranged as follows: Section II literature reviews the relevant works, Section III describes research methodology of our proposed method SkNet, Section IV describes the result analysis and discussions of our experiment and lastly, Section V concludes the paper.

II. Literature Review

Identifying several kinds of skin cancer from the image is very challenging because they have different features. Many researchers have already analyzed to develop new techniques to identify skin cancer. Some prior research works affiliated to our work are narrated below in this section.

Saket et al. [1] have utilized a MobileNet model pre-trained on approximately 12,80,000 images and fine tuned on 10015 dermoscopy images from the HAM10000 dataset. Using Keras ImageDataGenerator they pre-processed the skin lesion images. To balance the HAM10000 dataset, they used Data Augmentation. Finally, the generated model achieved 83.1% overall accuracy on seven classes. In the work of [2] researchers combined the Self Organizing Map (SOM) and Radial Basis Function (RBF) to identify skin cancer. They mainly focused on differentiating the varieties of skin cancer by using image analysis. The dermoscopic image usually includes noises in the form of hairs, bubbles, etc. They enhanced the quality of cancer image and then identified the image using MATLAB. The overall classification accuracy after feature extraction was 93.15%.

Sertan et al. [4] have detected malignant melanoma and seborrheic keratosis using deep convolutional neural network based on Gabor wavelet. The system works in two sections. In the first section, the Gabor-based CNN model recognizes skin lesion classes. In another section, the skin image helps to generate an image-based CNN model. After combining the two-part, a final output is generated that recognizes melanoma and seborrheic keratosis classes. In [8] Brij Rokod and Dr. Sureshkumar Nagarajan used Deep Residual Network for Skin Cancer diagnosis. To implement the system, they used RGB images. They converted those into binary and classified the ResNet classes to improve the accuracy. But the accuracy of the model is not up to the mark with an accuracy of 77%. In this system, data augmentation and faster inference was needed to improve image quality and focusing.

In the work of [9] image processing was used to analyze melanoma diagnosis. To separate other parts from the picture, image segmentation was used . In this system, some extra process was added like background subtractions, edge detection and masking to detect the object accurately. In the last stage, they classified the image using ANN. The final accuracy resulted in 96.9%. Peizhen et at. [10] classified four types of critical melanoma diseases. CNN was used to differentiate between melanoma and nevus cells. The image was correctly identified using Regions of Interest (ROI). They used histopathology images for four types of key diagnostic tasks. Using VGG19 and ResNet50 model, they identified four kinds of critical classification and compared their performance.

Zahangir et at [11] developed a new technique and it works with two several steps. NABLA-N network applied for dermoscopic image segmentation. For semantic segmentation they used several layers which consisted of encoding and decoding units. In the crucial decoding stage, v-net model was applied to produce better representation and features. On the other hand, IRRCNN model recognized skin cancer from dermoscopic image also helped to compare the testing performance of inception and residual networks. Using tensorflow in the backend, the classification shows approximately 87% testing accuracy. Esther et at [12] they applied a combined method including Gabor filter and CNN model for skin cancer diagnosis. To extract information perfectly and reduce overfitting they used Gabor filter bank which identified object information, edges and textures accurately. Finally, CNN classified the type of skin cancer.

In [13] researchers proposed a deep CNN based efficient framework and FV encoding like encoding strategies in order to produce more representative features. To identify large variations of melanoma classes and due to limitations of datasets, they used Support Vector Machine (SVM). They used CNN to compare with the state-art-method. In the work of [14] we can see that, They applied three classifiers such as Support Vector Machine (SVM), Random Forest (RF) and Neural Network (NN) to enhance the quality of the medical image whereas NN shows the best performance. Data Augmentation includes Geometrical augmentation, Color augmentation and Data warping based on specialist's knowledge to solve the overfitting problem. Latest version GoogleNet was implemented for feature extraction.

In our paper, we proposed a novel CNN model which is based on Deep Convolutional Neural Network [15]. Among many researches done before, the researchers worked with CNN to identify only Melanoma Skin Cancer and also used VGG16, GoogleNet (Inception V3), MobileNet. In our model, we recognized four types of serious skin cancer (BCC, Actinic Keratosis, SCC and Melanoma) which is totally unique.

III. Research Methodology

In this segment, we described our workflow and architecture for SkNet. The whole process requires several steps which are described in the following. Fig. 1 illustrates the overall workflow of our model.

A. Dataset

Dataset plays a very important role in any kind of research. It's very tough to conduct medical research as the dataset is very scarce. Specially from skin cancer patients, collecting medical data is remarkably a challenging task [16]. We collected our data from some hospitals and flocked together some pictures available online. Our dataset has four different classes of Skin Cancer including Actinic Keratosis (AK), Basal Cell Carcinoma (BCC), Malignant Melanoma (MM) and Squamous Cell Carcinoma (SCC). The total number of images for our experiment stands at 4800 images. We have pre-processed the

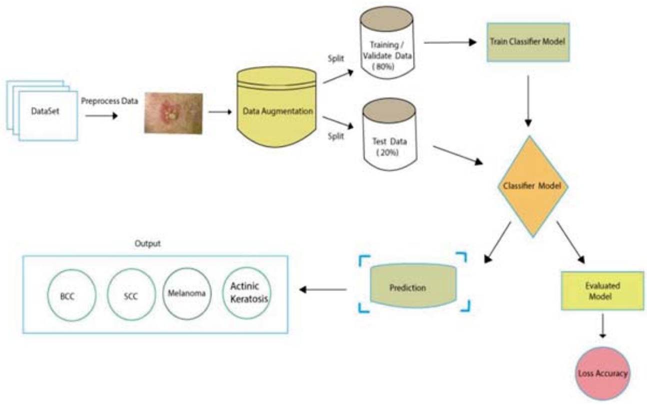

Fig. 1. Workflow of our experiment.

images by resizing them into 224 x 224 which is feasible for our experiment.

B. Data Augmentation

Deep Learning approach generally requires the dataset to be large in number. For our similar approach, the dataset was not enough. So, we applied some augmentation techniques to increase our dataset artificially. The augmentation techniques include right rotation by 30 degree, left rotation by 30 degree, horizontal flip, shading and translation. After augmentation, we split the images into training, validation and testing sets. We used 3840 images (80% of our total dataset) for training and validation purposes. The rest 960 images (20% of our total dataset) were kept for testing purposes. Fig. 2 shows a illustration of our dataset.

Fig. 2. Sample of our dataset.

C. Proposed Model

Our proposed model SkNet consists of 19 convolution layers including convolution layers, several regularization schemes, maxpooling layers, flatten layers, fully connected layers [15], [17]. It is the Convolution layer which is perceived as the part and parcel of CNN. For the purpose of creating a feature map using the kernel, the convolution layer operates on the input data. In Fig. 3 represents the architecture of our proposed SkNet. We used four convolution layers containing 8, 16, 32, 64 filters respectively and the kernel size was 3 x 3 for all convolution layers. We used the activation function ReLU (1) in each convolution layer.

$$RELU(x) = MAX(0, X) \tag{1}$$

We transformed our dataset by using Keras image data generator. The 224 x 224 x 3 shaped images were passed through the input layer where 3 indicates the number of channels. In maxpooling layers, we used a pool size of 2 x 2 with a stride of size 2. We used three dense layers in our model. After flattening, we passed the tensor through two fully connected layers each with 128 units. We used Softmax as an activation function in our output layer. Here, Table I the detailed summary of our proposed SkNet.

TABLE I
THE SUMMARY OF THE PROPOSED MODEL WITH LAYERS, ITS CONFIGURATION AND OUTPUT SHAPE.

Layers	**Configuration**	**Output Shape**
Conv2D	224x224x8; kernel size: 1x1; padding: same; activation function: RELU	224x224x8
Max-pooling2D	Kernel size: 2x2	112x112x8
Conv2D	112x112x16; kernel size: 3x3; padding: same; activation function: RELU	112x112x16
Max-pooling2D	Kernel size: 2x2	56x56x16
Conv2D	56x56x32; kernel size: 3x3; padding: same; activation function: RELU	56x56x32
Max-pooling2D	Kernel size: 2x2	28x28x32
Conv2D	28x28x64; kernel size: 3x3; padding: same; activation function: RELU	28x28x64
Max-pooling2D	Kernel size: 2×2	14x14x64
Dropout	0.25	14x14x64
Flatten	N/A	12544
Dense	unit:128; activation function: RELU	128
Dropout	0.50	256
Dense	unit:128; activation function: 'Softmax'	4

D. Evaluation Matrix

The Confusion Matrix [18], [19], [20] is sort of a table that narrates the performance of a classification model in test data. We presented our model in a Confusion Matrix to observe the performance of the model. The role of Confusion Matrix is to evaluate certain features that help to get a better grasp on the performance of the model. We calculated Accuracy, Precision, Recall and F1-Score by using True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN) values. We acquired the desired results by using the following equations (2) to (9).

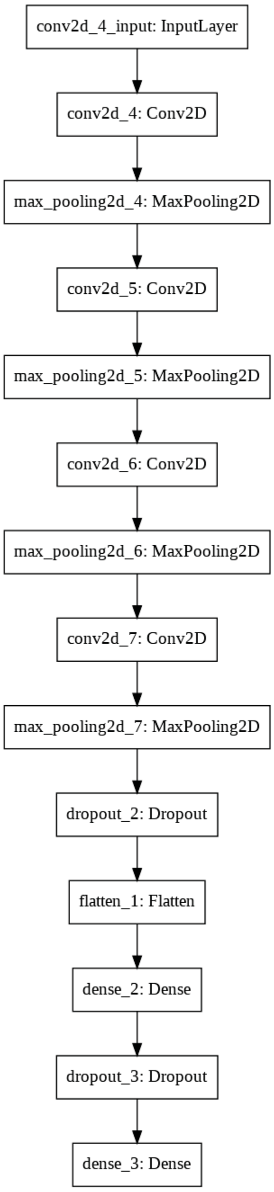

Fig. 3. The architecture of our proposed SkNet

$$TP_i = a_{ii} \tag{2}$$

$$FP_i = \sum_{j=1, j=i}^{n} a_{ji} \tag{3}$$

$$FN_i = \sum_{j=1, j=i}^{n} a_{ij} \tag{4}$$

$$TN_i = \sum_{j=1, j=i}^{n} \sum_{k=1, k=i}^{n} a_{jk} \tag{5}$$

The overall calculation has been made with the help of following equations in details [21].

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{6}$$

$$Precision = \frac{(TP)}{(TP + FP)} \tag{7}$$

$$Recall = \frac{(TP)}{(TP + FN)} \tag{8}$$

$$F1 - Score = \frac{(2 * Recall * Precision)}{(Recall + Precision)} \tag{9}$$

IV. Experimental Result Analysis and Discussion

Here, Fig. 4 shows the Confusion Matrix of our proposed model. It expressed the Confusion Matrix of the introduced and it's been calculated. The graphical view of SkNet has been depicted below based on the equation of (2) to (9).

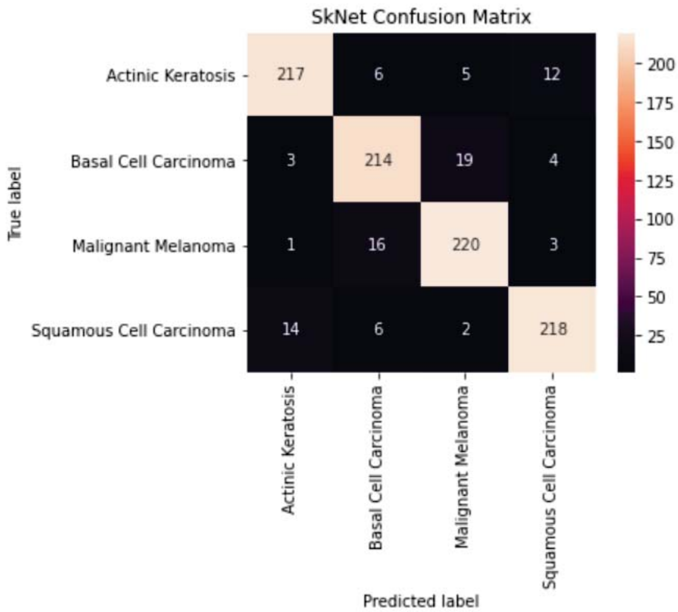

Fig. 4. The graphical representation of confusion matrix on our SkNet

TABLE II
PERFORMANCE EVALUATION OF OUR PROPOSED SKNET.

	Recall	Precision	F1-Score	Accuracy
Actinic Keratosis	92%	90%	91%	95.7%
Basal Cell Carcinoma	88%	89%	89%	94.4%
Malignant Melanoma	89%	92%	91%	95.2%
Squamous Cell Carcinoma	92%	91%	91%	95.7%

In Table II, we displayed the overall performance of our proposed method on our dataset in terms of precision, recall and f1-score. To draw the clear distinction, we have charted the highest of precision, recall and f1-score of the 4 classes which exposes the performance of SkNet on our Dataset. Here,, we can see the highest precision 92% which belongs to MM. Along with the precision, 92% recall which is the best rate belongs to Classes AK and SCC. On the other hand f1- score is 91% in AK, MM and SCC.

TABLE III
PERFORMANCE OF OUR PROPOSED MODEL

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
10	0.55	85.68%	0.92	69.04%
20	0.28	90.36%	0.51	81.41%
30	0.24	93.31%	0.25	93.03%
40	0.23	95.72%	0.24	95.11%
50	0.23	98.23%	0.23	97.97%

Our proposed model scored 95.26% accuracy on our private dataset. After 50 epochs, It has gained the training accuracy of 98.23% and the validation accuracy at 97.97% on our dataset. After analyzing the different epoch values from Table III, we can evaluate that our proposed SkNet has a excellent performance on our dataset in both training and testing set. With every increasing epoch, the loss has increased and on the final epoch, SkNet has achieved the final training loss of 0.23, and the validation loss also 0.23 on our dataset. After the illustration of the 50 epochs from Table IV, we can say that our method has performed tremendously well with excellent accuracy and minimalistic loss on our dataset.

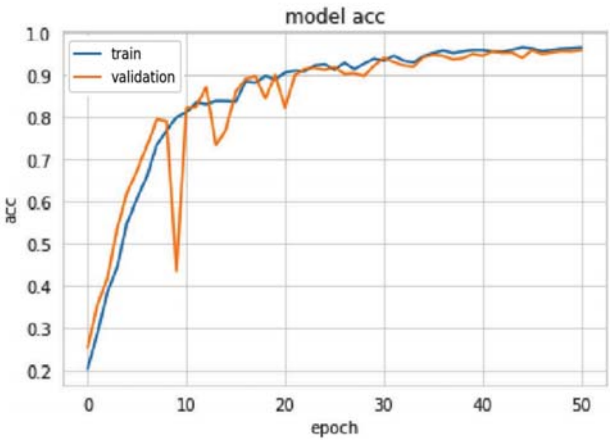

Fig. 5. The graph of the training accuracy vs the validation accuracy of Sknet

The training and the validation accuracy graph of SkNet is represented in Fig. 5. Here the blue line specifies how well the model performed on the training data and the orange line specifies the model performance on validation data. X-axis indicates each epoch whereas Y-axis shows the increasing accuracy.

The training and the validation loss graph of SkNet is represented in Fig. 6. Here the blue line specifies how well the model performed on the training data and the orange line specifies the model performance on validation data. X-axis indicates each epoch whereas Y-axis shows the decreased loss.

In Table IV, It clearly seemed that the previous works of CNN were comparatively lower than our proposed CNN model based on pixels. In addition, S. R. Stefan Jianu et al, P. Dubal et al, M. A.A. Milton et al and Kawahara et al experimented results was 80.52% , 76.9%, 74% and 75.1% respectively, while our proposed system accuracy is achieved 95.26%.

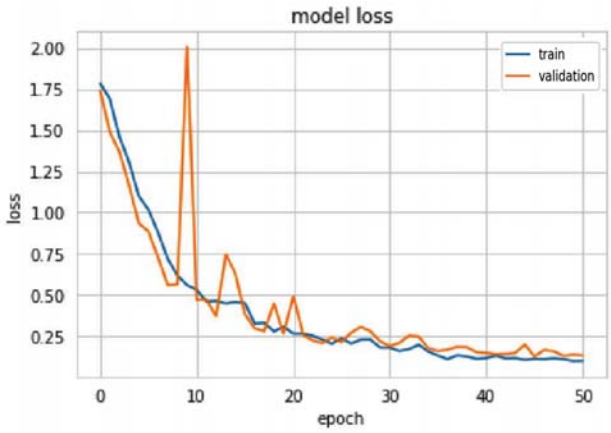

Fig. 6. The graph of the training loss vs the validation loss of Sknet

TABLE IV
COMPARATIVE RESULTS BETWEEN OUR WORK AND OTHER WORKS.

Work Done	Approach	Size of Dataset	Accuracy
S. R.Stefan Jianu et al. [22]	CNN	1000	80.52%
P. Dubal et al. [23]	ANN	463	76.9%
M.A.A. Milton et al. [24]	InceptionResnetV2, PNASNet5-Large, SENet154, InceptionV4	2000	70%, 76%, 74%, 67%
Kawahara et al. [25]	Multi-tract CNN	1300	79.5%
Our Proposed Work	**CNN**	**4800**	**95.26%**

V. Conclusions and Future Works

In this research, we have developed our own CNN model that can classify different types of skin cancer. Here, we have compared our SkNet with some previous works. Our model performed comparatively better with a classification accuracy of 95.26%. Our custom dataset was larger containing four different types of Skin Cancer images. We augmented our dataset to get variations in order to get a better training result. We can claim that our approach can detect the discussed Skin Cancer types with highest accuracy.

As our future work, we would like to add more images per class and increase the classes of skin cancers. We haven't applied other image processing techniques. Maybe the use of image processing techniques could result in better work and improved performance. We would also like to apply segmentation techniques to improve the result. Overall, our plan is to develop a reliable system to detect skin cancers within a short time.

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