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(Research Article)

Skin cancer classification using NASNet

Mohammad Atikur Rahman [1,*], Ehsan Bazgir [1], S. M. Saokat Hossain [2] and Md. Maniruzzaman [1,3]

[1] *Department of Electrical Engineering, School of Engineering, San Francisco Bay University, Fremont, CA 94539, USA.*
[2] *Department of Computer Science and Engineering, Jahangirnagar University, Savar, Dhaka-1342, Bangladesh.*
[3] *Department of Electrical and Computer Engineering, North South University, Dhaka-1229, Bangladesh.*

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Abstract

The importance of making an early diagnosis in both the prevention and treatment of skin cancer cannot be overstated. A very effective medical decision support system that can classify skin lesions based on dermoscopic pictures is an essential instrument for determining the prognosis of skin cancer. In spite of the fine-grained variation in the way different types of skin cancer appear, Deep Convolutional Neural Networks (DCNN) have made great strides in recent years toward improving the ability to detect skin cancer types using dermoscopic images. It has been claimed that there are a few different machine learning techniques for the accurate diagnosis of skin cancer using medical photos. A good number of these methods are predicated on convolutional neural networks (CNNs) that have already been trained, which makes it possible to train models using only a small quantity of available training data. However, because there are so few sample images of malignant tumors available, the classification accuracy of these models is still typically severely restricted. The primary purpose of this study is to construct a DCNN-based model that is capable of automatically classifying different types of skin cancer as either melanoma or non-melanoma with a high level of accuracy. We propose an optimized NASNet architecture, in which the NASNet model is enhanced with additional data and an additional basic layer that is employed in CNN is added. The strategy that has been proposed enhances the model's capacity to deal with incomplete and inconsistent data. A dataset of 2637 skin images are used to demonstrate the benefits of the technique that has been proposed. We analyze the performance of the suggested method by looking at its precision, sensitivity, specificity, F1-score, and area under the ROC curve. The accuracy of Optimized NASNet Mobile and NASNet Large provides an accuracy of 85.62% and 83.98%, respectively for Adam optimizer.

Keywords: Skin cancer; Transfer learning; Deep learning; NASNet; CNN; AUC; ROC

1. Introduction

Approximately 15% of an individual's average body weight and 20 square feet in area are devoted to the skin, the largest organ of the body [1]. All three layers of the skin—the epidermis, dermis, and hypodermis—perform vital roles that contribute to the skin's overall health. Physical injuries, pathogens, ultraviolet radiation, and substances are among the external hazards against which it functions as a barrier [1]. In addition to its other functions, the dermis facilitates contact sensation, aids in the regulation of body temperature, and prevents water loss. Additionally, melanocytes, which are specialized cells located in the epidermis and are responsible for generating the pigment melanin [1], stipulate the skin's color. The epidermis is, nevertheless, vulnerable to diseases, notwithstanding its protective functions. The skin can also be affected by cancer, which is distinguished by the unregulated proliferation of aberrant cells [2]. Tumors may result from this condition. Acute and malignant tumors are distinguishable among these, the former possessing the capacity to metastasize to distant anatomical sites and inflict substantial damage [2]. Particularly, malignant skin cells are found in the epidermis or dermis, the outermost and innermost layers, respectively [3]. Skin cancer is a prevalent form of cancer that sprouts uncontrolledly from skin cells, resulting in the formation of a lesion or mass [5], as reported

* Corresponding author: Mohammad Atikur Rahman

by the World Health Organization (WHO) [4]. Basal cell carcinoma, squamous cell carcinoma, and melanoma are the three form of skin cancers that are most commonly encountered [5]. The annual occurrence of skin malignancies worldwide is estimated to be between two and three million [4]. This figure represents an increase in incidence over the past few decades. One in every three cancer diagnoses is associated with skin cancer, according to data from the Skin Cancer Foundation [6]. Based on projections, 12,470 fatalities in the United States will be attributed to diverse forms of skin cancer in 2023 [7]. Aware of and implementing preventative measures is imperative in light of these alarming developments. Sun exposure during recreational activities, tanning bed usage, and a prior history of sunburn are frequently individual culpability and controllable for the development of skin cancer [8]. In order to substantially mitigate the prevalence of skin cancer among the general population, it is vital that individuals possess knowledge regarding these risk factors and adopt proactive measures to shield their skin from detrimental ultraviolet (UV) radiation [9]. Physical inspection, noninvasive dermoscopy [10] of the skin, and biopsy of any suspicious lesions [11] are customary procedures utilized in the diagnosis of skin cancer. After that, the malignancy status of the biopsy sample [12] is determined by microscopy analysis. Additional examinations may be performed to ascertain the precise nature and magnitude of the malignancy, should the biopsy validate its presence. Surgery, radiation therapy, chemotherapy, immunotherapy, or other therapeutic modalities may be utilized to treat cutaneous cancer, contingent upon its type and stage [13]. In most cases, early-stage skin cancer can be effectively treated with surgical excision of the malignant lesion, which is the most prevalent method of treatment. Metastatic cutaneous cancer, as well as cancer that has metastasized to other anatomical sites, is managed through the implementation of radiation therapy, chemotherapy, and immunotherapy [14].

Deep learning (DL) and ML have brought about a significant transformation in the realm of skin cancer identification and categorization in the past few years [15-25]. Dermatology heavily relies on ML algorithms like SVMs, decision trees, and DL algorithms, which are pivotal in this context. These algorithms employ statistical models and artificial neural networks to scrutinize extensive datasets containing skin images.

Image processing plays a vital role in the process of classifying cancer by extracting valuable information from medical images to ensure accurate classification. This process involves several interconnected stages. It starts with enhancing the quality of the images through techniques like color correction, illumination correction, contrast enhancement, and edge enhancement. These techniques improve the image quality and make it easier to extract relevant information. Following this, image segmentation algorithms are applied to divide the image into regions of interest. This is done using techniques such as thresholding, region growing, active contour models, and DL-based segmentation methods. Once the image is segmented, feature extraction techniques are used to identify essential features that can be used for classification. Techniques like Haralick texture features, Gabor filters, and scale-invariant feature transform (SIFT) are commonly used for this purpose. In order to handle high-dimensional data, dimensionality reduction techniques like principal component analysis (PCA) and linear discriminant analysis (LDA) can be applied. Once all these steps are completed, the final result is input into machine learning (ML) and deep learning (DL) models for accurate classification. The combination of these techniques ultimately leads to accurate and robust cancer classification. ML and DL techniques have several advantages over traditional methods in the field of skin cancer detection and classification. Firstly, they can automate the process of identifying and diagnosing skin cancer, reducing the need for human interpretation and minimizing the risk of human error. Secondly, they can provide faster and more accurate diagnoses, improving patient outcomes and reducing the risk of delayed or misdiagnosed skin cancer. Lastly, they can make the process of diagnosing skin cancer more accessible, especially in settings with limited resources where access to trained dermatologists is limited.

2. Literature Reviews

As a result of the advancement of deep learning, an increasing number of unique networks are being created in such a way that it is possible to train them from beginning to end. Over the course of the past several years, a variety of approaches utilizing a single deep CNN have been put up as potential solutions for the categorization of skin diseases. The methods of creating a deep CNN that have been employed in the works that have been gathered for this study mostly involve the use of self-building deep networks, the employment of already popular networks (such as GoogleNet and ResNet), and the implementation of an attention mechanism. In 2016, Nasr [26] et al. developed a CNN for the purpose of melanoma classification using non-dermoscopy photos captured by digital cameras. This CNN has two convolutional layers and two FC layers. The algorithm is useful not just as a telemedicine tool but also as a supporting system that may aid medical professionals. It can be used in apps that are web-based or mobile. Demyanov [27] et al. trained a five-layer CNN for the purpose of identifying two different kinds of skin lesion data. On the ISIC dataset, the approach was evaluated, and the best mean classification accuracies for the "Typical Network' and "Regular Globules' datasets were, respectively, 0.8 and 0.83. A single GoogleNet Inception V3 network was trained in [28] for the aim of classifying skin lesions using just pixels and sickness labels as inputs. This was done in order to accomplish their goal. They accomplished this by utilizing a single network solely. The dataset that they utilized in their research contains 129,450 clinical pictures covering 2032 different illnesses. They used this dataset to conduct their study. In addition to this, they evaluated the performance of the CNN to the performance of 21 board-certified dermatologists using biopsy-proven clinical pictures with two crucial binary classification use cases. These two types of use cases for binary categorization were keratinocyte carcinomas and benign seborrheic keratoses, as well as malignant melanomas and benign nevi. The results showed that an artificial intelligence was able to classify skin cancer with a level of competence comparable to that of dermatologists. This was demonstrated by the fact that the CNN delivered performances that were on par with those of all evaluated specialists across both tests. The study on dermoscopy pictures categorization that was presented by Walker [29] et al. analyzed two different inputs that were obtained from a dermoscopy image. Both of these inputs were considered independently. These inputs were visual characteristics that were established by a deep neural network that was based on the Inception V2 network [30] and signification of deep learning node activations, which were then classified by either humans or machines. The high level of accuracy of this decision assistance system was independently confirmed by a controlled laboratory study (LABS) as well as a prospective observational study (OBS). Mishra [31] et al. carried out study with the purpose of determining how effective the deep learning algorithms that are now available are for the classification of skin disorders.

3. Methodology

In this section, the proposed methodology will be discussed in details.

3.1. Description of Dataset

The performance of the deep learning techniques is based on the availability of a suitable and valid dataset. The following dataset is being used in this research.

The dataset [32] includes 2637 dermoscopic images, 1197 images related to malignant, and 1440 benign skin lesions. Every image is associated with one of these patients through a unique patient identifier. We used 1197 images of benign class and 1140 images of melanoma. The dataset looks a balanced dataset. After that, various data augmentation strategies were performed, including rescaling, width shift, rotation, shear range, horizontal flip, and channel shift. Sample images are showed in Figure 1.

Table 1 Image Distribution

Class Levels	Training	Testing
Malignant	949	248
Benign	1160	280
Total	2109	528

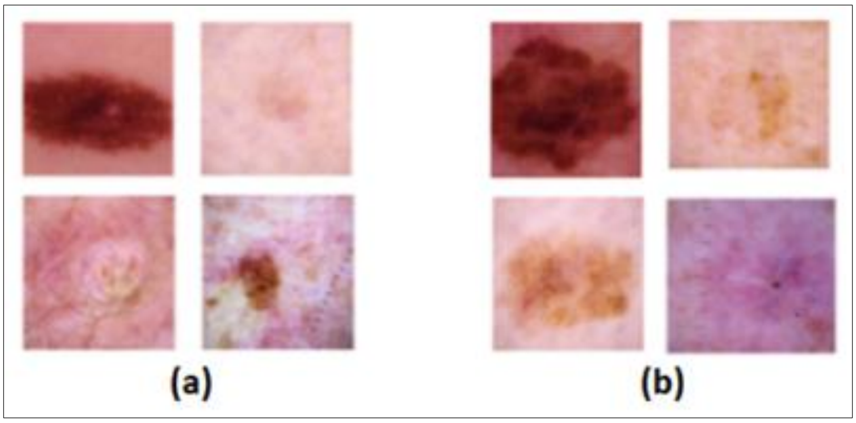

Figure 1 (a) Benign and (b) melanoma lesions images

3.2. Image Pre-Processing

To obtain higher consistency in classification results and improved features, preprocessing is employed for all input images of dataset. The DL approach requires a massive amount of repetitive training; for this purpose, a large-scale image dataset was required to prevent the danger of over-fitting.

3.2.1. Image Resizing

All images in the dataset is resized to 224 × 224. It will reduce the model performance dramatically and speed up the processing process.

3.2.2. Data Augmentation

The classification of skin images relies heavily on augmented data. The ultimate success of pulmonary image classification is highly dependent on the quality of the data augmentation process. Because it is considered a medical image, it follows that skin images will likewise suffer from the same limitations. Medical picture labeling, unlike voice data or text data, cannot be contracted out to a third party. Professional radiologists are the only ones qualified to assign labels to these data, and it takes them thirty minutes or more to carefully examine each image several times and manually assign labels to indicate where nodules are located. Because of this severe shortage of skilled professionals, medical image data will continue to struggle (far fewer than the number of professionals who can annotate other voice or text data). Data augmentation is important because it allows the training data to be increased sufficiently and rationally on the small skin cancer imaging data set, which in turn improves the model's generalization capacity. The model's stability is increased by including reasonable and acceptable noise data.

To combat overfitting and expand the variety of the dataset, many data augmentation strategies have been used on the training set using the picture data generator function of the Keras library in Python. By employing scale transformation, lower pixel values were used within the same range, reducing the computational cost. With the help of the parameter value (1./255), this meant that the range of each pixel's value was from 0 to 1. Using the rotation transformation, the photos were rotated 15 degrees. The width shift range transformation was used to shift the images arbitrarily to the right or left; the width shift parameter was set to 0.1. With a height shift range parameter value of 0.1, the training images were shifted vertically. If the zoom range argument was greater than 1.0, the photos were magnified, and if it was less than 1.0, the images were zoomed out. Therefore, the image was magnified using a zoom level of 0.2. The horizontal image was flipped using the flip function. The zoom range was 0.5–1.0 since the brightness transformation was utilized, where 0.0 means no brightness and 1.0 means maximum brightness. According to Table 2, the closest fill mode was achieved by applying the 0.05 channel shift range. This is because in channel shift transformation, the channel values are moved by a random number chosen from the range.

Table 2 Image Augmentation Techniques

Methods	**Value**
Scale_Transformation	Ranged from 0 to 1
Rotation_Range	15 degree
Width_Shift_Range	0.1
Height_Shift_Range	0.1
Zoom_Transformation	0.2
Horizontal_Flip	True
Vertical_Flip	True

3.3. Pre-trained DL Model

3.3.1. NASNet Model

The AutoML and NAS have taken the throne in the field of CNN's. NASNet is a convolutional neural network that is trained using the millions of images included in the ImageNet dataset. The network was trained with a robust feature for picture recognition; the input image size is 224 by 224. NASNet's design and search method for the best CNN architecture are depicted in Fig. 2. NASNet comes in two flavors: NASNetMobile for small networks and NASNetLarge for more extensive networks. When compared to NASNetLarge, the NASNetMobile network is more lightweight. It employs a search approach to look through tiny picture datasets for the most effective convolutional layers or cells. Better classification results can be obtained with lower computing costs by employing the convolution cells. We can then use these convolutional cells to construct normal and reduction cells, allowing NASNet to be used with pictures of any size. Several different configurations of normal cells and reduction cells are used, and a collection of NASNet structures have been developed to provide the most accessible CNN architecture with little computational overhead. Although NASNet's overall architecture is predefined as shown below, the cells or building blocks that are searched by the strengthening learning search method are treated as free parameters; for example, N is the number of repetitions used for scaling, while the number of initial convolutional filters is not. When comparing the normal cell to the convolutional cells, the size of the feature-map is not altered in the normal cell calculation. However, the reduction cell halves the size of the feature map in both dimensions. The controller RNN solely looks into the cell structures themselves.

Table 3 liiustrates the basic parameters used in order to train the NASNet Mobile model. Adam, and Nadam optimizers are used. Categorical Cross-entropy is used as loss function.

Table 3 Parameters used in NASNet Mobile

Methods	**Value**
Type of Transfer	From Scratch Transfer Knowledge
Train Layers	All
Optimizers	Adam, Nadam
Learning Rate	True
Activation Function	ReLu and Sigmoid
Loss Function	Categorical Cross-entropy
Batch Size	32
Epoch	30

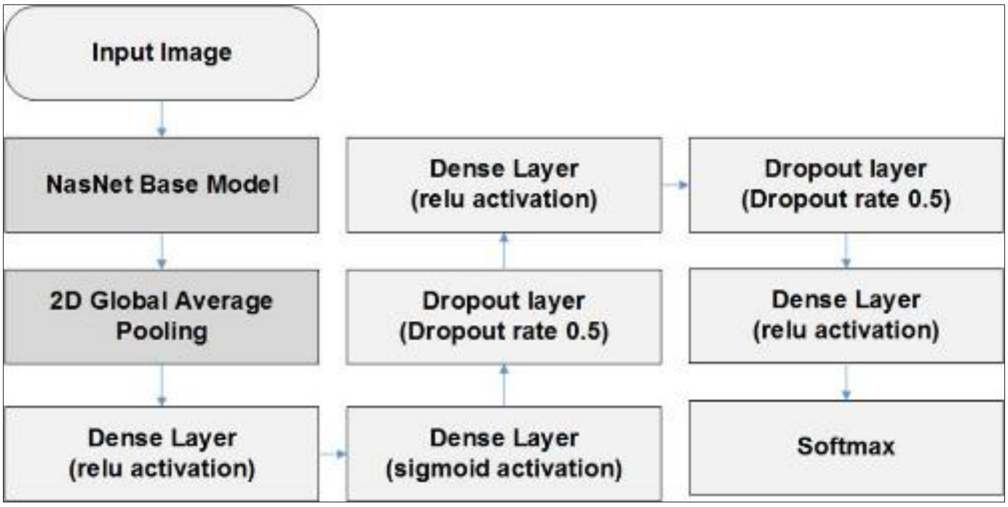

Figure 2 Optimization of NASNet Model

Fig. 2 describes the process of optimizing the NASNet Mobile model. From the figure, it can be seen that a 2D GAP layer is used after the NASNet base model. After that, a dense layer is used, which takes the output of the 2D GAP layer as an input. There are many choices of activation functions on the activation layer, such as Sigmoid, Relu, and Tanh. Its function is to add non-linear factors to enhance the expression of the models, so it must be non-linear. As a result, the Relu function, which has excellent performance in nonlinear systems, is selected as the activation function in the first stage, whereas sigmoid activation is used in the second dense layer. Next, a dropout layer is used with a dropout rate of 0.5. The model's inferences about the new data will be influenced by overfitting. Using Dropout, which involves temporarily removing nodes to lower the complexity of the model and hence prevent overfitting, is one such technique [39-42]. Then, an additional series of dense layers and dropout layers is used. Finally, softmax is used for classification.

4. Performance Analysis

Table 4 and 5 describes the confusion matrix (CM) for NASNet Mobile and NASNet Large respectively using Adam optimizer.

Table 4 Confusion Matrix for NASNet Mobile

		Actually Positive	Actually Negative
		1: Malignant	**0: Benign**
Predicted Positive	1: Malignant	213	35
Predicted Negative	0: Benign	42	238

Table 5 Confusion Matrix for NASNet Large

		Actually Positive	Actually Negative
		1: Malignant	**0: Benign**
Predicted Positive	1: Malignant	198	50
Predicted Negative	0: Benign	37	243

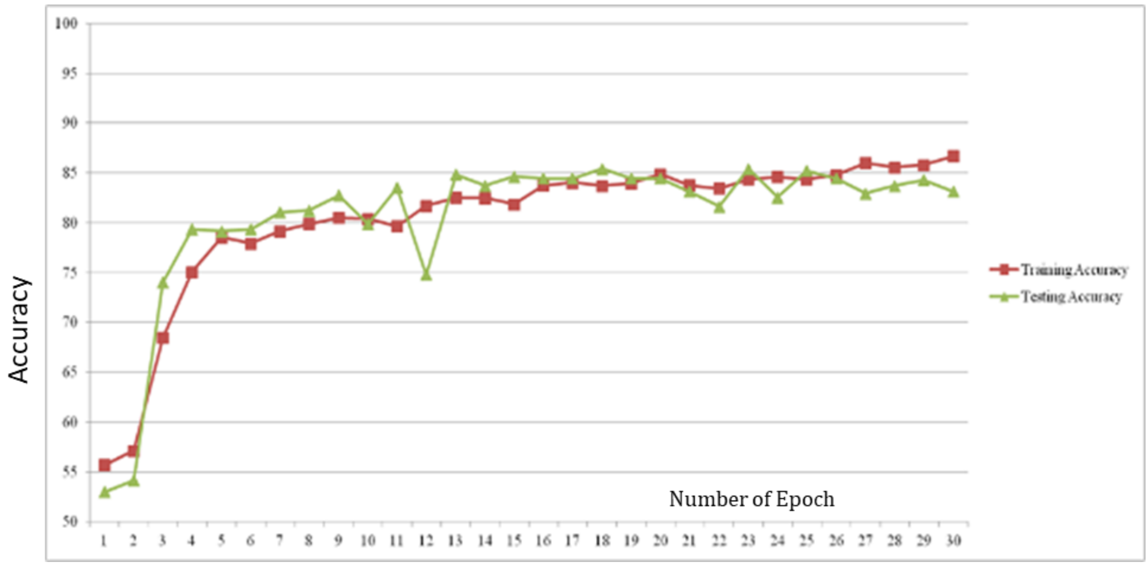

Figure 3 Epoch vs. Accuracy for NASNet Mobile Pre-training

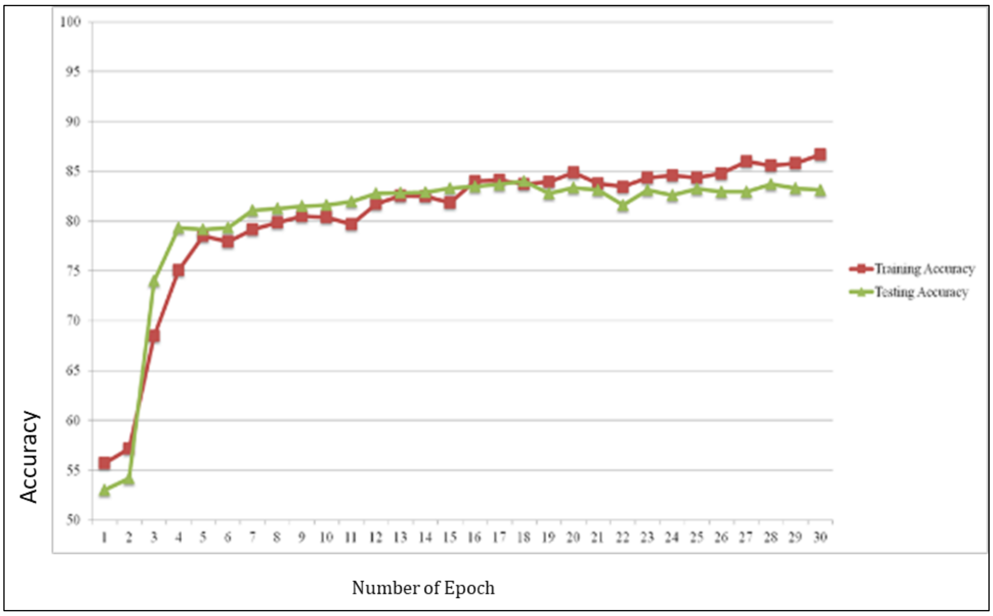

Figure 4 Epoch vs. Accuracy for NASNet Large Pre-training

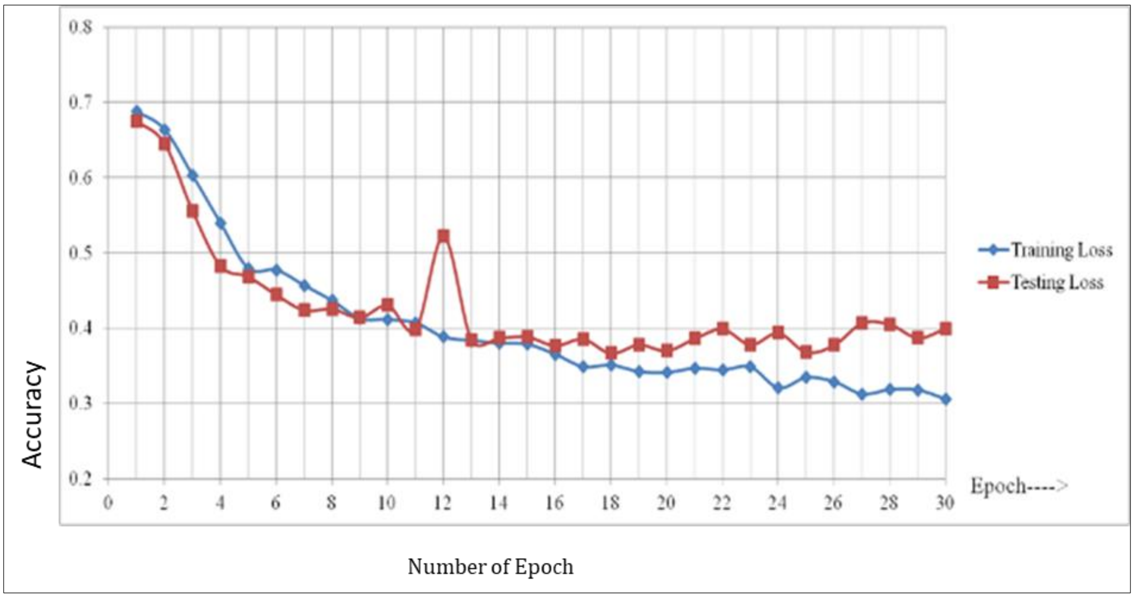

Figure 5 Epoch vs. Loss for NASNet Mobile

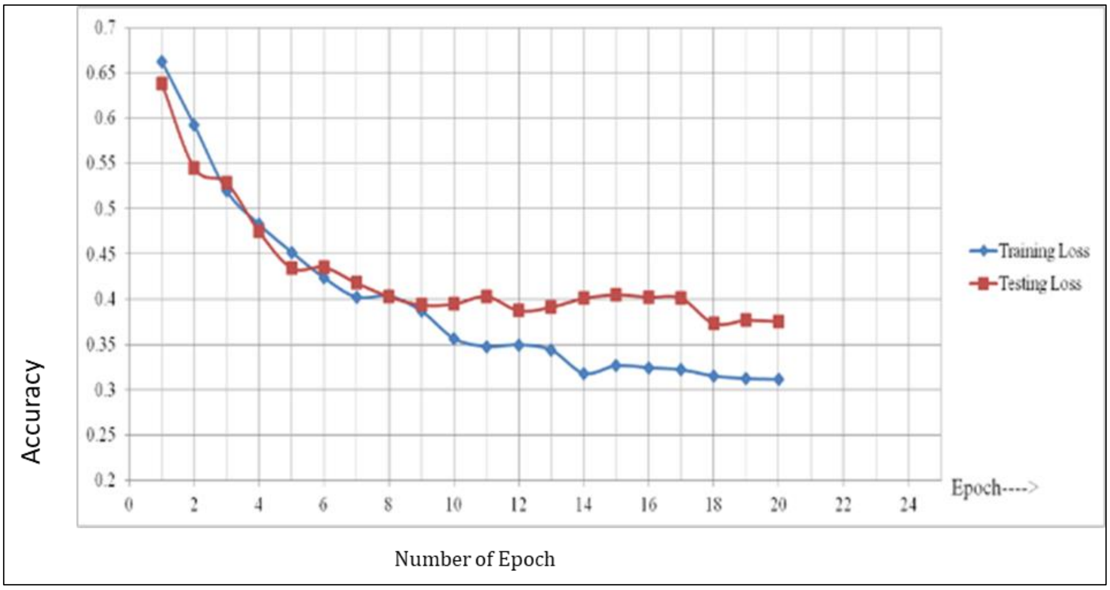

Figure 6 Epoch vs. Loss for NASNet Large

Figure 3 and 4 describes the Epoch vs. Accuracy for NASNet Mobile and Large, respectively. Figure 5 and 6 describes the Epoch vs. Loss for NASNet Mobile and Large model, respectively. Figure 7 illustrates the acquired ROC findings of the proposed NASNet models for the Adam optimizer. The results specifically highlight the superior performance of the optimized NASNet model in comparison to other models. In fig. 9 and fig. 10, the AUC for both class is 0.92 and 0.87, respectively.

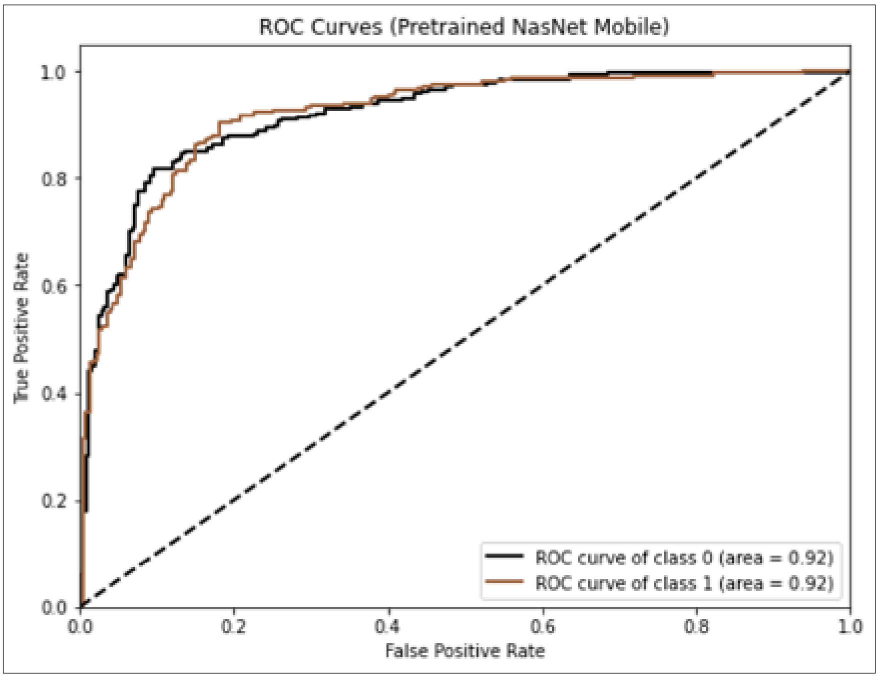

Figure 7 ROC Curve for NASNet Mobile for Adam Optimizer

From table 6, this can be concluded that the proposed optimized NASNet model provides good accuracy and sensitivity compared to some other DL models deployed already in other research paper.

Table 6 Comparison of proposed method with other models

Model	Sensitivity	Specificity	Precision	Accuracy
ResNet [33]	50.71%	74.10%	67.76%	75.31%
VGG 19 [33]	50%	71.89%	65.22%	73.11%
VGG Net [34]	78.66%	-	79.74%	81.33%
Shifted MobileNet V2 [35]	65.9%	95.2%	71.4%	81.9%
Shifted GoogLeNet [35]	58.1%	94.7%	68.5%	80.50%
CNN [36]	-	-	-	78%
ResNet-50 [37]	85%	-	86%	84.87%
VGG 16 [37]	81%	-	82%	81.27%
CNN [37]	76%	-	14%	76.33%
MobileNet [38]	-	-	-	77.31%
DenseNet [38]	-	-	-	79.39%
ResNet 50 [38]	-	-	-	81.05%
ResNet50 + DenseNet [38]	78.31%	82.42%	-	81.64%
Proposed NASNet (Ours Model)	84.23%	87.25%	86.19%	86.73%

5. Conclusion

Using NASNet on skin images, this research proposes a technique for skin cancer classification and compares it to existing approaches. Methods based on migration-based learning and skin cancer image categorization, in particular, can improve accuracy. Furthermore, the transfer learning neural network model outperforms the original DCNN model in skin picture classification on the database. Because the model for skin cancer imaging on the ISIC or other skin dataset can provide an efficient and rigorous computer-assisted diagnostic when skin image data is insufficient, it can benefit from the same fine-tuning that improved the accuracy of skin image classification using NASNet transfer learning. However, if the transfer learning network is selected incorrectly, a negative transfer problem may arise, resulting in a drop in accuracy and an increase in training time. Therefore, improving network selection for skin imaging tasks is a promising area for further study.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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