Design of inception architecture for skin melanoma classification

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Article Info	ABSTRACT
	The number of people diagnosed with skin cancer is increasing sharply. Both invasive and non-invasive methods of examination may be used to investigate it. However, the invasive method is more difficult for the patient because samples must be taken from the lesion itself, or the whole lesion must be cut out. It also requires more time and cost. To avoid invasive procedures, computer-based analysis and diagnosis have the potential to increase diagnostic accuracy and turnaround time. This study develops a unique discriminative deep learning architecture (DDLA) for dermoscopic image classification (DIC), called DDLA-DIC, which uses the concept of inception. Using this concept, the proposed DDLA-DIC system is designed wider and deeper and the network learns from various spatial patterns. The proposed DDLA-DIC system can extract image characteristics from dermoscopic images for skin cancer diagnosis in an effective and efficient way. The proposed DDLA-DIC system is evaluated by utilizing the dermoscopic images from the PH2 database, and the obtained classification results are based on a random split approach. The simulation results indicate that the framework has a great deal of potential with 99.79% accuracy.

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1. INTRODUCTION

The skin is the biggest organ in the human body and has the function of protecting us from harmful elements in the environment. There are primarily two categories of skin cancer: malignant melanomas (MM) and non-melanoma skin cancers. Melanoma, often known as skin cancer, is the most deadly form of the many diseases that can damage the skin. It is also the most common form of skin cancer. Even though it is one of the most serious types of cancer, there is a high chance of survival for people diagnosed with it at the earliest possible stage. A neural-based hybrid deep learning (DL) approach is discussed in [1] to identify and classify skin cancer. ImageNet is a back propagation technique that integrates AlexNet, visual geometry group (VGG), and GoogleNet for a reliable system and a convolutional neural network (CNN) model into a single neural network architecture for image classification. An ensemble model is described in [2] for categorizing melanomas. Hair removal is based on partial differential equations, and a neural network model for segmenting lesions is devised. The correlation-based strategy selects the features from the retrieved characteristics, such as colour, border, and texture features. A single hidden layer and two hidden layers' designs are used in the development of the ensemble model. A multi-view filtered transfer learning (TL) technique is described in [3] for the categorization of skin lesions making use of cross-source domain-labeled data. It is based on a deep

neural network (DNN) that uses a multi-view weighting representation module. The multi-view TL network can do an accurate analysis of the discriminative information included within the raw images. The contourlet transform is described in [4] to classify melanomas. A Bayesian classifier predicts skin cancer from the contourlet sub-band energy characteristics.

A skin cancer localization and classification system are described in [5] using deep feature fusion. It uses computerized discriminant feature selection. During pre-processing, a dull razor and median filter remove hair and smooth the surface. Using rank-based entropy-controlled neighbourhood component analysis, features are selected, and then the ensemble k-nearest neighbor classifier classifies malignant skin cancer. The DL method and a CNN model for skin cancer detection are discussed in [6]. Skin lesion traits, including symmetry, colour, size, and shape are extracted to distinguish skin images. Rectified linear unit (ReLU) gives the network non-linearity, whereas max pool minimizes computational cost by down-sampling data.

An implementation of the differential box-counting technique combined with the fractal feature-based probabilistic classifier is discussed in [7]. The fractal qualities may be acquired by using differential box counting. The skin images are broken down utilizing the energy features obtained from the empirical wavelet transform. A neural network utilizing spectral colour data is discussed in [8]. A 3x3 MobilenetV2 with ReLU filters enables easy and fast categorization. This classifier uses texture characteristics, which define pixel colour and intensity. MobilenetV2's convolutional layer with long short-term memory connects image features with the existing features. A generative adversarial networks (GANs) based approach is discussed in [9] for skin melanoma classification. During the pre-processing stage, the raw dermoscopic image is given to a black top-hat filter to remove the hair. The matrix transformation approach entails the images being flipped, resized, and rotated to get the desired result. This technique in the design of GANs, together with the TL approach-based DenseNet201 model, offers an acceptable way of extracting features for correctly categorizing high-quality lesion images. A GAN binary classifier for melanoma classification is discussed in [10]. Hair is removed using coarse-grained hair to approximate a hairless distribution. Lesions' important characteristics are preserved by decreasing L1 norm reconstruction loss under laplace noise.

An improved technique for categorizing of melanomas is described in [11]. In the preprocessing stage, unwanted hair is removed using the dull razor technique, and then the contrast is increased. The Boltzman entropy is used to select features from shape, colour, and texture, and a support vector machine (SVM) classifier is used to categorize those chosen features. A computer-aided metadata processing block model for skin cancer categorization is described in [12]. Features from the metadata processing block are combined with dermoscopic images for better performance [13]. Then, an automated DL model is used to accurately predict and diagnose skin cancer [14]. Multi-modal image fusion system in which input images are decomposed by applying discrete wavelet transform (DWT) at four levels and nonsubsampled contourlet transform (NSCT) at two levels that assists to defending essential data from the sender images [15]. This system demonstrates an important development in pixel clarity and continues the data at the corners and edges of the fused image with no data loss [16]. A machine vision application utilizing an image processing method established a new method of rice seed classification that applies hashing techniques for preprocessing image prediction [17]. The linear regression algorithm which calculates the value of a dependent variable, establishes an independent variable [18]. The hybrid bat algorithm and genetic algorithm model are employed on noisy medical images to reduce noise, and their performances have been determined by arithmetical analyses such as peak signal-to-noise ratio (PSNR) [19]. DL is employed to classify three focal diseases in the liver besides the normal liver [20].

The accuracy of typical classification systems is dependent on the characteristics that are retrieved from the data as well as the classifiers that are chosen. In addition, the development of a precise classification method requires two separate modules for successful classification. Recent years have seen the development of architectures that are based on DL to solve these challenges. The primary goal of this effort is to design and implement an effective inception architecture that can provide accurate and reliable skin cancer diagnosis utilizing dermoscopic images. The remaining section of the paper is structured as follows: the proposed inception architecture for effective skin melanoma classification is discussed in section 2, and the results derived from the proposed model for skin cancer diagnosis are analyzed and discussed in section 3. In the 4 section, both findings and recommendations for further research are discussed.

2.   METHOD

The availability of medical images is an extremely important factor in the research, development, and testing of image processing algorithms customized for a specific medical image analysis. Figure 1 shows the proposed inception architecture for skin melanoma classification. The dermoscopic image is the input for the proposed skin melanoma classification system. The classification process begins with the extraction of deep features after preprocessing the input image, followed by the use of a dense layer and an output layer gives the classification result.
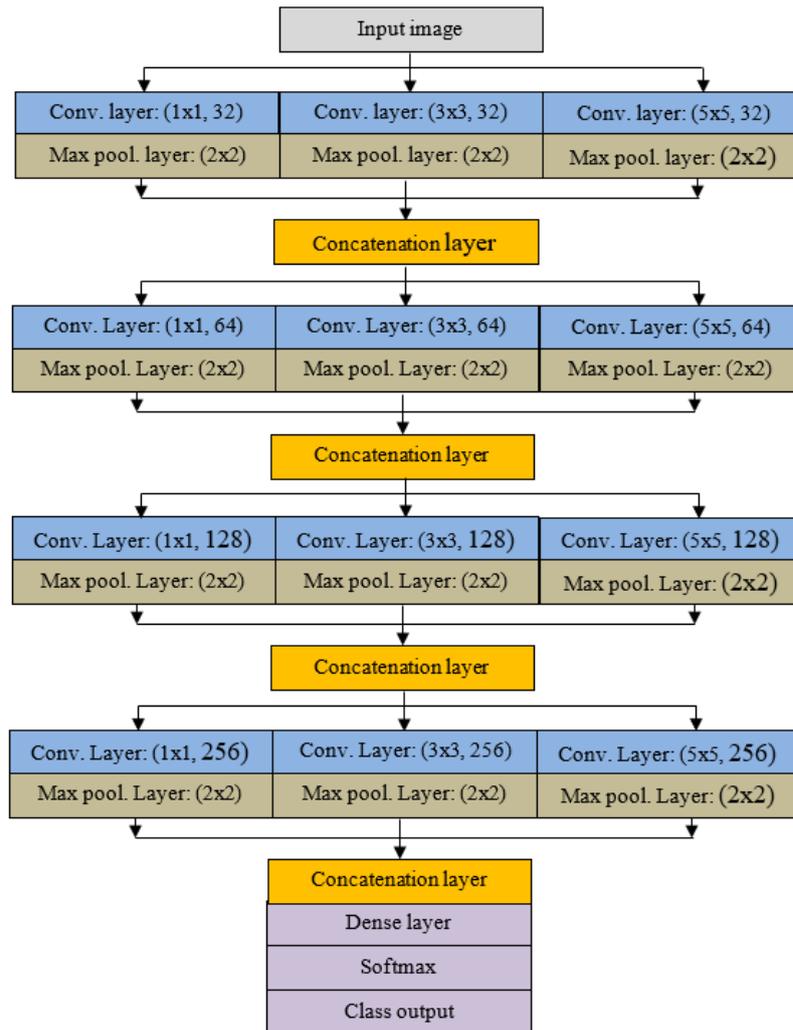
Figure 1. Proposed inception architecture for skin melanoma classification

The visual information obtained from dermoscopic images is the primary basis for diagnosing of skin cancer [21]. The recent availability of skin images enables such a diagnosis through computerized image processing. This processing includes a wide range of different methods or algorithms, the result of which is an enhanced version of the original image that was fed into the pattern recognition system. Based on the information included in the input, the system generates either a descriptor (features) or a decision. It may be necessary to use some fundamental preprocessing techniques to strip unnecessary information from the acquired images. Following the step of preprocessing, a computerized skin image analysis system will extract the concealed properties and perform an analysis of them.

2.1. Preprocessing

Several preprocessing stages are often incorporated in the majority of computer vision algorithms. The application of filters to data (input) to extract the relevant information is the preprocessing phase that occurs most often. If the extracted features from the dermoscopy images include redundant data, such as noise or hair, this will degrade the system's overall performance. Therefore, in the preprocessing module, a strategy called median filtering is used. In the preprocessing stage, dermoscopic images should preserve their important features, such as edges and curves, while the noise is removed. The technique of non-linear filtering (median filtering) has the potential to preserve the abovementioned features more than linear filters. The size of the filter window used in this investigation is 21 pixels on each side [22]. Figure 2 shows the preprocessed median-filtered dermoscopic image. Figure 2(a) shows the original images from the PH^2 database, and the preprocessed images by the median filter are shown in Figure 2(b).

(a)

(b)
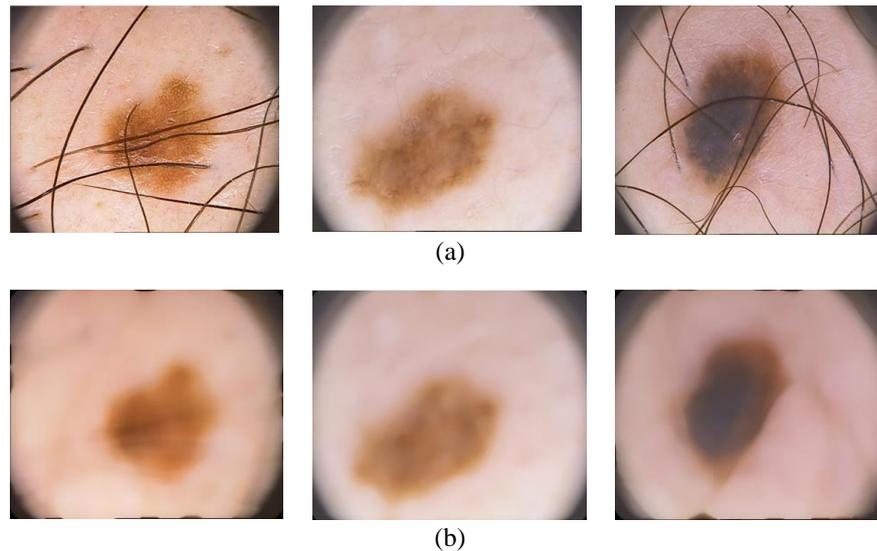
Figure 2. Dermoscopic images (a) original and (b) preprocessed by median filter

2.2. Features by inception architecture

To effectively develop an image classifier, one of the most important steps is to extract and use of useful characteristics from the images. Nevertheless, the generation of additional features will lead to an increase in computing complexity, which will result in practical issues. This is particularly true when there is a need to complete classification tasks in real-time. It is desired to build a technique with limited production of essential characteristics without difficulty conducting correct classification. This may be accomplished via the arrangement of layers, as shown in Figure 1, which can work with a limited generation of necessary features.

The proposed discriminative deep learning architecture (DDLA)-dermoscopic image classification (DIC) system uses three different sizes of convolution filters, such as 1×1, 3×3, and 5×5. The main advantage of using a 1×1 convolution filter is that the dimensions of the data across the network are shrunk, which has the added advantage of making the network wider and deeper. Because of the diverse widths of the convolution filters (3×3 and 5×5), they teach the network how to recognize a wide variety of spatial patterns at various scales. The convolution operation is defined in (1).

$$y(i,j) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} h(m,n) \bullet x(i-m, j-n) \tag{1}$$

Where y is the convolved output, x is the input, and h is the convolution filter of size (m,n). After the input image is convolved with 1×1, 3×3, and 5×5 convolutional filters, the dimension of the convolved outputs is reduced by half using max pooling layer with a stride of 2. Then the reduced feature maps are concatenated and given to the next inception module for extracting deep features.

2.3. Classification by dense layer

Information processing with neural networks involves modeling the biological nervous system to handle numeric data and developing nonlinear correlations between input and output. The structure and function of the biological nervous system, such as the brain, served as inspiration for its imitation of the neural network system's structure and operation. The neural network consists of many processing components that work better to solve certain issues. It is possible to respond to vast and complicated situations in which there may be hundreds of predictor variables that have a great deal of interaction between them. Dealing with image data and tackling various pattern recognition issues are also some areas in which neural networks perform very well. In order to construct a linear discriminant function to resolve non-separable issues, the window-hoff approach is the appropriate starting point. Coupled with one another. These elements are called neurons, and they work. In feed forward neural networks (FFNNs), nonlinearity is implemented by adding a layer of 'hidden' processing units or neurons that have a differentiable activation function, as well as an extra layer of adaptive weights [23]. This creates a neural network that is capable of learning. Backpropagation networks are flexible and have applications in a wide variety of domains, including classification, control, and pattern recognition. In this network, the data are not sent back into the network; instead, they are fed forward into the network. Because of this, all interconnections are unidirectional, and there are no connections between neurons on the same layer. Figure 3 provides a schematic representation of a model for a FFNN.
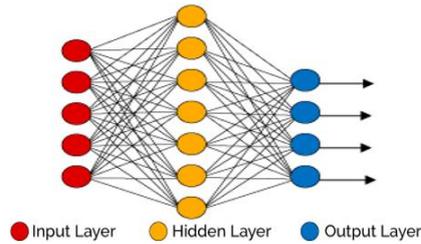
Figure 3. Schematic representation of a model for a FFNN

The network is started by assigning random weights to each node. During the forward pass, the calculation results performed at each neuron of each layer are sent across the network layer by layer, ultimately leading to the actual output. The local gradient for each neuron will be computed as the weights. In the forward pass, no adjustment of weights takes place. During the backward pass, the actual output is deducted from the desired output. When there is no evidence of error, the weights remain unchanged, or the error will be sent down from the output to the inputs, and at each layer, the weights are adjusted. The error function or loss function used in the develops a unique discriminative deep learning architecture (DDLA-DIC) system is defined as,

$$CEL = -\sum_{j=1}^{c} t_c \, log(p_c) \tag{2}$$

where the probability for the ith class is p_c and its truth label are t_c. During training, the model weights are optimized so that the CEL is reduced to its smallest possible value. The weight adjustment dependent on the loss gradient is controlled by the learning rate (0.001), with a maximum iteration or epoch of 20. Rectified the Linear activation function ReLU is utilized in the input layer and the softmax activation function is employed in the output layer for the classification. Figure 4 shows the activation functions used in the proposed DDLA-DIC system. Figure 4(a) shows the ReLU function, and Figure 4(b) shows the Softmax activation function.

(a)	(b)
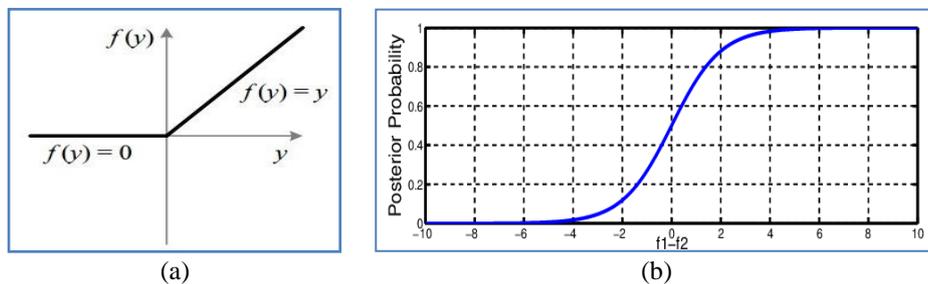
Figure 4. Activation functions; (a) ReLu and (b) softmax

3. RESULTS AND DISCUSSION

The findings discussed in this section are achieved by applying the proposed inception architecture to the dermoscopic images in the PH2 database [24], [25]. Researchers use the PH2 database more often than any other database that is currently accessible. In this study, it is used to measure how well the proposed system classifies things in terms of accuracy, sensitivity, and specificity. The dermoscopic image has a resolution of 758 by 328 pixels, and there are 200 dermoscopic images in the PH2 database. It includes forty melanomas ranging in size from small to large, eighty examples of atypical nevi, and eighty examples of common nevi. Figure 5 displays the dermoscopic image samples from the PH2 database. Figure 5(a) shows normal dermoscopic images and Figure 5(b) shows abnormal samples from the PH2 database.

The DL system's performance heavily depends on the number of training samples used to train the network. This is the main issue when dealing with limited data, and one of the best solutions is to enrich the already available data. The data augmentation approach allows generating new training samples from an original dataset without altering the data category (class). This is a transformative use of technology. Image classification, object identification, semantic segmentation, and information retrieval are just a few of the numerous applications of this technology that have been used effectively in image processing.

(a)

(b)
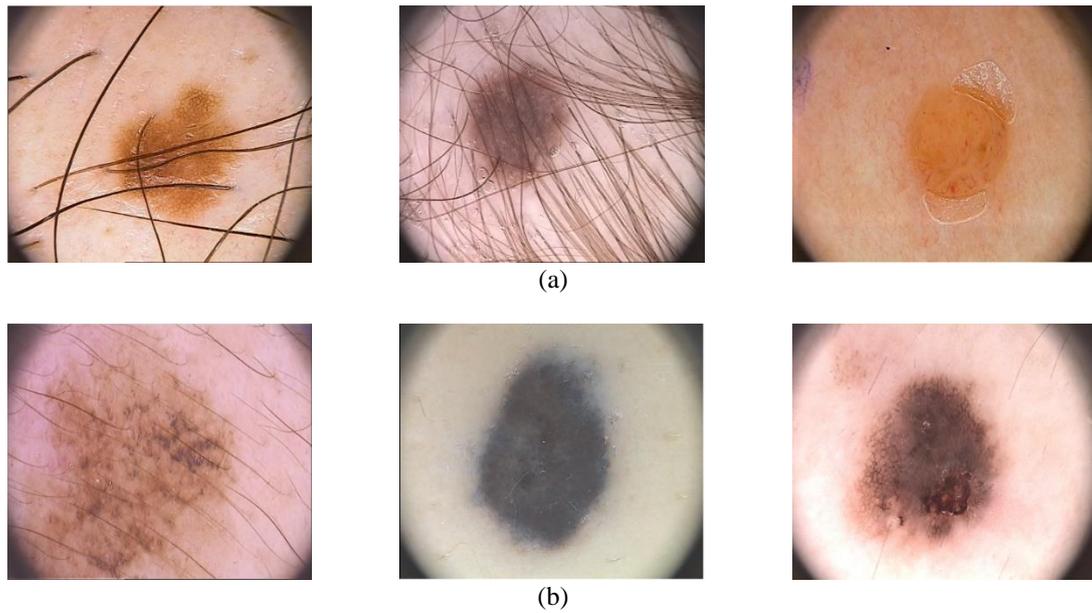
Figure 5. PH^2 skin images (a) normal and (b) abnormal

To create more images from a single image, the augmentation method applies transformations to the image, such as rotating it, translating it, shearing it, scaling it, or reflecting it (flipping it). The enhanced images that are acquired by rotation and flipping are shown in Figure 6. Figure 6(a) shows the original image, Figure 6(b) shows the original image rotated by 90 degrees, Figure 6(c) shows the original image rotated by 180 degrees, Figure 6(d) shows the original image rotated by 270 degrees, Figure 6(e) shows the flipped image, Figure 6(f) shows the flipped image rotated by 90 degrees, Figure 6(g) shows the flipped image rotated by 180 degrees and Figure 6(h) shows the flipped image rotated by 270 degrees.

| (a) | (b) | (c) | (d) |
| (e) | (f) | (g) | (h) |
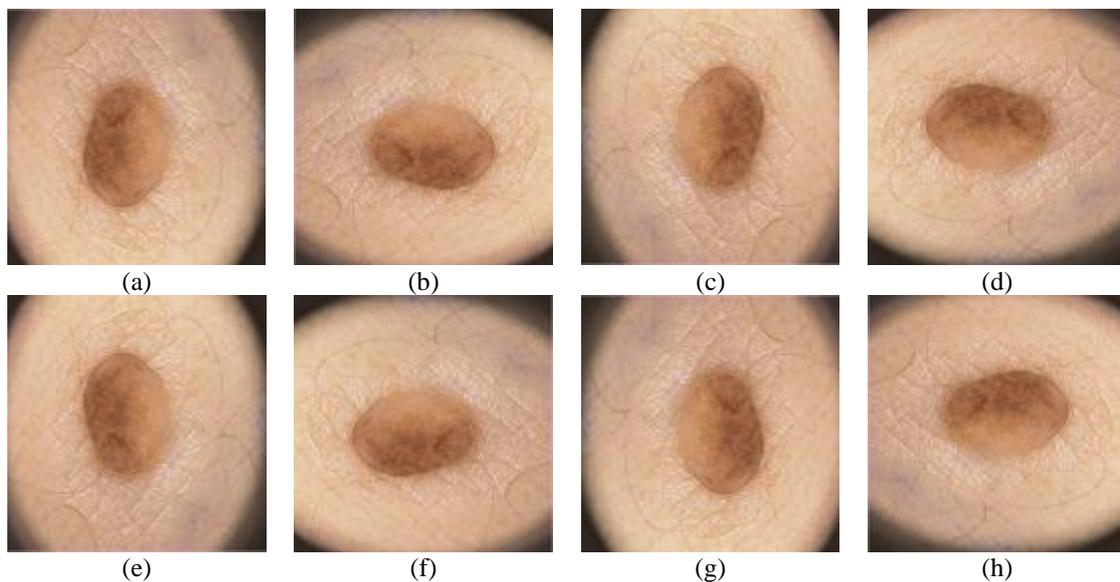
Figure 6. Data augmentation (a) original image, (b) 90 degree, (c) 180 degree, (d) 270 degree, (e) flipped image, (f) 90 degree of flipped image, (g) 180 degree of flipped image, and (h) 270 degree of flipped image

The performance of the DDLA-DIC system is measured by conducting an empirical test on the classifier, during which one keeps a number of incorrect classifications produced by the algorithm for a given

testing set. It is essential to ensure that the training samples and the testing samples are statistically different from one another. In order to make this process more manageable, the data provided is often separated into a training set and a test set. In this study, a random split approach (70% training: 30% testing) is used for data partitioning. Table 1 lists the performance metrics used to demonstrate the successful implementation of the proposed system.

Table 1. Performance metrics of the DDLA-DIC system

Performance measures	Description
$S_n = \dfrac{TP}{TP + FN}$	TP=number of correct classifications of abnormal skin images FN=number of misclassifications of abnormal skin images S_n=Sensitivity
$S_p = \dfrac{TN}{TN + FP}$	TN=number of correct classifications of normal skin images FN=number of misclassifications of normal skin images S_p=Specificity
$A_c = \dfrac{TP + TN}{TP + FN + TN + FP}$	A_c=Accuracy

3.1. Analysis on input images (no preprocessing)

The performance of the DDLA-DIC system is analyzed using the PH^2 database images and augmented images without any preprocessing. Table 2 shows the obtained confusion matrices of the DDLA-DIC system. The output from the classifier is compared with the ground truth data to compute the confusion matrix.

Table 2. Confusion matrices of the DDLA-DIC system-no preprocessing

Data augmentation	Category	Normal	Melanoma	TP	TN	FP	FN	Ac	Sp	Se
No	Normal	34	2	22	34	2	2	**93.33**	94.44	91.67
	Melanoma	2	22							
Yes	Normal	284	5	187	284	4	5	**98.13**	98.61	97.40
	Melanoma	4	187							

It can be seen from Table 2 that the performance of the DDLA-DIC system increases from **93.33%** to **98.13%** when using augmented images. This is because the DDLA system learns the texture patterns that distinguish melanoma from normal and vice versa using a vast number of training images. Figure 7 shows the receiver operating characteristic curves (ROC) drawn using the parameters in Table 2. Figure 7(a) shows the ROC obtained without preprocessing the augmented images, and Figure 7(b) shows the ROC obtained using augmented images without preprocessing.

(a)   (b)
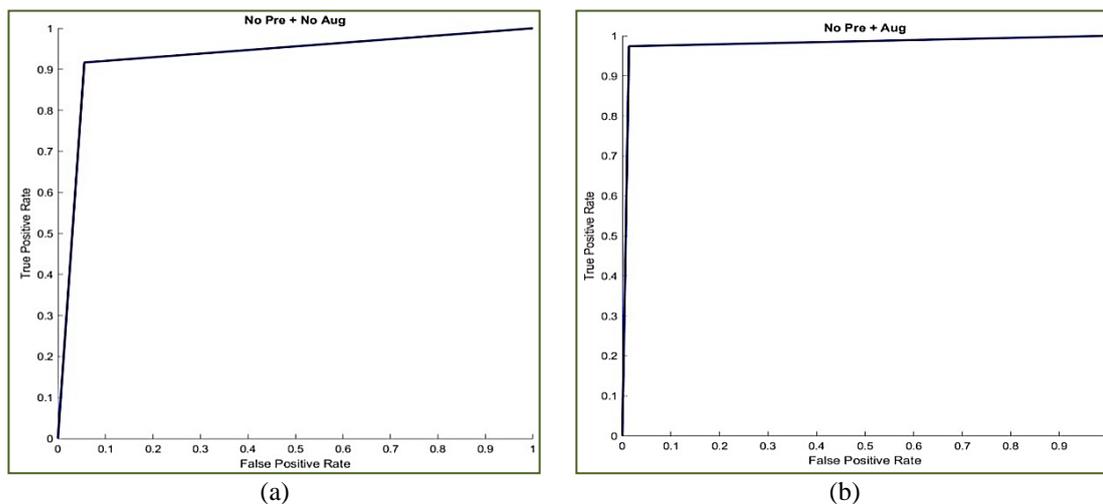
Figure 7. ROCs (a) no preprocessing+no augmented images and (b) no preprocessing+augmented images

The ROC curve is drawn using two parameters; sensitivity and specificity. The area under the curve is used as the analysis metric for the system's performance. The inference from the ROC is based on the area occupied under the curve. Under the ROC, the area occupied by the system using augmented images is 0.9813, whereas the system using original images has a value of 0.9393.

3.2. Analysis on preprocessed images

This section analyzes the performance of the DDLA-DIC system using preprocessed images. Both augmented and original images are preprocessed using a median filter and then fed to the system for evaluation. Table 3 shows the obtained confusion matrices when using the preprocessed images as input to the DDLA-DIC system.

Table 3 Confusion matrices of the DDLA-DIC system-preprocessed images

Data augmentation	Category	Normal	Normal	TP	TN	FP	FN	Ac	Sp	Se
No	Normal	35	1	23	35	1	1	**96.67**	97.22	95.83
	Melanoma	1	23							
Yes	Normal	287	0	192	287	1	0	**99.79**	99.65	100
	Melanoma	1	192							

It can be seen from Tables 2 and 3 that the performance of the DDLA-DIC system using preprocessed images provides more promising results than the original images. This is because the features extracted from the original images contain unwanted information from the noisy data and hairs in the dermoscopic images, degrading system performance. Figure 8 shows the ROCs drawn using the parameters in Table 3. Figure 8(a) shows the ROC obtained using preprocessing with original images, and Figure 8(b) shows the ROC obtained using augmented images with preprocessing.
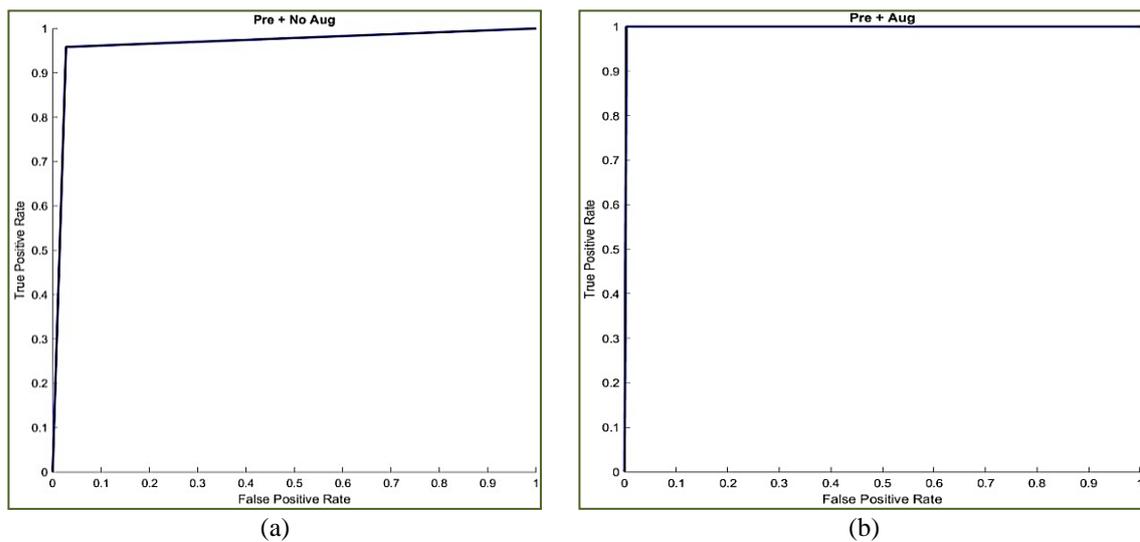
Figure 8. ROCs (a) preprocessing+no augmented images and (b) preprocessed and augmented images

Based on the total area covered by the ROC curve in Figure 7 proves that the system delivers superior performance when using augmented and preprocessed images compared to the others. Because the ROC is so near the y-axis and the top edge of the graph, thus occupies the maximum area under the curve (0.9979). Table 4 shows the comparative analysis of the DDLA-DIC system with other systems.

Table 4. Comparative analysis with other systems

Techniques	Sensitivity	Specificity	Accuracy
Ensemble of Neural Networks+colour and textures [2]	83.3	95	91.1
contourlet+Bayesian classifier [4]	97.5	96.3	96.7
Fractal model [7]	95.8	93.8	95
Wavelet+Deep learning [14]	98.33	99.03	98.67
Colour and textures+Boltzman entropy [11]	97.7	96.7	97.5
Proposed DDLA-DIC system	99.65	100	99.79

It can be shown from Table 4 that the categorization of melanoma skin cancer images utilizing the DDLA-DIC approach delivers the greatest performance compared to other relevant research for skin cancer diagnosis. The wavelet and DL-based system in [14] achieved the second-best performance with 98.33% sensitivity and 99.03% specificity.

4. CONCLUSION

The field of computerized diagnosis using image processing has attracted much attention recently. New applications for image analysis are now feasible due to the availability of low-cost software and hardware, and most automated diagnostic systems are designed to perform a specific medical image analysis for disease diagnosis. In recent years, DNN and other forms of DL algorithms have attracted much interest and accomplished outstanding classification results in computer vision. This work proposes an efficient inception architecture design to classify skin melanoma from dermoscopic images. The DDLA-DIC system has been built to be wider and deeper, and the network can learn from diverse spatial patterns. The system is tested using dermoscopic images included in the PH2 database. The results show that the DDLA-DIC with augmented and preprocessed images achieved better accuracy of 99.79% and 96.67% without augmentation for skin cancer classification. The sensitivity and specificity of the DDLA-DIC system are well above 98%. It is also observed that the DDLA-DIC system can provide more accurate results than existing systems.

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