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Research Article

SkCanNet: A Deep Learning based Skin Cancer Classification Approach

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Abstract: Skin Cancer classification has been one of the most challenging problems for dermatologists; it is a tremendously tedious process to detect the kind of lesion/cancer form it is for just the human eye. Deep learning has become popular due to its potential to learn complex traits from the huge dataset. A prominent deep learning model for image categorization is the convolutional neural network (CNN). Many researchers have been conducted on the efficiency of CNN's use to classify skin cancer forms. In this paper, the efficiency of VGG bottleneck features and transfer learning have been used on 3 kinds of skin cancers namely, (a) squamous cell carcinoma, (b) basal cell carcinoma and (c) melanoma. The proposed model comprises of VGG-16 NET and Transfer Learning with 2 fully-connected layers. The proposed model is experimented on 1077 dermoscopy images in total (MSK-1, UDA -1, UDA-2, HAM10000). The experimental analysis proves that the proposed model achieves higher values for accuracy, specificity and sensitivity.

Keywords: ***Classification; CNN; Deep learning; pretrained model; Skin cancer; Transfer learning***

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1. Introduction

Among the types of cancers, skin cancer is the most frequent malignancies. As per a recent study[1], By the year 2022, an estimated 10,000,00 people in the America would have been identified with cancer, with roughly 7% of those diagnosed dying [1]. This clearly shows the threat the world is facing with the disease called cancer. Malignancy happens when typical cells experience a change and develop and duplicate without normal controls. Skin cancer is common cancer that can be diagnosed visually and later with other diagnostic methods such as biopsy or dermoscopic analysis. Skin cancer can be classified as melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC). Among the skin cancers listed melanoma is the deadliest kind of skin cancer that affects white men and women. SCC and BCC are non-melanoma kinds of skin cancers [2]. Merkel cell tumours and dermatofibrosarcoma protuberance (DFSP) are other rare types of skin cancers. WHO (World Health Organization) approximates that around 2 to 3 million non-melanoma skin malignant symptoms and 1.3 million melanoma skin diseases develop each year over the world. As a result, untimely detection of melanoma skin cancer is an important problem [3].

The recent advancements in computer-aided diagnosis, classification of malignant images from benign images are possible yet challenging. Skin cancer images are composed of fine-grained variance with more complex features of skin lesions. This made the automated skin lesion image classification challenging.

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[1] http://www.cdc.gov/cancer/dcpc/research/articles/cancer_2020.htm

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Artificial Intelligence (AI) is emerging, it gives computers the potential to learn and think like humans. AI has been there for a long time but due to the increasing availability of the data in the recent decades dictates its success. Machine Learning (ML) a part of AI it has many sophisticated techniques for various applications. ML is especially used for medical data where it assists the doctors and researchers in diagnosing or predicting the diseases at the early stages. ML can learn different attributes of the medical data including images, however the performance of ML will be saturated at a particular point even if we have more data. Deep Learning (DL) a subset of ML, its performance improved with the increased availability of data. DL models can ascertain complex parameters from the input data. Neural networks is the base for DL, which is developed to mimic the properties of the brain neurons. It consists of input, hidden, and output layers. There can be any number of neurons based on the complexity of the model. There are many deep learning models build based on neural networks for different types of data and applications. Convolutional Neural Network (CNN) is a DL model that can work well with image data. It has the capability to learn the low-level complex features from images and its higher classification accuracy [4]. There have been many kinds of researches carried out to classify skin lesions using CNN and it is found that the efficiency of such researches are better than experienced dermatologists [5].

One of the challenges in the deep learning model is the time taken for training the network. As the volume of the dataset increases, the DL model's performance increases. Therefore, the model training is time-bound to the size of the dataset. Pretrained network models that are trained with a specific dataset and consist of trained weights and bias values. The time complexity is largely reduced through pretrained models. Pretrained models can be adapted for any image classification tasks. Generally, the low level features of any image is the edges and the pattern of the image, this can be easily aligned with new dataset when we train some layers from the pretrained model. Pretrained models beneficial in medical image analysis also as the last few layers of the models can be trained so they can be used with different types of datasets. Another advantage of pretrained models is that when we have limited number of records in the datasets which is not adequate for a deep learning model, then pretrained models are handy in yielding better accuracy.

Though, there are many DL based approaches published in the recent past for the skin lesion classification, still there is a possibility of improvement as the models are either very deep or not giving appropriate accuracy to be relied on the results of the model. Hence in this work, a pretrained model based skin cancer classification approach called SkCanNet is proposed. The objective is to identify and classify skin lesions of melanoma, SCC, and BCC. This approach utilizes the VGG16 pretrained model which has millions of trained parameters we utilize them to learn the features from skin lesion images. The model is evaluated through common performance metrics such as specificity, sensitivity, and accuracy.

2. Literature Survey

The state-of-the-art literatures proposed to classify skin cancer classification is presented in this section. Deep learning approaches based on CNN are commonly utilised to solve image classification problems. Kawahara *et al.* [6] presented a special CNN ensemble architecture to classify skin lesions. The proposed CNN model augments a single image into different resolutions and they are used in all parts of the network model. Finally, the output layer merges the different dimensions into a single layer. Through end-to-end learning, the weighting parameters are optimized and the interactions between the image resolutions are identified by CNN. The public dermofit image library [7] has opted for experimentation and the classification accuracy of the algorithm is 79.5%. The findings of research [8], propose profound learning frameworks are vastly improved in distinguishing the type of skin disease, the outcomes presumed that the models were fabricated utilizing deep learning studio (DLS). The models were tested with HAM 10000 - an AI benchmark dataset and have got promising results. It produces a higher ROC value that shows that the model fails very rarely. The results of pretrained models are analyzed and it is observed that the ROC of ResNet model is poor compared to Inception V3, DenseNet, and SqueezNet. Thus the DLS models are producing better results than other models. An AI based skin cancer classification is proposed by Hekler *et al.* [9]. The AI system uses a CNN based model to classify skin cancers into five categories. The model used 11,444 dermoscopic images to train the CNN model. Further hospital datasets and skin lesions biopsy is also used in the training to build a classifier. The accuracy of the model was 82.95 percent. A similar study was conducted with the same dataset by Maron *et al.* [10] who proposed a classification model based on CNN for skin lesions of common pigmentation. The results of the models are evaluated in two end-points such as primary and secondary. In primary end-points, the values of sensitivity and specificity are 74.4% and 59.8% and at the second end-point, they achieved 56.5% and 89.2% respectively.

Pomponiu *et al.* [11] presented a DL model for skin mole categorization using a pretrained deep learning network. Skin mole images taken from a digital camera is used for experimentation. The model is implemented using AlexNet and *k*NN classifier. The first few layers of the AlexNet and the *k*NN classifier are merged to obtain better classification accuracy. The model achieved a classification accuracy of 93.64%, 92.1%, 93.64% sensitivity and specificity respectively. However, manual annotation of skin lesion imposes a heavy burden in this model. Lopez *et al.* [12] utilized another CNN pretrained VGGNet model. Determatoscopic images are used to classify the melanoma images from lentigines or nevi. The researchers have tried to group their proposed CNN and pretrained CNN models. In the proposed CNN models they used learning and solidified layers and the parameters are adjusted in the pretrained models. In [13] a similar configuration has experimented on the ISBI 2016 Challenge dataset with 379 images it achieved 81.33% accuracy. Marchetti *et al.* [14] presented a classification model for melanomas using ensemble CNN. The model experimented on a dataset that contains melanomas, nevi, and lentigines. The model consists of machine learning and non-learning approaches. The methods are fused to form a single classification output. ISBI 2016 dataset of 279 dermatoscopic images were used for training and it achieved 58% ad 88% of sensitivity and specificity respectively. In [15], a CNN-based skin cancer diagnosis model that uses feature extraction approaches to extract characteristics from dermoscopic pictures. It achieved an accuracy of 89.5 percent throughout the testing phase. The detection accuracy, on the other hand, was insufficient and has to be increased. Overfitting occurred between the testing and training stages, which was a weakness in that study. To identify and classify skin cancer, Li and Shen suggested a deep learning based lesion indexing network (LIN). By extracting additional features, they were able to get good results using DL-based LIN. However, in order to improve the results even further, segmentation performance needs to improve.

Albahar [16] employed a unique regularizer to castigate the weight matrix and manage model's runtime. Each layer of the network has this regularizer integrated in it. On the ISIC dataset, 97.49 percent is the average skin lesion categorization accuracy. An attention based residual learning model is presented by Zhang *et al.* [17] for skin cancer classification. Using the attention based model on the ISIC dataset, lower-layer attention maps are produced from higher-layer feature maps. The average accuracy of their classification was 91.7 percent. Hosny et al. utlized transfer learning and AlexNet to classify skin lesions in another investigation [18]. MedNode, DermIS-DermQuest, and the 2017 ISIC Challenge were the three datasets they utilised. Image rotation was used as the basis for their augmentation approach. They rotated the photos in two different ways. The first method was arbitrary rotation, whereas the second was systematic rotation. For transfer learning, they employed a modified AlexNet and the final layer is replaced with a softmax layer. The CNN model's weights were updated through a stochastic gradient descent approach with minimal learning rate. For the Derm, MedNode, and ISIC datasets, their system performance was tested at 96.9%, 97.7%, and 95.9%, respectively. For classification of cutaneous lesions, Mahbod et al. combined deep characteristics. The dataset for this study was taken from the ISIC Challenge 2017. Image preprocessing, normalisation, and resizing were the first phases in their workflow. Four CNN models were then trained for feature extraction: AlexNet, VGG16, ResNet18, and ResNet101. The fine tuning network's dense (FC) layers outputs were used as the features. The last FC and output layers are replaced with two more FC layers in the networks. SVM classifiers were trained for three classes after extracting features. With the merging of all fine-tuned networks, the best performance was achieved. For melanoma the accuracy of 87.26 percent and 95.52 percent.

Table 1 gives a summary of numerous state-of-the-art studies of classification of skin cancer. Table 2 compare performances of a variety of cutting-edge models. Despite the fact that there are many recent skin cancer classification approaches they still have its own drawbacks as the number of malignancy in the dataset is comparatively lower than the benign sets. This creates a data imbalance and that resulted in poor results of the model.

Table 1. State-of-the-art skin cancer classification comparative analysis

Reference	Methodology	Advantages	Disadvantages
[9]	The potential advantage of merging human and artificial intelligence for skin cancer categorization is being investigated.	The man-machine team obtained an accuracy of 82.95 percent in the multiclass challenge. This was an increase of 1.36 percent.	The combined classifier's specificity dropped from 89.2% to 84.4%.
[10]	A single CNN was compared to the sensitivity and specificity of 112 German dermatologists from 13 university institutions.	For the bcc class, dermatologists and the classifier performed well.	The mel class had the lowest score for the classifier, with a specificity of 94.2 percent (AUC of 0.902).
[17]	A skin lesion border segmentation stage and a numerous skin lesions categorization stage were proposed as part of an integrated diagnostic system.	By putting the segmented skin lesions into a deep learning convolutional network, notable and representative characteristics may be retrieved.	The size of the tagged skin lesion pictures used for deep learning network training and testing was still restricted.
[18]	Using Multi task CNN, proposed the notion of simultaneously estimating food groups and calories for food photographs.	It has been discovered that through training with the multitask CNN, both estimates and performance may be improved.	Many results for relatively high-calorie items with calorie numbers have been discovered to be incorrect.
[19]	Color variation, asymmetry, and textural traits are among the information that the proposed diagnosing tool may retrieve.	Provides researchers an idea of which strategies to use in the automated identification of skin malignancies in order to get the best results.	It is only a building block for the detection process because it does not go into enough detail about the classification process and instead focuses on image processing.

Table 2. Comparative analysis of various skin cancer literature

Reference	Accuracy	Specificity	Sensitivity	Research Focus
[6]	79.5%	-	-	Classification of skin lesions
[11]	93.64%	55.18%	92.1%	Skin mole lesion classification.
[12]	81.33%	-	-	Classification of skin lesions
[14]	62.5%	88%	58%	Skin Imaging Collaboration. Verifying the accuracy of the automated systems with the dermatologist's manual
[15]	95.4%	-	-	Skin cancer diagnosing from dermatologic spots
[16]	82.95%	81.5%	89%	AI based skin cancer classification
[17]	65% for melanoma	89.2	98.8	CNN based skin cancer classification
[20]	96.86%	96.9%	96.9%	Classification of skin lesions through pretrained networks
[21]	98.7%	-	-	k-means technique for skin cancer detection
[19]	85%	-	-	Skin cancer detection strategies based on machine learning and image processing
[8]	98.89	86.6%	86.6%	Deep learning based skin cancer classification

It is observed from the literature study that deep learning based classification model have been a research focus in recent times and it has been efficiently used in skin cancer disease prediction. Most of the models used CNN model for classification. However, to reduce the training time pretrained models are effective solution.

3. Methodology

3.1. Dataset Details

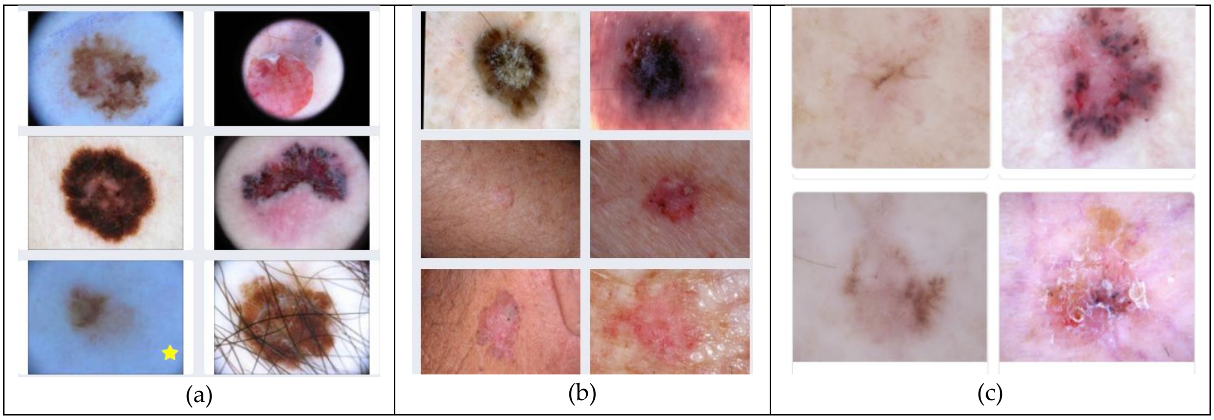


Figure 1. Sample dataset images of (a) Melanoma (b) SCC (c) BCC

In our experiment we used skin cancer image datasets such as MSK-1, UDA-1, UDA-2, HAM10000 from the ISIC[2] archive. A total of 1077 images were used for training and validation segregated into 3 classes of (a)melanoma, (b) SCC and (c)BCC. The model implementation is done on Google's interface colab GPU server. The skin cancer photos from the dataset are shown in Figure 1. Although the photos may be distinguished with the human eye, the deep learning model labels the images according to their kinds, including non-cancerous ones.

3.2. Dataset Preparation

We use data preparation to alter original data into a usable format so that we can build an effective model. Image sets comparing similar lesions from different views or shots of the same lesions on the same body make up our data collection. Although certain foggy and distant photographs were removed from the test and validation datasets, they were nevertheless included in the training. Feature selection, data cleaning, data transformations, dimensionality reduction, feature engineering, and other aspects helps to prepare the dataset for training.

3.3. Dataset Pre-processing

There are 1077 skin lesion photos in the original training set, all at different resolutions. Some lesion pictures have resolutions more than 1000 X 700, necessitating a hefty computational expense. For the deep learning network, the lesion images are rescaled for the input. All the training images in the dataset are rescaled to 224 X224. It is also possible to crop the skin lesion regions for the model training but doing so will have an impact in the results as the cancerous parts are in different positions in the images. So we chose to rescale the images without missing the important values.

3.4. Dataset Augmentation

Data augmentation is a methodology of artificially boosting the quantity of data by inserting marginally changed copies of original training data without literally collecting new data. The training dataset size can be intentionally enlarged to protect the model against overfitting by using data warping or oversampling. To avoid overfitting, we used PCA to enrich our data using rotation, random cropping, mirroring, and color-shifting.

3.5. VGG16

VGG16 is pretrained network that is proposed by Simonyan and Zisserman in the year 2015. ImageNet dataset is used for VGG16 training that consists of 15M high resolution images with 22 thousand classes. It takes an image input of size 224 X 224 X 3. The 3 in the dimension of the image represents the number of channels in the images. That is for a color image the number of channels would be 3. The VGG16 model made up of 13 convolutions and three dense layers. Convolution layers are the basic building blocks of CNN. It consists of convolution operations and kernel filters. The kernels are usually of smaller dimensions than the input image. It extracts the characteristics of the images through strides. Maxpooling, FC, ReLu, dropout, and SoftMax layers are among the 41 total layers. Pooling layers are the next important layer in a CNN. Pooling layers are of three types Max, Min, and Average. In VGG16 maxpooling layers are available it is to resize the images to better extract the features. FC is a fully connected or dense layer which is another component in a CNN network. FC connects all the neurons of the i-1 to the i^{th} layer in order to find the relationship between the features. Generally, the FC layers are found at the end of the CNN model. Rectified Linear Unit (ReLu) is a non-linear activation function used in VGG16. Dropout is an important layer to avoid overfitting of the model. At times our model may produce better training accuracy and poor test accuracy. This is the sign of overfitting that our model is not learning from the training rather it memorizes the training data. This can be avoided using dropout layers. For dropout layers the dropout rate can be specified. There are over 138,000,00 parameters that are computed. The structure is identical to that of a standard sequential model. We added our custom classifier after removing the last FC layer of networks. This classifier used a dense network with a thousand input neurons and a modified hidden layer with 40

[2] https://www.isic-archive.com/

input neurons due to the binary nature of classification. For this classifier, the number of output neurons is two. The activation function was likewise tuned to ReLu, with a dropout of 0.2. We utilised the ADAM optimizer and the Negative log-likelihood Loss Function. Similarly, the learning rate was set at 0.001. The model was prepared for training after all of the definition was completed.

3.6. Proposed Network Architecture

This section discusses the proposed skin cancer classification based on pretrained model. The aim is to classify three major forms of skin cancers that are melanoma, SCC, and BCC. For skin cancer classification, the suggested technique employs the VGG-16 pretrained model. The suggested skin cancer classification model's design is shown in Figure 2. A 224 X 224 RGB picture is accepted by the model. The picture is then processed using a convolution and pooling layer stack. The feature map is extracted from the input photos using convolution layers. The filter measures 3 × 3 pixels and has a 1 pixel stride. Pooling layers with a dimension of 2 X 2 and a stride of 2 pixels employ maxpooling. By deleting the original FC layers and replacing them with modified FC layers with random weights and Adam optimizer, the pretrained VGG16 model is trained for skin cancer images. ReLu is used as an activation function. The actual VGG 16 layers are followed by the flatten layer and the dense layer which is the skin cancer trained fully connected layer. Dense is also called fully connected layers that work better for classification problems. In a FC layer, every node in the previous and current layer is connected and uses the ReLu activation function.

Model optimization and regularization are important tasks in deep learning model. The proposed model should predict the classes without underfitting and overfitting. Underfitting is eliminated by using large dataset of images from the pretrained model. To avoid overfitting, we used dropout layer as regularization. Overfitting produces incorrect results such as poor test accuracy but high training accuracy. It occurs when the model learns from the dataset's erroneous data and noise. Hence, it produce unpleasant results. SoftMax function is used to for binary classification. It calculates the probability of the particular class to be classified. In multiclass problem SoftMax returns the probability of all the categories. The proposed model consists of multiple classes of skin lesions. It is appropriate to use SoftMax function. Adam optimizer is used for optimization. The proposed model is experimented with Adam and RMSprop optimizers and found Adam optimizer give better accuracy.

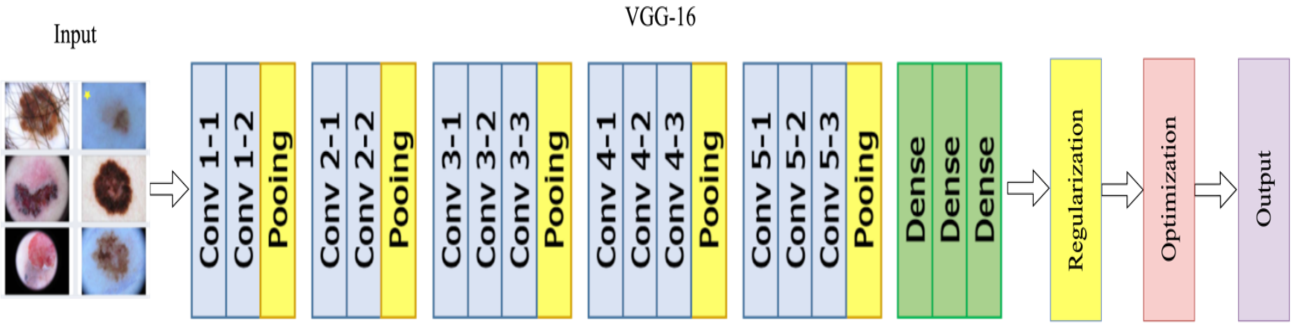


Figure 2. Proposed Skin Cancer Classification Model Architecture

In transfer learning, we take a pre-trained model (network + weights), and then removes the FC network, and construct our own in place of it. Doing so, it will remove the pre-trained weights at those layers. When training on the new data set commences, the actual model layers preceding the FC network is now frozen, leaving just the newly added FC network to be taught. In this scenario, the bottleneck characteristics are the inputs to the FC network. They represent the network's final convolution layer's activation map. Pretrained weights are used to extract significant feature activations as bottleneck features in our newly incorporated FC network as a result of the frozen weights in the main network, and now this second FC network gives us with the necessary inference. The model summary of the proposed network model are given in Figure 3. It shows the number of blocks in the proposed model, each block is a combination of convolution and pooling layers. It also shows the input and output shape of the data from one layer to the other. The number of trainable parameters are also listed for each layers.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten_1 (Flatten)	(None, 25088)	0
dense_2 (Dense)	(None, 512)	12845568
dropout_1 (Dropout)	(None, 512)	0
dense_3 (Dense)	(None, 1)	513

Total params: 27,560,769
Trainable params: 12,846,081
Non-trainable params: 14,714,688

Figure 3. Model Summary and Parameter Details (Snapshot)

4. Results

Training of the proposed model is done with 70% of data from the input dataset. The model was trained for 60 number of epochs until it reached a saturation level of accuracy. The trained model is then evaluated with 30% of test data. Our proposed model has efficiently classified the skin lesions according to the classes. The detailed experimental analysis is as follows.

4.1. Experimental Analysis

The experimental findings and performance evaluation of the suggested model are given in this section. The proposed pretrained deep learning based skin cancer classification model is evaluated based on common performance metrics such as accuracy, specificity, and sensitivity. evaluate the results of our training and testing with common classification performance metrics. Recall and Sensitivity are interchangeable terms. The equations for specificity and sensitivity are given in (1) and (2).

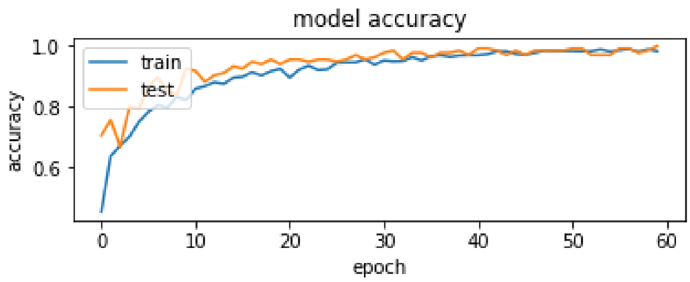
$$Specificity = \frac{TrueNegative\ (TN)}{TrueNegative\ (TN)+FalsePositive\ (FP)} \quad (1)$$

$$Sensitivity = \frac{TruePositive\ (TP)}{TruePositive\ (TP)+FalseNegative\ (FN)} \quad (2)$$

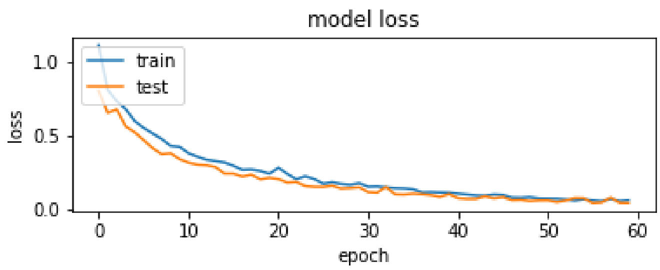
$$Accuracy = \frac{TruePositive(TP)+TrueNegative(TN)}{TruePositive(TP)+ TrueNegative\ (TN)+FalsePositive\ (FP)+FalseNegative(FP)} \quad (3)$$

Where, True Positive number denotes the classes that are correctly classified, False Positive are the classes that are incorrectly classified, True Negative number represents the wrong classes which are classified as correct and False Negative number represents the wrong classes that are classified as wrong.

Accuracy is one of the performance metrics used in classification problem that is used to evaluate the number of correctly classified classes. Figure 3 (a) shows the model accuracy versus epochs. The performance is compared between training and testing the minimal variation between them shows the model is trained without overfitting or underfitting. The proposed model have achieved 97.2% of accuracy at the 60th epoch then it is saturated. Figure 3 (b) shows the model loss which is important in model training. Loss should be kept minimal through regularization and optimization techniques. It is evident from the graph that the model loss is minimal with the increase in epochs thus the proposed model is proved to be effective and accurate. Figure 4 shows a sample testing of the proposed model. The input is a SCC skin lesion the model predicted it correctly.



(a)



(b)

Figure 4. Experimental results of the proposed model: (a) Model Accuracy (b) Model Loss

In our experiments we used different pretrained networks such as LeNet5, AlexNet, ResNet and VGG16 to evaluate proposed model's performance. It is clear from the findings that the proposed VGG16-based deep learning model performs better in classifying skin lesions. The VGG16 based model has outperformed the other pretrained networks in terms of accuracies and loss values. Table 3 presents the details.

Table 3. Comparison of various pretrained network results

Network	Train_loss	Val_loss	Train_Acc	Val_Acc
LeNet5	0.3745	1.4633	88.05%	48.57%
AlexNet	0.1013	1.5534	96.48%	47.15%
ResNet	0.0202	0.3067	99.26%	89.95%
Proposed VGG16	0.0234	0.0301	98.6%	97.2 %

4.2. Performance Evaluation

Many attempts to analyse medical images have been performed in recent past, thanks to deep learning and CNN for the enormous success medical field. The major goal of this paper is to demonstrate the pretrained CNN model capability on the diagnosis of various sorts of dermoscopy skin lesion images. We proposed deep learning model with VGG-16 pretrained network. The proposed model's hypermeter is tuned for better optimization. We have considered three major skin cancers they are melanoma, SCC, and BCC. The proposed model is experimented on the skin cancer images downloaded from ISIC. To assess the proposed model's performance, accuracy, sensitivity, and specificity are utilized. Our proposed skin cancer classification model is evaluated with similar studies [9] [10] [11] that used common datasets. Experiments reveal that our proposed model has a classification accuracy of 97.2 percent, a specificity of 96.5 percent, and a sensitivity of 98.2 percent. Table 4 shows the comparison of the performances skin classification models. As indicated by the comparison, the suggested model clearly outperforms previous state-of-the-art research.

Table 4. Proposed model performance comparison

Reference	Accuracy	Specificity	Sensitivity
Pomponiu et al. [11]	93.64 %	55.18 %	92.1 %
Hekler et al. [9]	82.95 %	81.5 %	89 %
Maron et al. [10]	65 %	89.2 %	98.8 %
Proposed Model	97.2 %	96.5 %	98.2%

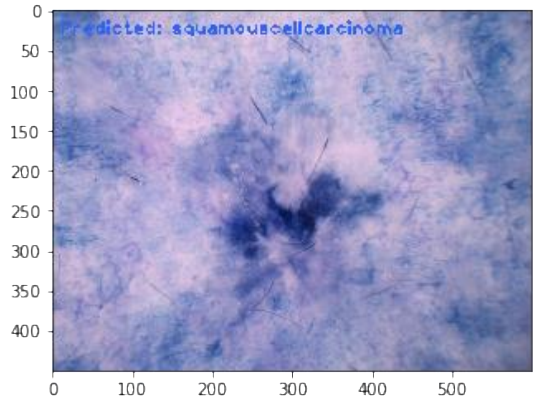


Figure 5. Model testing - Skin cancer image classified as squamous cell carcinoma

5. Discussions

Skin cancer diagnosis are time consuming and need experts to analyse the images to categorize them as benign or malignant also the malignancy level. At times, due to human error the patients may be wrongly diagnosed and that could be fatal. Skin cancers are mostly curable if a patient is diagnosed at the early stage. Hence in this work, a DL pretrained model based skin cancer classification model that can classify the types of cancer is presented. Melanoma is fatal in cancer types. Based on the results we obtained it is clear that CNN models can be useful in cancer diagnosis. Especially in this work it is able to efficiently classify the skin lesion according to its types. We used skin cancer image datasets such as MSK-1, UDA-1, UDA-2, HAM10000 from the ISIC[3] archive that includes melanoma, SCC, and BCC type of cancers. The proposed model's accuracy is 97.2% which is one of the best compared to similar studies. The model's performance is evaluated based on the sensitivity and specificity. As in medical images there will be less number of malignant data and huge number of benign data would be available. This creates a data imbalance so the model that is evaluated only based on accuracy would lead to wrong results. As a result, sensitivity, which is defined as the number of properly categorised images out of the total number of malignant images, and specificity, which is defined as the number of inaccurate classifications out of the total number of negative instances, are critical for medical imaging. Not just in terms of accuracy, but also in terms of sensitivity and specificity, our model outperforms the competition. Table 4 shows comparison of the values with similar works.

[3] https://www.isic-archive.com/

The experimental results on various pretrained models are shown in table 3. We have implemented deep learning models such as LeNet5, AlexNet, ResNet and VGG16 networks to analyse the performance. VGG16 model achieves the highest validation accuracy of 97.2%. Though the training accuracy of other models are higher that our model they failed miserably in validation. Validation accuracy is more crucial than training accuracy when evaluating a model. Also it is noticed that there is a minimum difference between training and validation accuracy this shows that our model is free from overfitting. We have also mentioned the train loss and validation loss and our proposed approach is better than other approaches.

To conclude, the pretrained based classification models are efficient when we have less amount of data for training. Based on the experiment carried out on the skin cancer datasets it is clear that such deep learning models can assist the dermatologists and doctors in diagnosing the cancer effectively without any errors. The proposed VGG16 based model is efficient when compared with other pretrained models. Hence, VGG16 model can be used for other medical image diagnosis too.

6. Conclusion

Millions of people are projected to be diagnosed with skin cancer, which is one of the most common illnesses. Early detection of malignancy in the skin lesions can greatly reduce the mortality rate and for successful treatments. This paper presents a DL based skin cancer classification model that utilizes the advantage of pretrained networks. We experimented our model with MSK-1, UDA-1, UDA-2, HAM10000 from the ISIC datasets. We have implemented LeNet5, AlexNet, ResNet and VGG-16 pretrained models to be trained with skin lesion images. The model is focused to detect and classify three major types of skin cancer. The proposed model performance of the VGG16 model is compared with other pretrained networks such as LeNet5, AlexNet and ResNet. The suggested VGG16-based model outperforms the competition in terms of validation accuracy. The performance of the model is assessed based on accuracy, specificity, and sensitivity. Through the regularization and optimization techniques of deep learning model the performance is enhanced. In terms of both experimental and performance assessments, the suggested model outperforms current deep learning techniques. This will make the job of dermatologists much simpler and help them to come up with suggestive treatments much faster than usual. In future, the model is focused to be trained with a greater number of skin cancer classes.

Author Contributions

The tests were designed and planned by J.A.O. and V.U.N. Experiments were carried out by V.U.N. M.K.S. and J.E. assisted in the writing of the text, while M.H.W. and N.S. assisted in the interpretation of the findings. The project was overseen by J.A.O. All of the writers contributed constructive criticism and assisted in the development of the research, analysis, and article.

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