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Skin cancer classification using Inception Network

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Abstract

Since skin disease is a universally recognized condition among humans, there has been a growing interest in utilizing intelligent systems to classify various skin ailments. This line of research in deep learning holds immense significance for dermatologists. However, accurately determining the presence of a disease is a formidable task due to the intricate nature of skin texture and the visual similarities between different diseases. To address this challenge, skin images undergo filtration to eliminate unwanted noise and undergo further processing to enhance the overall quality of the image. The primary purpose of this study is to construct a deep neural network-based model that is capable of automatically classifying several types of skin cancer as either melanoma or non-melanoma with a prominent level of accuracy. We propose an optimized Inception architecture, in which the InceptionNet model is enhanced with data augmentation and basic layers. 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. Proposed InceptionNet provides an accuracy of 84.39% and 85.94%, respectively for Adam and Nadam optimizer. The training process in each subsequent layer exhibits a notable enhancement in effectiveness. An examination of this inquiry can assist experts in making early diagnoses, thereby providing them with insight into the nature of the infection and enabling them to initiate the necessary treatment, if deemed necessary.

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

1. Introduction

Skin disease is one of the most widely recognized forms of cancer, and it poses a significant threat to individuals. In the United States, it is the most prevalent type of cancer and affects a huge portion of the population. The occurrence of deadly lymphoma, a type of skin tumor, results in numerous fatalities each year. However, if detected early, it can be effectively treated through simple extraction procedures. On the other hand, late-stage diagnosis is associated with a higher risk of mortality, with a survival rate of less than 20% after luminary stage recognition. Dermatologists have access to various non-intrusive tools for diagnosis, including visible images captured by cameras or smartphones. Unfortunately, these images often suffer from inadequate quality. To overcome this limitation, dermatoscopic devices provide the best visual representation and serve as valuable non-invasive tools for detecting deadly pigmented skin lesions. Dermoscopy allows for better differentiation between different types of sores based on their appearance and morphological characteristics [1-5].

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Melanoma, as a highly malignant disease, presents significant challenges when it comes to identification using traditional methods like ordinary cameras. This disease affects the DNA, leading to overexposure of skin cells to harmful ultraviolet (UV) rays and subsequent skin pigmentation. If melanoma goes undetected in its early stages, it can infiltrate deeper into the body, causing damage to lymph nodes and blood vessels. In such cases, deep learning methods like Convolutional Neural Networks (CNN) and InceptionNet play a crucial role in facilitating accurate diagnosis and treatment [6-14].

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]. Deep learning is highly suitable for analyzing large amounts of medical data and can be used to extract valuable information from it. This advanced form of artificial intelligence has the potential to automatically identify abnormalities, suggest potential diagnoses, and even generate preliminary radiology reports. In fact, the renowned global company IBM is already working on developing radiology applications with its system called Dr. Watson. This system encompasses all the functions mentioned earlier, including automatic detection and quantitative analysis of medical images to identify abnormalities. The rapid advancement of AI technology necessitates that radiologists familiarize themselves with it to understand its capabilities and how it may soon impact radiology practice to understand its capabilities and how it may impact radiology practice soon. We firmly believe that the integration of machine learning-based analytic tools in radiology practice will occur. However, we also believe that this does not equate to replacing radiologists entirely, although certain specific tasks may be automated. These automated processes will not truly serve as a complete substitute, but rather as a valuable enhancement to the overall field of radiology, complementing the indispensable and exceptional skills of human radiologists.

2. Literature Reviews

Xie et al. [26] put forward a system for the classification of skin lesions, wherein lesions were categorized into two primary classes: benign and malignant. The system operated in three phases. In the initial phase, a self-generating neural network was utilized to extract lesions from images. In the second phase, features such as tumor border, texture, and color details were extracted. The system extracted a total of 57 features, including 7 innovative features pertaining to lesion border descriptions. Principal component analysis (PCA) was employed to reduce the dimensionality of the features, thereby leading to the selection of the optimal set of features. Finally, in the last phase, lesions were classified using an ensemble model consisting of neural networks. The ensemble neural network improves the performance of classification by combining backpropagation neural networks and fuzzy neural networks. Furthermore, the classification results of the proposed system were compared with other classifiers, such as support vector machines (SVM), k-nearest neighbors (KNN), random forest, Adaboot, and so on. With an accuracy of 91.11%, the proposed model achieved a performance in terms of sensitivity that was at least 7.5% higher than the other classifiers.

Masood et al. [27] proposed a diagnostic system for skin cancer based on artificial neural networks (ANN). The performance of three learning algorithms of ANN, namely Levenberg–Marquardt (LM) [28], resilient backpropagation (RP) [29], and scaled conjugate gradient (SCG) [30], was also investigated in this study. The comparison of performance revealed that the LM algorithm exhibited the highest specificity score of 95.1% and remained efficient in the classification of benign lesions. On the other hand, the SCG learning algorithm yielded better results when the number of epochs was increased, resulting in a sensitivity value of 92.6%. For the early diagnosis of melanoma skin cancer, a system for mole classification was proposed [31]. The proposed system extracted features based on the ABCD rule of lesions, where ABCD denoted asymmetry, border, color, and diameter of a mole. The assessment of a mole's asymmetry was carried out using the Mumford–Shah algorithm, while the borders were extracted using the Harris Stephen algorithm. In the proposed system, moles with colors other than black, cinnamon, or brown were considered melanoma. Moreover, melanoma moles typically had a diameter greater than 6 mm, which served as the threshold value for melanoma detection. To classify moles into three classes (common mole, uncommon mole, or melanoma mole), the proposed system utilized a backpropagation feed-forward artificial neural network with an accuracy of 97.51%.

In [33], the Convolutional Neural Network (CNN) algorithm was employed to classify images by discerning the gender of the detected object. To determine the most effective architecture, an architectural model was constructed through transfer learning with the utilization of three pre-trained models: VGG-16, Inception-V3, and MobileNet-V2. The optimization algorithms Adam and RMSProp were employed in this experimentation. The Inception-V3 model yielded the most favorable outcomes in gender prediction from the image, with an accuracy and loss validation value of 0.9350 and 0.1550, respectively. In comparison, the VGG-16 and MobileNet-V2 models achieved values of 0.9320 and 0.1660, as well as 0.8760 and 0.3000, respectively. In [34], NasNet model was applied to the same dataset [37] used in our experiment for malignant and benign skin images classification.

3. Methodology

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

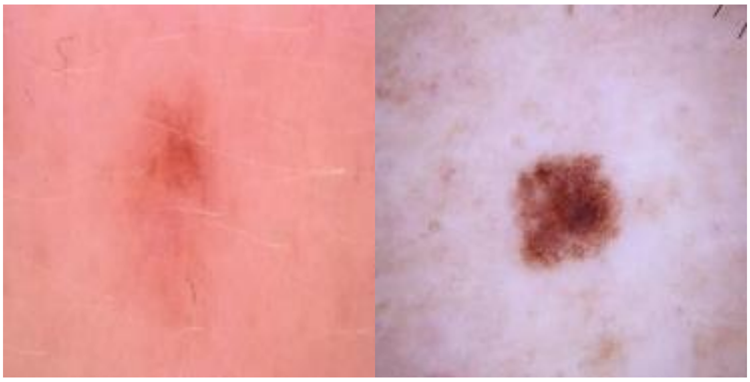
3.1. Description of Dataset

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 [37] 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 Set	Testing Set
Malignant	949	248
Benign	1160	280
Total	2109	528



(a) (b)

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

3.1.1. 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.

3.1.2. 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.

3.1.3. Data Augmentation

Due to the limited availability of qualified professionals, annotating skin images is a challenge in medical image data. The quality of the data augmentation process plays a vital role in determining the ultimate success of skin image classification. As skin images are considered medical images, they are subject to the same limitations. Unlike voice data or text data, medical picture labeling cannot be outsourced to a third party. Only professional radiologists possess the necessary qualifications to assign labels to these data, and it takes them thirty minutes or more to carefully examine each image multiple times and manually assign labels to indicate the location of nodules. Due to the limited availability of skilled professionals, the annotation of skin images in medical image data will continue to face challenges, with a significantly smaller number of professionals available compared to voice or text data. Data augmentation is crucial as it allows for sufficient and rational expansion of the training data set for small skin cancer imaging data, thereby improving the model's ability to generalize. Including reasonable and acceptable noise data enhances the stability of the model.

To address overfitting and increase the diversity of the dataset, various data augmentation strategies have been implemented on the training set using the picture data generator function of the Keras library in Python. Scale transformation was employed, using lower pixel values within the same range to reduce computational cost. By setting the parameter value to 1./255, each pixel's value ranged from 0 to 1. Rotation transformation was used to rotate the photos by 15 degrees. The width shift range transformation allowed for arbitrary horizontal shifts of the images, with a width shift parameter of 0.1. The training images were vertically shifted using a height shift range parameter value of 0.1. If the zoom range argument exceeded 1.0, the photos were magnified, while values less than 1.0 resulted in zooming out of the images. In this case, the image was magnified using a zoom level of 0.2. The flip function was used to horizontally flip the image. The zoom range was set to 0.5-1.0, as brightness transformation was applied, with 0.0 representing no brightness and 1.0 indicating 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 randomly shifted within the specified 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

3.2. Inception V3 Model

A convolutional Neural Network is described as a technique for classifying data in images [37], with a particular focus on image recognition problems. The strength of the CNN model lies in its hierarchical learning layer, which can be intensely trained once the model topology matches the input features. By leveraging the spatial relationship of visual patterns, the model efficiently reduces the number of parameters, thereby improving performance accuracy. Inception V3, developed by Google, is a convolutional neural network architecture specifically designed for image classification tasks. It is the third iteration of the Inception architecture and was introduced in 2015. Inception V3 builds upon the concepts of its predecessors and aims to enhance both the performance and efficiency of image classification tasks. The architecture of Inception V3 is deep and intricate, consisting of a stack of interconnected inception modules. Each module combines different types of convolutional and pooling layers to extract various features from the input image. A notable feature of Inception V3 is its utilization of factorized convolutions, which decrease the network's parameter count while maintaining a high level of accuracy. Factorized convolution enables the network to learn both local and global features of an image, thereby improving the model's accuracy. Inception V3 employs a combination of 1x1, 3x3, and 5x5 convolutional filters to extract features from the input image. The 1x1 filters are used to reduce the input's dimensionality, while the 3x3 and 5x5 filters extract more intricate features from the image [32].

Another notable characteristic of Inception V3 is its utilization of batch normalization, a technique employed to standardize the inputs to the network. Batch normalization aids in stabilizing the training process and mitigating the internal covariate shift, which refers to the alteration in the distribution of the network's inputs during training. Inception V3 is initially trained on a vast dataset known as ImageNet, which comprises over 14 million images and 1000 distinct classes. This enables the model to be applied to transfer learning for other image classification tasks with a smaller dataset, where it can be fine-tuned for a specific task. Transfer learning is a technique that allows a pre-trained model to be repurposed for a different task by adjusting the model on a new dataset. This can significantly reduce the amount of data and computational resources required to train a new model from scratch. Inception V3 has been widely utilized for image classification tasks and has exhibited excellent performance on various benchmarks. It has been employed in diverse applications such as object detection, image segmentation, and video classification. Its incorporation of factorized convolutions and Inception modules makes it an exceedingly efficient and accurate model for image classification tasks. In addition, its pre-training on the ImageNet dataset renders it a versatile model that can be applied to a range of applications with a commendable degree of accuracy. Inception V3 is a potent CNN architecture that has been extensively employed for image classification tasks and has proven to excel in various benchmarks. Its use of factorized convolutions and Inception modules makes it a highly efficient and precise model for image classification tasks. Its pre-training on the ImageNet dataset allows for transfer learning on other image classification tasks with a smaller dataset, enabling fine-tuning for a specific task and thereby reducing the amount of data and computational resources required to train a new model from scratch. The Inception-V3 architectural model possesses an advantage due to its more intricate architecture and more efficient computation, containing approximately 4 million parameters, significantly smaller compared to VGG, with a more complex architecture, and this model does not employ a fully-connected layer but rather replaces it with a pooling layer only. These fewer parameters result in a smaller model size, facilitating faster model calculations [27]. Figure 2 describes the structural schematic diagram of the Inception-v3 model. By allowing the network to integrate many kernel types on the same level, essentially "widening" the network, InceptionV3 architectures aim to address the problem of excessive changeability in the position of prominent parts in the images under analysis.

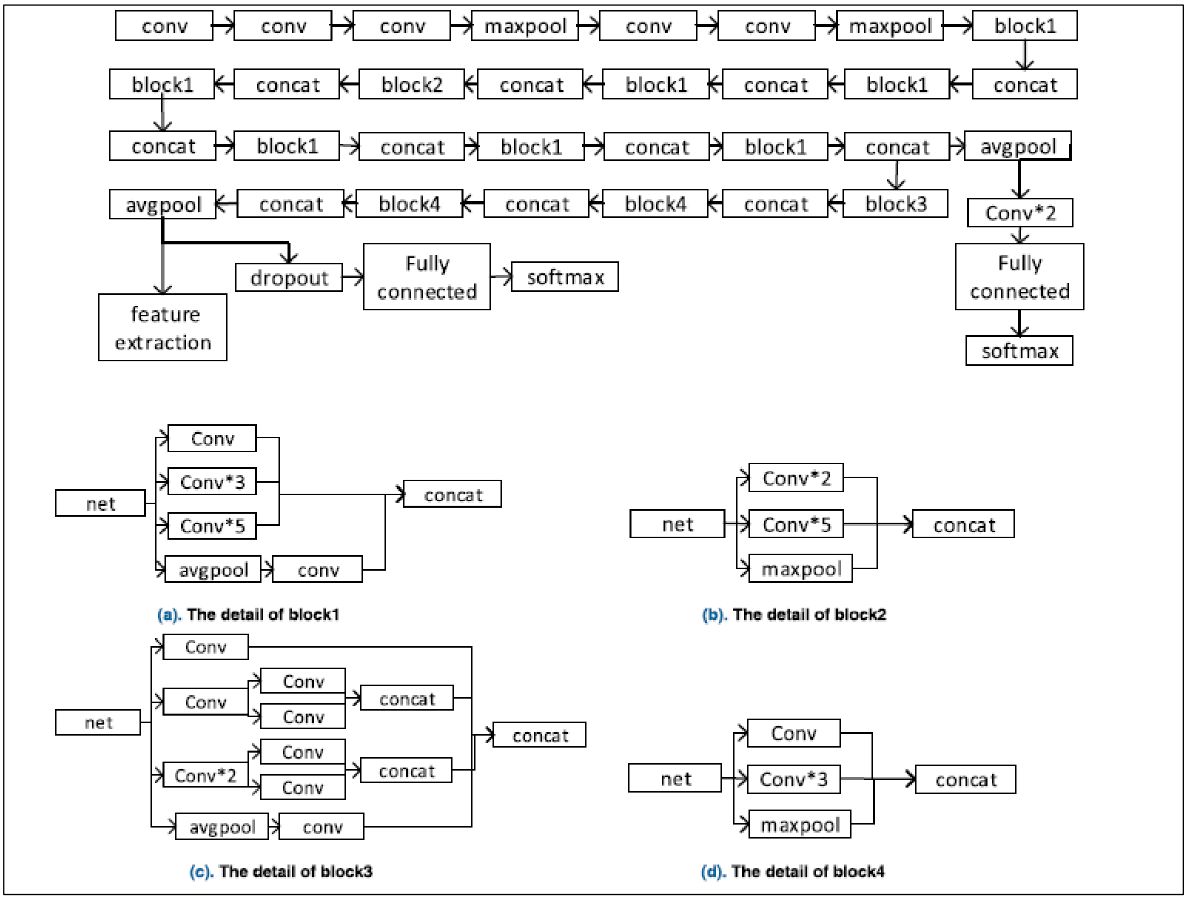


Figure 2 The structural schematic diagram of the Inception-v3 model. The detail of block 1_4 are shown in Figure (a), Figure (b), Figure (c) and Figure (d).

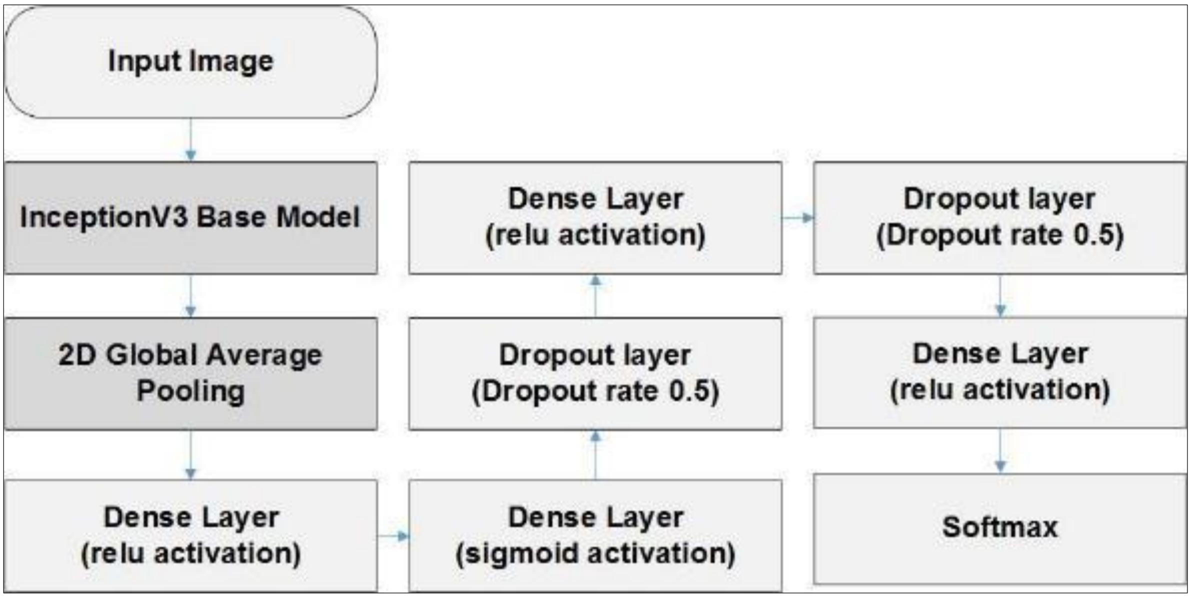


Figure 3 Optimization of Inception V3 Model

Figure 3 describes the process of optimizing the Inception V3 model. From the figure, it can be seen that a 2D GAP layer is used after the Inception V3 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. Then, an additional series of dense layers and dropout layers is used. Finally, softmax is used for classification.

Table 3 liiustrates the basic parameters used in order to train the Inception V3 model. Adam, and Nadam optimizers are used. Categorical Cross-entropy is used as loss function.

Table 3 Parameters used in Inception V3 Model

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

3.3. Performance Analysis

Table 4 describes the confusion matrix (CM) for Inception V3. Table 5 illustrates the Accuracy, Sensitivity, Specificity, Precision for Adam and Nadam.

Table 4 Confusion Matrix for Inception V3

		Actually Positive	Actually Negative
		1: Malignant	**0: Benign**
Predicted Positive	1: Malignant	215	51
Predicted Negative	0: Benign	33	229

Table 5 Comparison of Accuracy, Sensitivity, Specificity, Precision for Adam and Nadam

Optimizer	Sensitivity	Specificity	Precision	Accuracy
Adam	86.69	81.79	80.83	84.39
Nadam	86.89	81.98	80.97	85.94

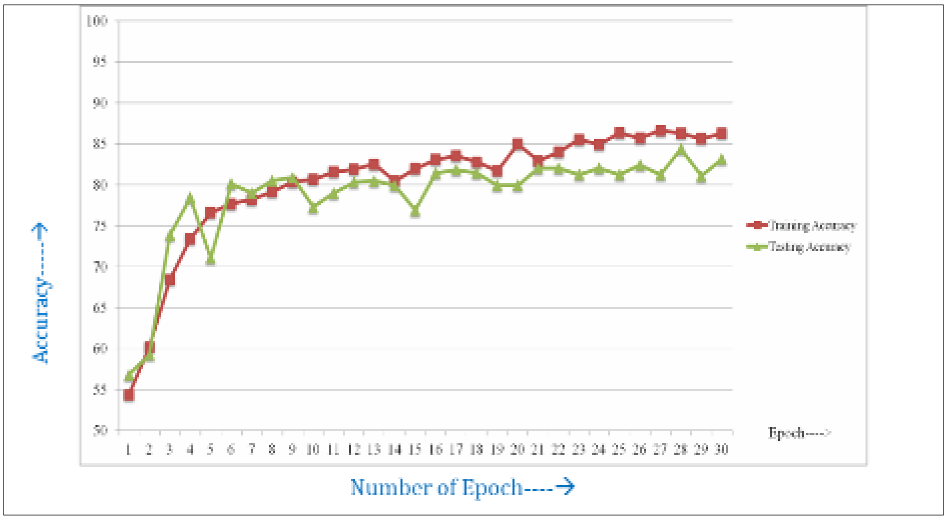


Figure 4 Epoch vs. Accuracy for Adam Optimizer

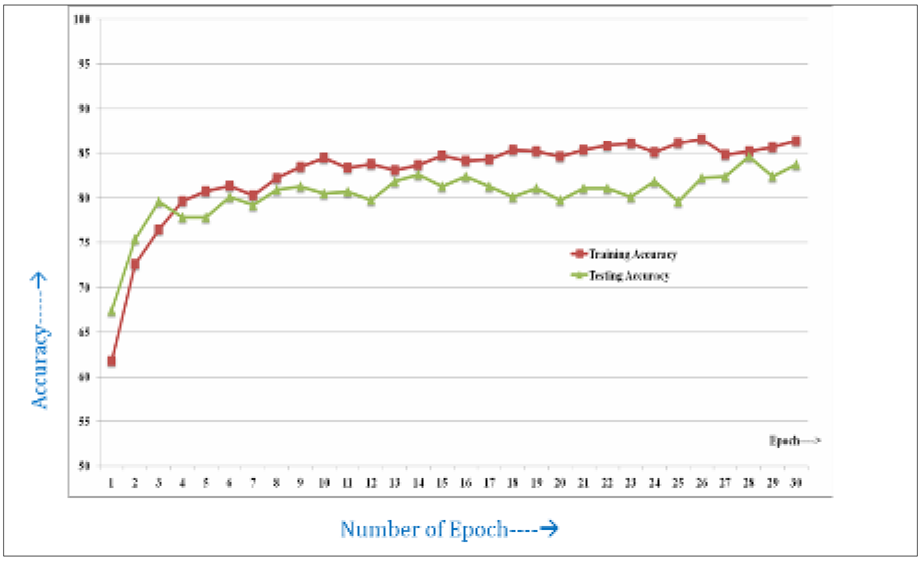


Figure 5 Epoch vs. Accuracy for Nadam Optimizer

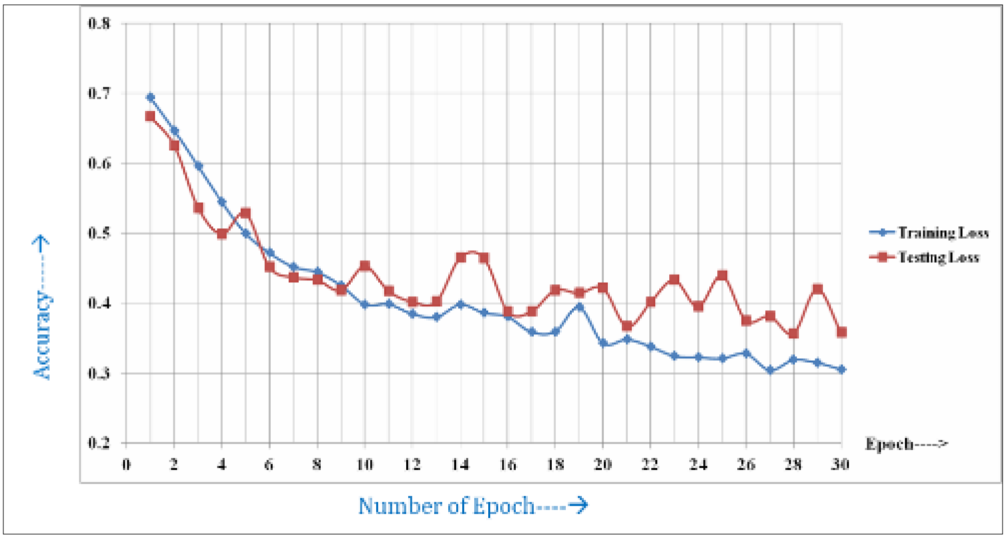


Figure 6 Epoch vs. Loss for Adam Optimizer

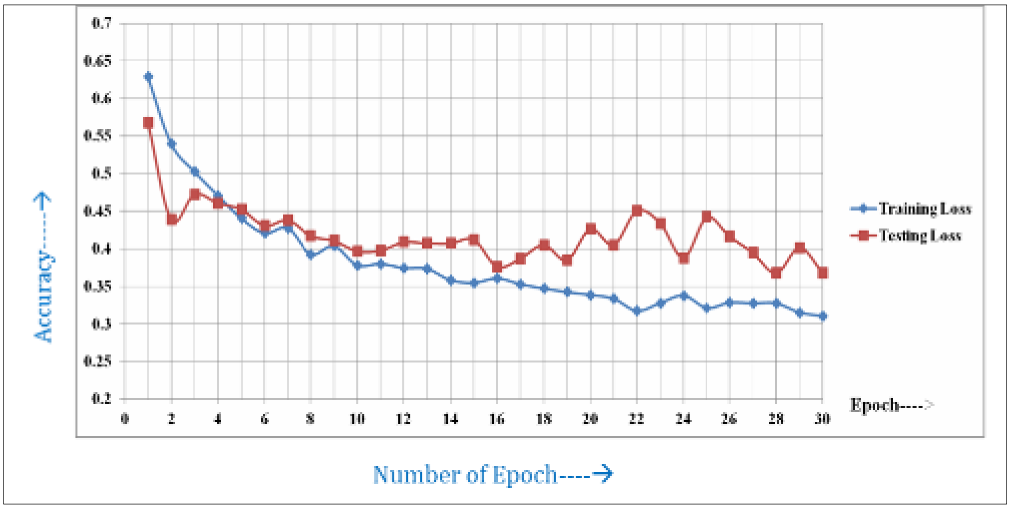


Figure 7 Epoch vs. Loss for Nadam Optimizer

Figure 4 and 5 describes the Epoch vs. Accuracy for Adam and Nadam optimizer, respectively. Figure 6 and 7 describes the Epoch vs. Loss for Adam and Nadam optimizer, respectively. From table 6, this can be concluded that the proposed optimized Inception Network 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

DL Model	Sensitivity	Specificity	Precisio	Accuracy
ResNet [38]	50.71%	74.10%	67.76%	75.31%
VGG 19 [38]	50%	71.89%	65.22%	73.11%
VGG Net [39]	78.66%	-	79.74%	81.33%
Shifted MobileNet V2 [40]	65.9%	95.2%	71.4%	81.9%
Shifted GoogLeNet [40]	58.1%	94.7%	68.5%	80.50%
CNN [41]	-	-	-	78%
ResNet-50 [42]	85%	-	86%	84.87%

VGG 16 [42]	81%	-	82%	81.27%
CNN [42]	76%	-	14%	76.33%
MobileNet [43]	-	-	-	77.31%
DenseNet [43]	-	-	-	79.39%
ResNet 50 [43]	-	-	-	81.05%
ResNet50 + DenseNet [43]	78.31%	82.42%	-	81.64%
Linear classifier CNN deep learning [46]	-	-	-	85.5%
Proposed Inception V3 (Ours Model)	86.89%	81.98%	80.97%	85.94%

4. Conclusion

This research presents a technique for skin cancer classification using Inception V3 on skin images and compares it to existing approaches. The accuracy can be enhanced by utilizing methods based on migration-based learning and skin cancer image categorization. Moreover, the transfer learning neural network model exhibits better performance than the original DCNN model in classifying skin pictures in the database. When the skin image data is insufficient, the model for skin cancer imaging on the ISIC or other skin dataset can efficiently assist in diagnosing skin conditions with computer assistance in a rigorous manner. The same fine-tuning that improved the accuracy of skin image classification using InceptionNet learning can be applied, thus resulting in potential benefits. However, if the transfer learning network is erroneously chosen, a negative transfer problem may arise, leading to a decrease in accuracy and an increase in training time. Therefore, there is a promising opportunity for further research in enhancing network selection for skin imaging tasks.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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