University of Ibadan
Journal of Science and Logics in ICT Research

Deep Convolutional Neural Networks Architecture with Pre-Filtered and Segmented Dermoscopic Images

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Abstract
Deep Convolutional Neural Networks (DCNN) involve alternating convolutional layers, non-linearity layers and pooling layers for identifying patterns in input. The pooling retains important information while down sampling the dimensionality of the feature map on dermoscopic images used for early cancer diagnosis. Existing DCNN for dermoscopic image analysis employs Max Pooling (MP) and Average Pooling (AP) due to their efficiency. The MP works best on images of dark background with lighter object, while AP works better on images of lighter background with darker object. An online International Skin Imaging Collaboration (ISIC) dermoscopic image dataset obtained from 2016 - 2019 was used for the research. A novel DCNN, IP-DCNN developed and configured with rectified linear unit activation function, multiclass cross entropy loss and Softmax functions. Evaluation of the IP-DCNN with filtered-segmented images was done by comparing its performance with existing current studies which used DCNN architectures. The developed interpool deep convolutional neural networks provided an improved performance over the pure deep convolutional neural networks and its existing variants.

Keywords: Pooling, Black hat morphology, Otsu binarisation, Balanced multiclass accuracy

1. Introduction

Globally, life expectancy has substantially grown over time, particularly since the age of enlightenment. People have made remarkable health progress over time in every nation on earth, which has increased life expectancy. Artificial Intelligence (AI) is just one of several things that have contributed to the increase in life expectancy. In order to provide healthcare in less time, doctors and nurses are empowered to make more educated decisions. By improving information sharing between medical professionals and patients, healthcare has improved. The usage of various models that give medical professionals and patients quick decision help and are powered by Deep Learning is one of the main ways that AI is being used to improve life. Self-administered blood-glucose monitoring for earlier problem diagnosis and intervention before dangerous emergency crises are examples of an emerging class of smartphone and app-based medical devices taught with deep learning that are becoming increasingly widespread.

A computer model called "Deep Learning," which learns categorization tasks directly from photos, text, or voice, has demonstrated its strength in accuracy that surpasses human performance. In particular for Computer Vision, Deep Convolutional Neural Network has emerged as the de facto algorithm for a wide range of Deep Learning applications. Convolutional Neural Network output feature maps have the drawback of being sensitive to the placement of the features in the input. Downsampling the feature maps is one method to deal with this sensitivity. As a result, the down sampled feature maps that are produced are more resilient to changes in the location of the feature in the image, or what is known as "local translation invariance" in technical terms [14].

Pooling layers is employed in Convolutional Neural Network to address the problem of output feature map to down sampling feature maps by summarizing the presence of features in patches of the feature map. Two common pooling methods are average pooling and max pooling that summarize the presence of a feature and the most activated presence of a feature respectively. These two pooling

Eweje Oluwafemi Williams, Adeniji Oluwashola David and Akinola Solomon Olalekan (2024). Deep Convolutional Neural Networks Architecture with Pre-Filtered and Segmented Dermoscopic Images. *University of Ibadan Journal of Science and Logics in ICT Research (UIJSLICTR),* Vol. 11 No. 2, pp. 85 - 97

methods both have their strengths and weaknesses and the strength of the two can only be earnest when interchanged as implemented in this research work.

By analyzing digital photographs of the skin, clinical decision support systems assist in the early diagnosis of skin cancer in the body. Digital dermoscopy photos, also known as skin lesion images, are pictures of the damaged skin area on the body and include both pictures with a light and a dark contrast background as well as pictures with different colored skin lesions. Due to the adoption of approaches that only perform well on high contrast images, existing decision support model designs have skewed and underperformed models. The feature map from the filter layer is reduced using a technique called pooling. While some pooling techniques, like maximum pooling, are good at extracting features from images with dark backgrounds and light regions of interest, Average pooling is good at doing the same for images with lighter backgrounds and darker regions.

The two pooling approaches can be coupled to maximize the strength of both by switching between them at the conclusion of each convolutional layer in a deep convolutional neural network architecture rather than employing each of them as a single feature map reduction technique. As a result, the performance of the decision support model for analyzing dermoscopy images will be improved since the features missed by one pooling technique will be noticed by the other, and vice versa. As opposed to mixed pooling, which is picked stochastically, each of these pooling approaches is chosen in a deterministic order.

2. Related Works

Deep learning has had considerable success in several branches of artificial intelligence during the past few years. Steven [24] demonstrates how deep learning has significantly raised the bar in a variety of fields, including image processing, speech recognition, visual object recognition, drug discovery, and genomics. Deep learning is particularly adaptable since it excels at identifying complex data structures. Furthermore, deep learning models are extremely quick even when used on huge photos because they are built on contemporary technology and software. Researchers are curious as to what deep learning can add to medical image analysis given its many benefits. Many academics in the field of medical image analysis are currently experimenting with deep learning to address a variety of problems.

The use of deep learning, according to Aminur, *et. al.* [2] is quite successful in carrying out medical image analysis for a variety of tasks (e.g., image classification, object detection, segmentation and registration), application areas, and diseases. As a result, deep learning is viewed as a very effective and promising technique in the analysis of medical images. However, research into deep learning's application to medical picture processing is still in its infancy. Minsky and McCarthy, the pioneers of AI, defined artificial intelligence as any activity carried out by a machine that would traditionally have been regarded as requiring human intelligence [23]. The idea and creation of computer systems that can carry out tasks that would typically need human intelligence, like speech recognition, decision-making, and language translation, is known as artificial intelligence (AI) [12]. These sophisticated computer-controlled systems are capable of carrying out activities that are typically attributed to human intelligence [10].

Artificial intelligence (AI) is a superset of machine and deep learning algorithms, and their use in medical imaging is gradually increasing [11]. The AI is used to denote an effort to simulate how the human brain functions in order to build more sophisticated computers. Narrow/weak AI, general/strong AI, and artificial super intelligence are the three main kinds of AI. A machine can be trained to respond to inputs with certain emotional linguistic reactions. Virtual assistants and chatbots are already extremely adept at keeping up a conversation [23]. Additionally, studies to train robots to recognize human emotions are currently underway. However, replicating emotional responses does not result in the machines being truly emotional.

The process of creating and training a neural network is very similar to that of gradient descent training any other machine learning model. The nonlinearity of a neural network leads the most intriguing loss functions to become non-convex, which is the main distinction between linear models and neural networks that has been established to date. This means that, in contrast to the linear equation solvers used to train linear regression models or the convex optimization algorithms with global convergence guarantees used to train logistic regression or SVMs, Neural Networks are typically trained by using incremental, gradient-based optimizers that simply drive the cost function to an extremely low value. Layered feed-forward ANNs employ the back propagation algorithm [6]. Accordingly, errors are propagated backwards after the artificial neurons, which are arranged in layers, deliver their signals "forward." Neurons in the network's input layer provide inputs, and neurons in the network's output layer provide output. There could be one or more intermediate hidden layers. During supervised learning, the back propagation algorithm receives samples of the inputs and outputs the network is expected to compute. The error is then calculated by the algorithm. Up until the ANN learns the training data, the back propagation technique aims to minimise this mistake,

The term "Convolutional Neural Network" denotes that the network makes use of the Convolution mathematical process [5]. A specific kind of linear processing is convolution. Simply said, convolutional networks are neural networks that, in at least one of their layers, use convolution rather than standard matrix multiplication. One feature map is created for each kernel in the convolution layer. As the depth of the network increases, so do the depth of the input or the number of filters utilised in convolutional layers, increasing the number of feature maps that are produced [14].

A convolutional operation must be carried out down through the depth of the input, which might be problematic when a Convolutional Neural Network has a lot of feature maps. When the images are too huge, the pooling layers section of CNNs would lower the number of parameters. Spatial pooling, also known as subsampling or down sampling, lowers the dimensionality of each map while preserving crucial data. In other words, the Pooling layer handles each feature map on its own. The feature map output of convolutional layers has the drawback of accurately recording the location of features in the input [2]. This implies that slight changes in the feature's location in the input image will produce a different feature map. Re-cropping, rotation, shifting, and other minor alterations to the supplied image can cause this. Pooling is a reliable and popular method to get around this constraint. The brighter pixels in the image are chosen. As seen in Figure 1, it is helpful when an image's interest is in its lighter pixels while having a dark background.

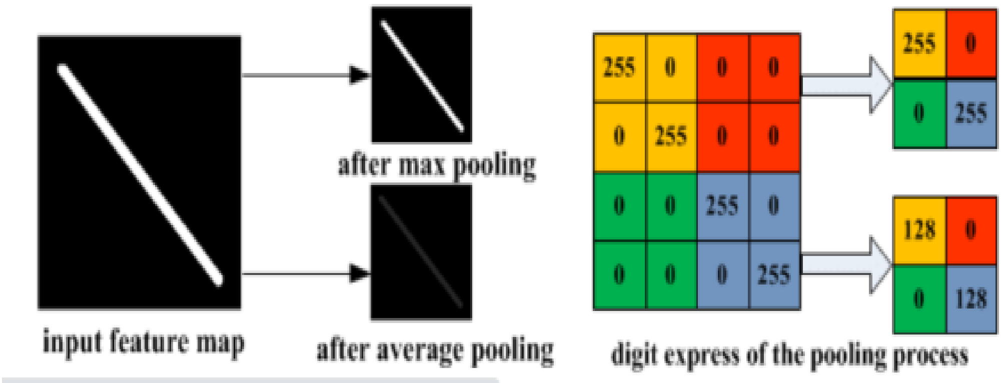

Figure 1: Illustration of Max Pooling drawback [3]

Figure 2 illustrates how poorly the Max pooling performs on photographs with a light backdrop and a darker object.

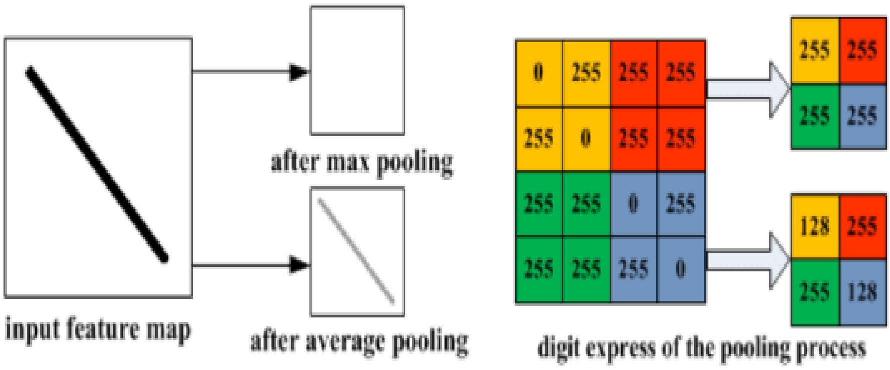

Figure 2: Illustration of Average Pooling Drawback [3]

Mixed pooling combines average and maximum pooling in a probabilistic manner. It employed a random number between 0 and 1, indicating the option of employing maximum or average pooling. In other words, the approach somewhat addresses the issues with max pooling and average pooling by stochastically changing the pooling regulation scheme. The frequencies of using the max pooling and average pooling methods related to the kth feature map are counted as Fk max and Fk avg. If Fk max ≥ Fk avg, then the max pooling method is applied in the kth feature map; otherwise, the average pooling method is used. In this regard, model averaging is a type of statistical pooling.

Due to the probability-based selection of the pooling to be utilised at each layer rather than the sequential switching of the two pooling approaches, this strategy still runs the danger of being one-sided. MobileNet was suggested as a way to develop lighter CNN models that can perform on par with the current state-of-the-art. Initially proposed by MobileNet, separable convolutions [30]. It was asserted that one may build a competitive yet computationally effective CNN model by keeping all these parameters modest. On the other hand, one can build a heavier model that is more accuracy-focused simply by raising the value of these parameters [17].

There are more than 5,000,000 new cases of skin cancer detected each year in the United States, making it a serious public health issue [28]. The majority of skin cancer fatalities are caused by the worst type of the disease, melanoma. Melanoma incidence was expected to be over 350,000 cases and about 60,000 deaths worldwide in 2015. Melanoma survival surpasses 95% when found early, despite a large amount of mortality [29]. Skin cancer can affect anyone, according to Lisa Chipps, MD, Harbor-UCLA Medical Center's director of dermatologic surgery. People of colour experience it less frequently, but it is frequently more severe. Because it's typically discovered later, when it's more difficult to cure [8].

Dermoscopy is an imaging method that takes out the skin's surface reflection. Removal of surface reflection improves the ability to see deeper layers of skin. Prior studies have demonstrated that dermoscopy offers greater diagnostic accuracy than conventional photography when utilised by experienced dermatologists. Automated dermoscopic assessment algorithms have a greater chance of improving patient care when low-cost consumer dermatoscope adapters for smartphones start to become available [22]. About 75% of skin cancer-related deaths are caused by melanoma, the worst type of skin cancer.

The recovery percentage of people with melanoma can be considerably increased by accurate early detection [23]. Nevertheless, manual melanoma diagnosis suffers from inter-observer differences and creates a significant demand for skilled professionals. It would be beneficial to create an accurate automatic melanoma recognition system that would improve pathologists' accuracy and productivity.

Federico, *et. al* [9] proposed a mobile automated method for classifying skin lesions that used the characteristics of the lesions and a k-NN (k-Nearest Neighbour) classifier to achieve classification. The outcomes were comparable to a clinician's assessment in terms of accuracy, sensitivity, and specificity (66.7%, 60.7%, and 80.5%, respectively). Using Very Deep Residual Networks, as suggested by Xiaoxiao, *et. al.* [30], was an alternative strategy for melanoma recognition. In this method, a bespoke model with more than 50 layers was utilised. Despite the algorithm's excellent performance (accuracy: 94.9%, sensitivity: 91.1%, specificity: 95.7%), training the algorithm takes a lot of time.

Additionally, melanoma detection ensembles have been used with gratifying accuracy, sensitivity, and specificity figures (89.3%, 75.5%, 77.1%, and 62.7%, respectively). For their research, Maxence [16] employed the HAM10000 dataset, which has 10015 photos. In the work, augmentation was done on a selected portion of the dataset. In comparison to a model without data augmentation, a model with data augmentation tends to learn more distinctive traits and properties. They contend that including data augmentation increases the model's accuracy, but until the model is robust, it cannot produce meaningful results with the testing data. As a result, the author applied the k-fold cross-validation procedure, which strengthened the model.

Nils [17] on the other hand used EfficientNet pre-trained architecture with 5-fold cross validation and they achieved 75% balanced accuracy. Andre and Pacheco [4] employed SeNet, DenseNet, Inception, MobileNet, Goognet and VGG pre-trained architectures. Even though their models outperformed Federico *et. al.* [9] model, they did not remove the unwanted artifacts such as hair, water bubble, gel from the skin images which could have improved their model performance. Packets Using Flow Labels in Open Flow Switch in Software Defined Network [30]. In addition, they used pre-trained architectures that are not optimised for dermoscopic images.

In this study, in order to improve performance, dermoscopic images were first filtered using blackhat and tophat techniques to remove the unwanted artifacts such as hair, water bubble, gel from the skin images, then Otsu Binarization was employed to separate the dermoscopic images background from the region of interest. This is to ensure that the training process focuses on the most important aspect of the image which is the lesion area. This improved the feature extraction performance and also reduced computation resources needed.

3. Methodology

The sections provide information on the developed models for analysing dermoscopic images. The various phases in the models were discussed. First the Filtering processing using blackhat techniques, followed by the region-based segmentation using Otsu binarization technique. The Interpool CNN architecture technique and the different evaluation metrics such as Recall, Specificity, Precision and Balanced Accuracy were also discussed.Determining structural changes between lesions can be quite difficult due to the variability in the background of the digital dermoscopic pictures. Accurate detection and categorization of dermoscopy pictures are also severely hampered by artefacts resulting from water bubbles, thick hairs, and gel.

3.1: Description of the Developed Architecture – Interpool Deep Convolutional Neural Network (IP-DCNN)

The developed model consists of four phases. The block diagram in Figure 3 shows the connectivity of the phases. The phase 1 is the filtering phase, the phase consists of Morphology Gray-scale, Blackhat, Contour contrasting and Inpainting techniques. In this phase, the dermoscopic images were fed into the Hierarchical filtering model which removed the unwanted artifacts such as hair, water bubble and gel from the images. The phase 2 is the segmentation phase, the filtered image in phase 1 serves as the input for the segmentation phase that removes the background of the skin leaving only the lesion area. The phase implemented morphology close, Otsu binarization, contour searching and contour drawing techniques. Phase 3 is the feature extraction phase. It consists of convolutional layers, non-linearity, and pooling. The output of the segmentation phase is fed as input into this phase. The last is the phase 4 which is fully connected layer. The output of phase 3 is flatten and fed into fully connected layer as input. The phase consists of flatten layer (input layer), hidden layer and the output layer (Softmax).

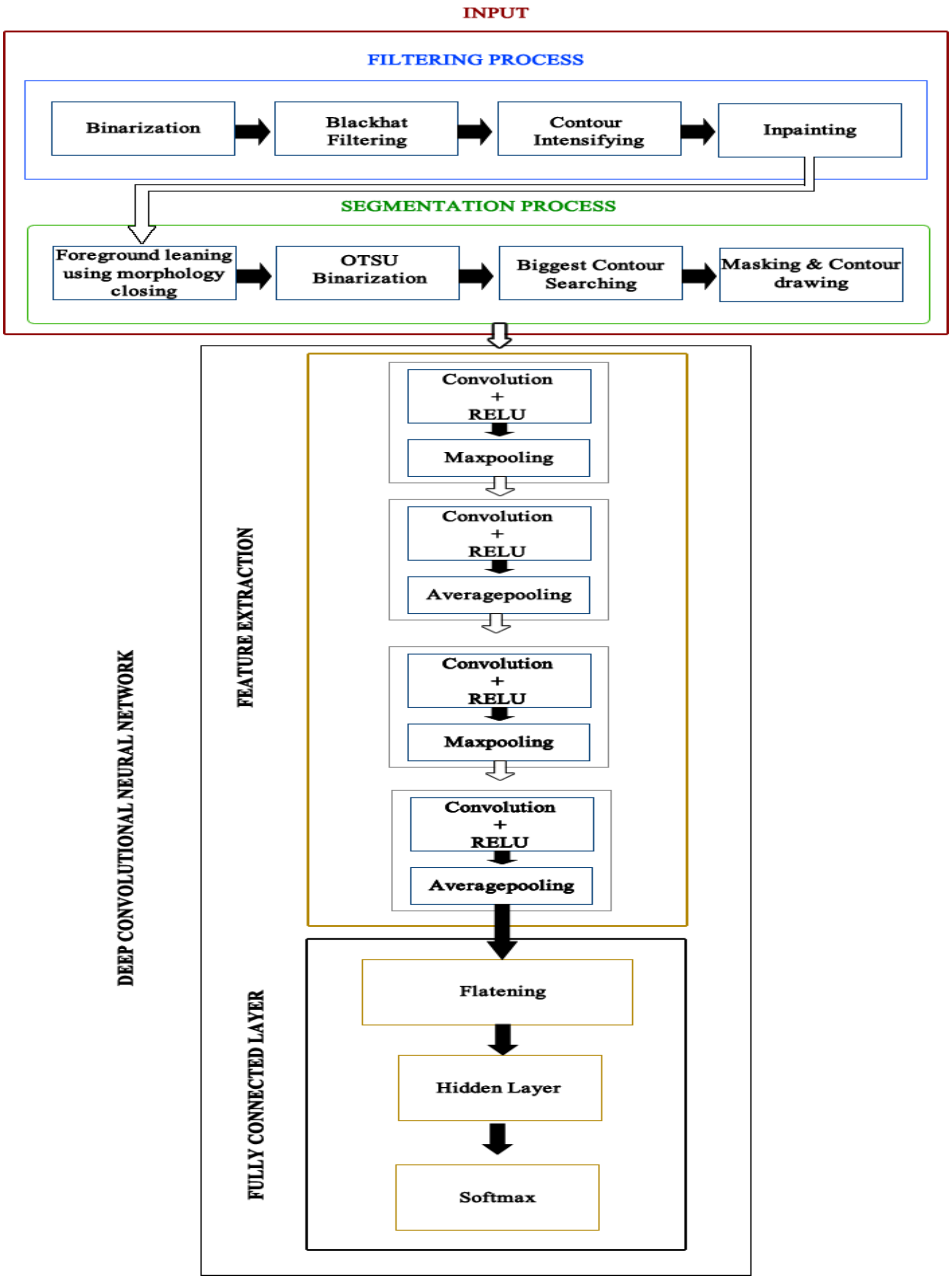

Figure 3: Detailed Framework for analysing dermoscopy image

3.2: Hierarchical Filtering Techniques

These stages are Morphology Gray-scale, Blackhat, Contour contrasting and Inpainting techniques. A grayscale image is a three-dimensional set with the x and y coordinates of each pixel as the first two elements and the grayscale value as the third. Images in the Gray-scale morphology technique are Euclidean space mapping functions. or grid E into where is the set of reals, ∞ is an element greater than any real number, and -∞ is an element less than any real number.

The grayscale dilation of f by b is given by the below formular where a picture is denoted by f(x) and the structuring function by b(x):

$$(f \oplus b)(x) = \sup_{y \in E}[f(y) + b(x - y)], \quad \text{.......... (3.1)}$$

where supremum is denoted by *sup*.

The erosion of f by b is similarly given by:

$$(f \ominus b)(x) = \inf_{y \in E}[f(y) - b(y - x)], \quad \text{.......... (3.2)}$$

where infimum denotes *inf*.

The opening and close, much like in binary morphology, are provided by:

$$f \circ b = (f \ominus b) \oplus b, \quad \text{.......... (3.3)}$$

$$f \bullet b = (f \oplus b) \ominus b. \quad \text{.......... (3.4)}$$

This was proceeded with flat structuring elements for morphological applications.

To highlight interesting dark things against a bright background, the blackhat operation was performed. The shapes of the hair were also discovered using it. Equation 3.1 below illustrates the Black Hat called function as follows:

Morphological Black Hat (MBh)

dst = blackhat(src, element)

= close(src, element) – src ……. (3.5)

3.3: Interpool Deep Convolutional Neural Network Technique

The filtered and segmented dermoscopic images were trained using an improved Deep Convolutional Neural Network architecture called InterPool Deep Convolutional Neural Network (IP-DCNN) architecture which is the interchange of two different pooling techniques called Max and Average Pooling. ReLU was also applied after flatten layer while Softmax was used at the output layer for classification. Softmax normalized output to sum up to 1. It helps training converge more quickly than it otherwise would. Softmax was also employed because the classification problem is a multiclass problem. After the loss function has been determined, the network was then optimised using Adaptive Moment Estimation (ADAM). Adam keeps an exponentially decaying average of past gradients M(t). M(t) and V(t) are values of the first moment which is the Mean and the second moment which is the uncentered variance of the gradients respectively.

This work used the Max pooling and Average pooling pooling techniques. At the conclusion of each ConvLayer with a (2,2) pool size, the two methods were switched. The input photos were flattened into a column vector after being transformed into a format appropriate for the multi-level perceptron. A feed-forward neural network receives the flattened output, and backpropagation is used for each training iteration. The model can categorise images using the Softmax Classification method across a number of epochs by identifying dominant and specific low-level features.

Table1: Diagnostic categories of ISIC dermoscopic image.

S/No	Diagnostic Categories	Abbreviations
1	Melanoma	(MEL)
2	Squamous cell carcinoma	(SCC)
3	Basal cell carcinoma	(BCC)
4	Benign keratosis	(BKL)
5	Melanocytic nevus	(NV)
6	Dermatofibroma	(DF)
7	Vascular lesion	(VASC)
8	Actinic keratosis	(AK)
9	None of the others	(UNK)

The number of instances in each diagnostic category is shown in Table 2. Melanocytic nevus has the highest number of instances followed by melanoma while Dermatofibroma has the least number of instances. It can be observed from Table 2 that the diagnostic categories have imbalance number of instances which make the classification problem not only multiclass but also imbalance class classification problem.

Table.2: Diagnostic categories and their respective number of data instance

S/No	Diagnostic Categories	Number of samples
1	Melanoma	4522
2	Melanocytic nevus	12875
3	Basal cell carcinoma	3323
4	Actinic keratosis	867
5	Benign keratosis	2624
6	Dermatofibroma	239
7	Vascular lesion	253
8	Squamous cell carcinoma	628
9	None of the others	0
	TOTAL	25,331

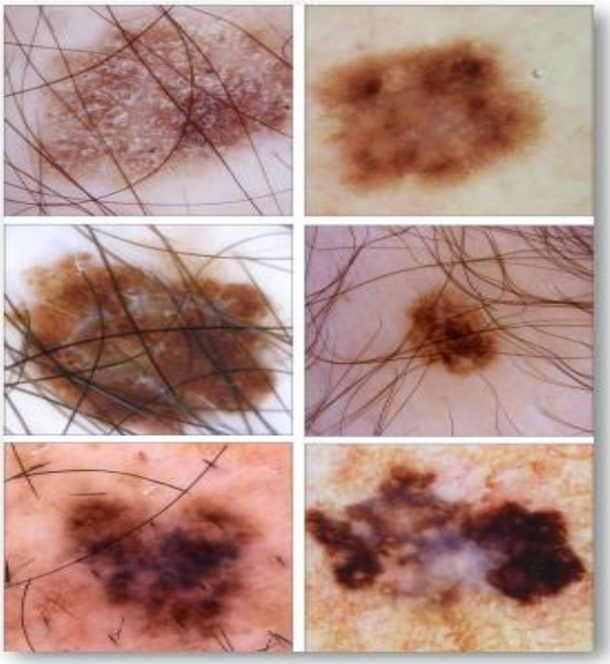

Figure 5: Sample Dermoscopy Image

3.4: Tools for the Implementation

The implementation of this work was carried out using Keras with Tensorflow, Scikit. TensorFlow, Scikit-Learn and Keras are standard Machine Learning environment in Python. The R-Environment is an alternative but the trend in R is more statistical. Support and Libraries in R are not as robust as Python**.**

4. Results and discussion

The study developed a hierarchical filtering technique to filter unwanted artifacts from dermoscopic image and a region-based segmentation technique was subsequently applied before feeding the processed images as input into the developed Interpool Deep Convolutional Neural Network architecture.Table 4.1 shows the comparison between filtered dermoscopic images and unfiltered images on a typical existing Deep Convolutional Neural Network (DCNN) and the developed Interpool Deep Convolutional Neural Network (IP-DCNN) using Balanced multiclass accuracy evaluation metric.

Table 1: Comparison of filtered and unfiltered dermoscopic images on a typical DCNN and the developed IP-DCNN using balanced multiclass accuracy.

	DCNN (%)	IP-DCNN (%)
Original Image	42.9	44.6
Filetered Image	48.8	52.6

Table 1 both show that, when the unfiltered and the filtered images were used as input image in a typical DCNN (existing architecture), the results are 42.9% and 48.8% respectively using balanced multiclass performance evaluation metric. Also, when the unfiltered image and filtered images were used as input image in the developed IP-DCNN architecture, the results are 44.6% and 52.6% respectively using balanced multiclass accuracy (bmAcc) performance evaluation metric. It can be inferred from the above that: The performances of the existing typical DCNN and the developed IP-DCNN architectures were improved with the filtered image fed as input to the architecture. The performance of the developed IP-DCNN is better than the existing DCNN on both the filtered and unfiltered images**.**

The above proves the relevance of the developed Hierarchical filtering technique in dermoscopic image analysis performance improvement using balanced multiclass (bmAcc) accuracy performance evaluation metric.

Table 2: Comparison of filtered dermoscopic images and segmented-filtered dermoscopic images on a typical DCNN and IP-DCNN using balanced multiclass accuracy.

	DCNN (%)	IP-DCNN (%)
Original Image	48.7	52.6
Filetered Image	70.1	80.7

When the ordinary-filtered images and the segmentedfiltered images were used as input image in a typical DCNN (existing architecture), the results are 48.7% and 70.1% respectively using balanced multiclass performance evaluation metric. Also, when the ordinary-filtered images and the segmented-filtered were used as input image in the developed IP-DCNN architecture, the results are 52.6% and 80.7% respectively using balanced multiclass accuracy (bmAcc) performance evaluation metric.

It can be inferred from the above that:

i. The performances of the existing typical DCNN and the developed IP-DCNN architectures were improved with the segmented-filtered as compared to ordinary filtered image when fed as input to the architectures.

ii. The performance of the developed IP-DCNN is better than the existing DCNN on both the ordinary filtered images and segmented-filtered dermoscopic images.

The above proves the relevance of the developed region-base segmentation technique in dermoscopic image analysis performance improvement using balanced multiclass (bmAcc) accuracy performance evaluation metric.

Confusion matrix that contains the values generated by the new model after training is shown in Table 3. The values were used to calculate the balanced multiclass accuracy, Accuracy, F1 Score, Prediction, Sensitivity, specificity and NPV performance evaluation metrics.

Table 3: Confusion matrix result Table for the 8 diagnosis categories of ISIC dermoscopic images.

		PREDICTED							
		MEL	NV	BCC	AK	BKL	DF	VASC	SCC
ACTUAL	MEL	610	453	129	15	142	1	4	10
	NV	243	3354	115	8	130	7	9	2
	BCC	50	159	680	22	71	9	4	10
	AK	24	38	98	50	47	1	1	5
	BKL	116	246	140	22	253	0	3	9
	DF	3	19	23	1	9	11	1	1
	VASC	4	19	6	1	5	2	39	0
	SCC	17	23	61	12	13	1	0	39

Table 4: shows the values of the standard evaluation metrics calculated from confusion matric in Table 3.

Table 4: Evaluation of IP-DCNN using standard classification metrics

Metric	**IP-DCNN (%)**
Accuracy	96.8
Balanced Accuracy	80.7
F1 - Score	66.3
Precision	66.3
Sensitivity	66.3
Specificity	95.2
NPV	95.2

Different standard evaluation metrics that include Accuracy, Balanced accuracy, F1 Score, Precision, Recall, Specificity and Negative Predicted Value (NPV) were used to measure the performance of the developed model. The work was later compared with four existing works that used transferred learning of existing CNN architectures for analysing dermoscopic images using the evaluation metrics.

5. Conclusion

The results indicate that the performances of the existing DCNN and the developed IPDCNN architectures were improved with the filtered image fed as input to the architecture. The above results also show that the performance of the developed IP-DCNN is better than the existing DCNN on both the filtered and unfiltered images.

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