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Skin cancer classification dermatologist-level based on deep learning model

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ABSTRACT. Medical image analysis is a significant burden for doctors, therefore, it is used to supplement image processing. Many medical images are assumed to be diagnosed as accurately as healthcare experts when the precision of image detection and recognition in an image processing approach matches that of a human being. Artificial Intelligence (AI) based predictive modelling is an important component of many healthcare solutions. This paper develops and implements a neural network-based method for skin cancer prediction to expose the neural network's strength in this field. This method determines which form of deep learning is best for diagnosing diseases with an accuracy exceeds human ability in terms of speed and accuracy, and determines the optimum number of layers and neurons in each layer for both Convolutional Neural network (CNN) and Deep Neural Network (DNN) to obtain the best possible precision. The results of the proposed method showed impressive results, especially for CNN. There is a clear superiority of CNN over DNN. The CNN (which relies on convolution filters) provides great results in extracting features due to the focus on the intended area of the image without the surrounding area region of interest. This led to a remarkable decrease in the number of parameters and the speed of attaining results with higher accuracy. The results indicated that CNN has a high accuracy rate compared with the other existing methods where the accuracy rate of CNN is 98.5%.

Keywords: skin câncer; cancer recognition; deep learning; convolutional neural network.

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Introduction

At present, medical science has an enormous amount of data, including major clinical trials, genomic analyses, and numerous imagery styles. Physicians in the clinical setting should be capable of quickly imaging and interpreting laboratory results to assess the best treatment plan. The identification of images in medical sciences plays a major role in the classification of images and diagnosis of diseases (Hasan, Mohammed, & Waleed, 2020).

In clinical medicine, the main challenge facing artificial intelligent is to develop a system that can as reliably judge medical conditions as a doctor (Flayyih, Waleed, & Albawi, 2020). Intelligent tools can provide beneficial assistance to physicians by enhancing disease detection and prevention. Predictive modelling represents an essential part of many healthcare challenges' solutions. It is important to use an alternative method in predicting illness, training an artificial neural network can assist experts and eliminate potential errors that can occur in many illness diagnoses (Ansari & Sarode, 2017).

Melanoma represents a form of skin cancer, also known as malignant melanoma. The proliferation of pigment-producing cells that gives colour to the skin is irregular. Cancers of Squamous cells and basal cells are also known to be cancers of non-melanoma (Ansari & Sarode, 2017). Per year, there are 5.4 million new skin cancers, and this disease causes over 10,000 deaths a year in the USA. Early diagnosis of skin cancer is very important because, if detected at the first stages, the average five-year rate of survival falls by more than 99% (Albawi, Amer Abbas, & Almadany, 2019).

Physical tests and biopsies have traditionally been used to diagnose diseases. The acquired sample is then analysed in the laboratory. In addition to being time-consuming, this procedure is expensive and may not provide accurate results per sample. Therefore, attention has been brought to the use of computer-aided diagnosis to accelerate the procedure, reduce the cost and improve the diagnosis accuracy (Esteva, 2017).

The techniques of deep learning have played an important part in various disease diagnoses. Deep Neural Network (DNN) and Convolutional Neural Network (CNN) are the most popular types of deep learning techniques. CNN is used lately to perform complex operations that involve the identification of local multi-dimensional features (Bhanothu, Kamalakannan, & Rajamanickam, 2020). CNN has become very prominent in the literature due to its ability to handle large amounts of data (O'Shea & Nash, 2015). Deep hidden layers have started to outperform traditional approaches in some fields, such as pattern and image recognition (Wu, 2017); (Hugo & Perez, 2019).

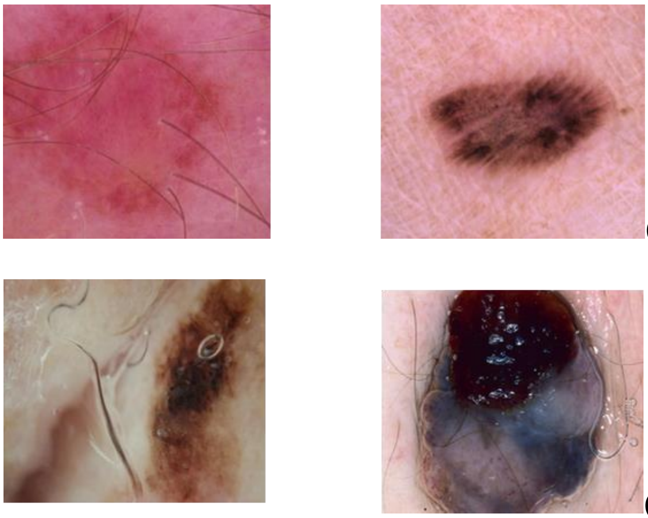
CNN inherits its name from the use of convolutional filters that collect multi-dimensional inputs to search for local features. It can have multiple types of layers; including various layers of fully connected, pooling, non-linear, and convolutional (Han, Yu, & Tashev, 2014); (Razzak, Naz, & Zaib, 2018). CNN performs exceptionally well, especially in environments that interact with image data. The findings achieved by CNN are very important in areas such as the largest image classification dataset (ImageNet), Natural Language Processing (NLP), and computer vision (Albawi, Mohammed, & Al-Zawi, 2017; Jose, 2019; Alam Milton, 2019).

Related works

Some of the various approaches and methods using image processing technique and deep learning that is used for skin cancer classification systems as in (Romero Lopez, Giro-I-Nieto, Burdick, & Marques, 2017) focused on the idea that a dermoscopic image that containing a skin lesion is classified as malignant or benevolent by a specialized problem of skin lesion classification. The presented approach was constructed using the neural network model of the VGGNet. The ISBI 2016 Challenge dataset for Skin Lesion Analysis towards melanoma detection was used for experiments. This dataset involves a representative mix of images labeled as benign or malignant, it was pre-partitioned into sets of 900 training images and 379 test images. Investigational findings are promising, and the obtained sensitivity was 78.66%. (Dubai, Bhatt, Joglekar, & Patii, 2018), The authors used Artificial Neural Network to train and test the presented system in which the utilized dataset was split into 80%, 10%, and 10% for training, testing, and validation, respectively. In this system, firstly the images were segmented, then the features were extracted by applying the ABCD rule. The accuracy of the classification obtained was 76.9%. (Lau & Al-Jumaily, 2009), presented a system in which the pre-processing stage resized the image, and this led to improving the speed performance and removing superfluous features such as noise and fine hair. Furthermore, the post-processing stage enhanced the image quality and sharpens the outline of the cancer cell. Feature extraction decomposed the useful feature without prior clinical knowledge. The neural network was utilized as a classifier to prove advances on predict new images. The recognition accuracy of the 3- layers back-propagation neural network classifier is 89.9% and the auto-associative neural network is 80.8%. (Refianti, Mutiara, & Priyandini, 2019), implemented the technology of deep learning with the CNN method. The network architecture that was utilized for classifying image data is the LeNet-5 model. The dataset was divided into 20% for training and 80% for testing. The attained classification accuracy by the model was 93%. (Alwan & Abdula, 2020), designed a system to detect and classify skin cancer with high accuracy and sensitivity by using CNN which was able to diagnose different types of cancer in human skin to provide more meaningful information to improve skin cancer and help physicians in the clinical diagnosis and accurate detection of the disease. The dataset was collected from the source for different categories of the most common skin cancer. The system is divided into two types which contain the following stages: image acquisition, pre-processing, and classification, while the second part consists of image acquisition and classification. There was a significant change between the classification with pre-processing and without pre-processing, as with pre-processing the accuracy decreased that return to the reason that the pictures that were taken to the skin are too close and do not require any pre-processing. The maximum obtained accuracy was 85.00%. (Zhang, Gao, Zhang, & Badami, 2020), implemented a meta-heuristic optimized CNN classifier for pre-trained network models. The optimization algorithm worked on developing the parameters of CNN models in the training stage. The dataset was split into 70% for training, 10% for validating, and 20% from dataset to testing. The proposed system was compared with ten classifiers using the same dataset. The accuracy of classification for the proposed model was 91%. The experimental results showed that the utilization of the optimized model provided better accuracy than other classification models.

Skin cancer dataset

The skin cancer dataset is released by the International Skin Imaging Collaboration (ISIC), which is used for training and testing models. This dataset contains a balanced number of images of benign skin cancer moles and malignant ones. The data consists of two folders each with 3,297 images of the two types. In our framework, the dataset is divided as follows: 80% for training and 20% for testing. Hence, the dataset is segmented into 2,637 images in the training set and 660 images in the test. This segmentation process is executed randomly, i.e., the images in each set are randomly selected. The ISIC provides the super pixel images, Figure 1 shows a sample of the two types (benign and malignant). The data set is publicly available on the website[1] for free access.



(a)

(b)

Figure 1. (a) Benign image symbol and (b) Malignant image symbol.

The Proposed Method

In this section, the proposed system which aims to recognize and classify skin cancer diseases is presented using a deep convolutional neural network (CNN) model, and their association with the performance of a deep neural network (DNN) model is also covered. Moreover, the general pipeline of the proposed system and the procedures for determining the setting of hyper-parameters are introduced. Each hyper-parameter is determined after testing the system several times to identify the best combination that makes the results statistically more reliable. The CNN and the DNN are trained using the skin cancer Images from the ISIC dataset. The DNN is also implemented to serve as a baseline model for comparison with the CNN model. The proposed models take all image pixels as input to the neural network, which explains the high number of parameters. The proposed system includes two models, as shown in Figures 2.

Dataset augmentation

The combination of colour modification and affine image transformations represents the most common modern technique for data augmentation. Shearing, scaling (zoom in/out), rotation, and reflection can be described as affine transformations, as demonstrated in Figure 3.

After various types of affine transformations, the same picture geometric distortions are typically used to maximize the number of samples for deep neural model training, balance the scale of datasets, and boost their reliability (Wąsowicz et al., 2017). Blurring, sharpening, white-balancing, enhancing brightness or contrast, and histogram equalization represent the most popular transformation methods (Galdran et al., 2017).

Data set preparation

The main idea of the proposed system is to have a more accurate result using the whole data. Also, the preprocessing operations are calculated over the entire image. Any image in CNN should have a defined resolution (e.g., all input images must have a resolution of 224×224 pixels). The fixed image size can provide us with more options in designing the CNN architecture.

[1] https://www.isic-archive.com/#!/topWithHeader/onlyHeaderTop/gallery?filter=%5B%5D

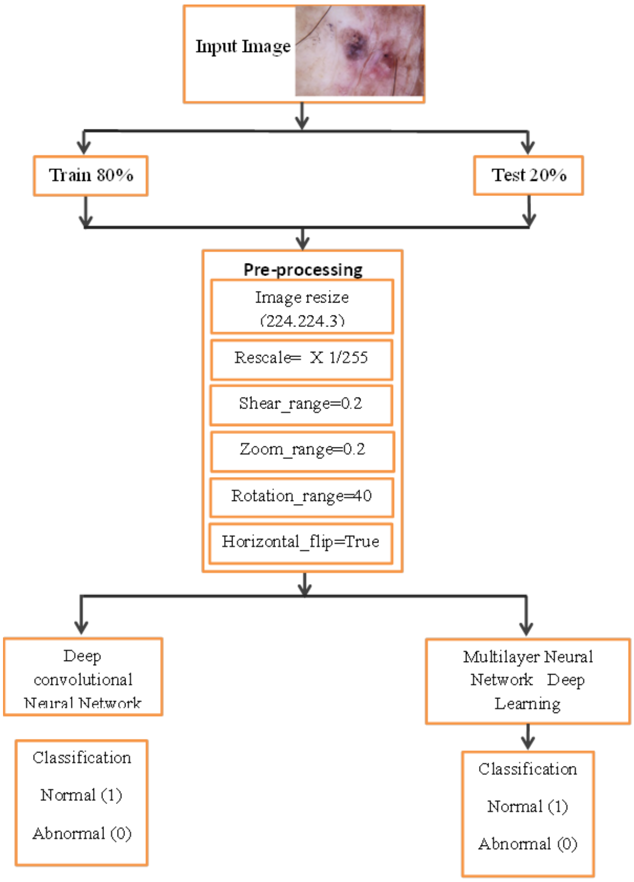


Figure 2. General block diagram of the CNN and DNN models for skin cancer classification using the ISIC dataset.

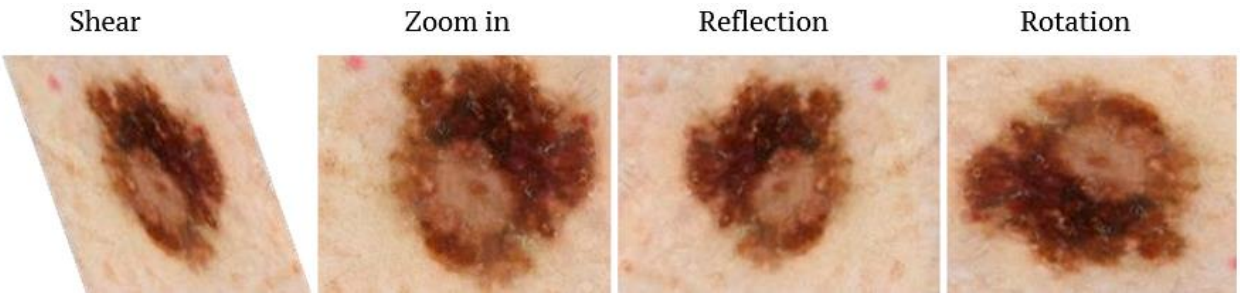


Figure 3. Affine transformations on the same image.

The samples are provided to the CNN as an image of fixed dimensions. The input image has three channels (RGB) and the dimension of the network input is set to 224×224×3. Finding the right image size is one of the most difficult aspects of our proposed system. The choice of an effective scale is a trade-off between precision (a larger size) and classification speed (a smaller size). specifically, a bigger image size requires more data and, hopefully, provides greater precision. While a smaller image size means a smaller volume of detail in real-world implementation and as a result, provides better classification.

The proposed network architecture

After selecting the image size for our methods. The second challenge is to find an optimal architecture for CNN. Therefore, firstly the input and the output structure of the network will be defined. Then, through some experiments, the optimal architecture will be presented based on the results. However, to have a powerful implementation, the input size should be fixed. The output shape in our method is the softmax function with 2 classes. A softmax layer is used as an output to select one, out of two, classes. Although the highest value is used in the output node as the calculated class, the values of the softmax consider other high probable hypotheses. The accuracy of the performance of the CNN depends on some parameters such as filter size and the number of filters used in convolutional layers. The number of feature maps is equal to the number of filters used, pooling filter size also affects the accuracy of the network. The number of convolutional layers has a significant effect on the result. And the output of the pooling layer is connected to several fully connected layers before being connected to the last layer (classifier layer). The number of layers and parameters of the first network with the fully connected CNN model explain in Table 1.

Table 1. The parameter of the CNN with a fully connected layer for skin cancers dataset.

Layer (type)	Output Shape	No. of Parameters
img_input (InputLayer)	[(None, 224, 224, 3)]	0
layer_1 (Conv2D)	(None, 224, 224, 32)	896
layer_2 (MaxPooling2D)	(None, 112, 112, 32)	0
Batch_normalization	(None, 112, 112, 32	128
layer_3 (Conv2D)	(None, 112, 112, 64)	18496
layer_3-1 (Conv2D)	(None, 112, 112, 64)	36928
layer_4 (MaxPooling2D)	(None, 56, 56, 64)	0
Dropout (Dropout)	(None, 56, 56, 64)	0
layer_5 (Conv2D)	(None, 56, 56, 128)	73856
layer_5-1 (Conv2D)	(None, 56, 56, 128)	73856
layer_6 (MaxPooling2D)	(None, 28, 28, 128)	0
dropout_1 (Dropout)	(None, 28, 28, 128)	0
layer_7 (Conv2D)	(None, 28, 28, 256)	295168
layer_8 (MaxPooling2D)	(None, 14, 14, 256)	0
dropout_2 (Dropout)	(None, 14, 14, 256)	0
layer_9 (Conv2D)	(None, 14, 14, 512)	1180160
layer_10 (MaxPooling2D)	(None, 7, 7, 512)	0
dropout_3 (Dropout)	(None, 7, 7, 512)	0
fc_1 (Flatten)	(None, 25088)	0
lyaer_11 (Dense)	(None, 512)	12845568
dropout_4 (Dropout)	(None, 512)	0
lyaer_12 (Dense)	(None, 128)	65664
dropout_5 (Dropout)	(None, 128)	0
lyaer_13 (Dense)	(None, 64)	8256
dropout_6 (Dropout)	(None, 64)	0
predictions (Dense)	(None, 2)	130
Total params: 14,672,834		
Trainable params: 14,672,834		
Non-trainable params:64		

Figure 4 demonstrates the structure of CNN. Each convolutional network consists of convolution, non-linearity, and pooling layers. And the output of the pooling layer is connected to several fully connected layers before being connected to the last layer (classifier layer).

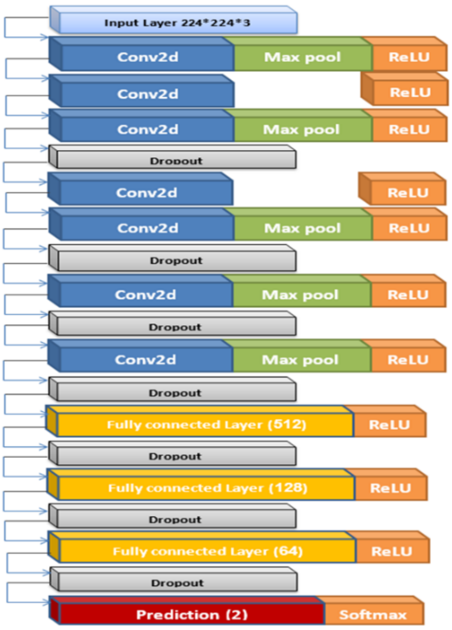


Figure 4. The structure of CNN for skin cancer.

In the DNN model, the input image parameters are more than the parameters used in the CNN model. This model is applied to make a comparison and fully understand the capacity of the CNN model. the selected and used approach is a Multi-Layer Neural Networks (MLNN). To have a fair comparison, similar to the CNN, the same size of the input image (224×224×3) is utilized with all image pixels in the input layer. To be interpreted by the DNN, the input image must be flattened. It implies that the images are transformed from a three-dimensional tensor to a one-dimensional vector. Since the input has such a large dimension, it consumes a lot of memory and takes a long time for the DNN to train, both computationally and in terms of output. The number of parameters is very high as explained in Table 2.

Table 2. The parameters of the DNN (multilayers) for skin cancers data set.

Layer (type)	Output Shape	No. of Parameters
img_input (InputLayer)	[(None, 224, 224, 3)]	0
fc_1 (Flatten)	(None, 150528)	0
lyaer_2 (Dense)	(None, 2048)	308283392
Dropout (Dropout)	(None, 2048)	0
lyaer_3 (Dense)	(None, 1024)	2098176
lyaer_4 (Dense)	(None, 512)	524800
lyaer_5 (Dense)	(None, 256)	131328
lyaer_6 (Dense)	(None, 128)	32896
lyaer_7 (Dense)	(None, 64)	8256
Layer_8 (Dense)	(None, 32)	2080
predictions (Dense)	(None, 2)	66
Total params: 627,755,042		
Trainable params: 627,755,042		
Non-trainable params:0		

Results and discussion

The data set is split into 80% for training, and this separation is not arbitrary, all data rates for training and testing have been investigated and start with 50% only for training data collection and 50% for testing until 90% of the training data versus 10% of the testing data. The highest percentage and the best result obtained were 80% for training and 20% for testing, especially for the testing process that depends on the classification and detection process of cancer diseases. Table 3 illustrates these percentages versus the total accuracy.

Table 3. Comparison of the different ratios of the size of data in training and testing and the overall accuracy.

No.	Training dataset and testing dataset percentage	Overall accuracy in training	Overall accuracy in testing
1	50% training _ 50% testing	70.55%	69.60%
2	60% training _ 40% testing	81.57%	60.40%
3	70% training _ 30% testing	89.22%	86.01%
4	80%training_20% testing	98.63%	98.51%
5	90% training _ 10% testing	90.60%	87.98%

The best number of layers for CNN model is shown in Figures 5.

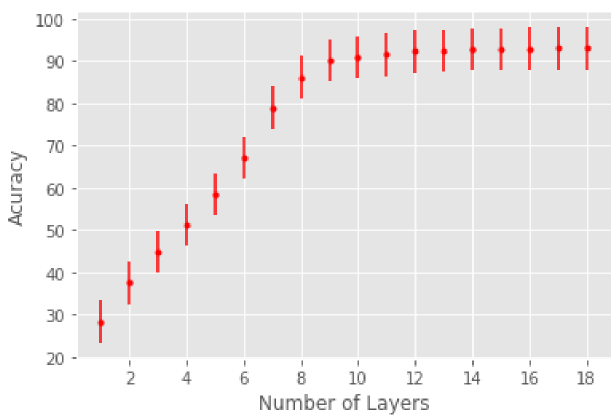


Figure 5. The effect of layers number on recognition accuracy for skin cancer dataset.

The classification was performed by deciding the various training epochs to achieve the best results as shown in Figure 6.

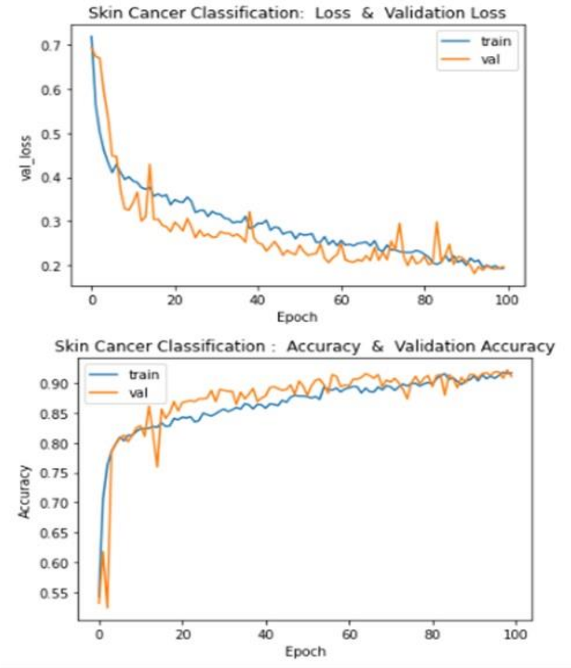


Figure 6. The Epochs numbers for best accuracy and loss of skin cancer.

To evaluate the performance of the proposed CNN-based skin cancer classification model, 20% remaining of the dataset is utilized for the testing phase. The attained outcomes of the CNN model from training were measured against the (660) skin cancer images, and the test data were determined using the confusion matrix, as demonstrated in Figure 7.

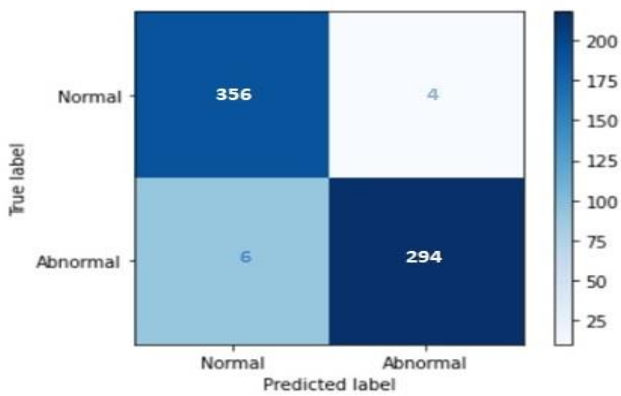


Figure 7. The Values of Confusion Matrix for CNN model.

According to equations 1, 2, 3, and 4 accuracy, Recall, Precision and F1-scor are computed for the CNN model as bellow.

$$Accuracy = [TP + TN / (TP + TN + FP + FN)] \times 100 \quad (1)$$

For CNN = 650/660×100=0.985%

$$Recall = TP / (TP + FP) \quad (2)$$

For CNN = 356/362=0.983%

$$Precision = TP / (TP + FP) \quad (3)$$

For CNN = 294/298=0.986%

$$F1-score = 2\times P\times R/(P+R) \qquad (4)$$

For CNN = 1.938/1.969 = 0.985%

The outcomes of the second model contain the results of the classification of skin cancer data for the proposed system using the DNN model. In this model, the images of skin cancer are classified according to the MLNN algorithm. When the network for training is set up, it gives the weights randomly, and the network trains these weights for several epochs until it becomes stable. The best training performance for this model is achieved at epoch 100, as demonstrated in Figure 8.

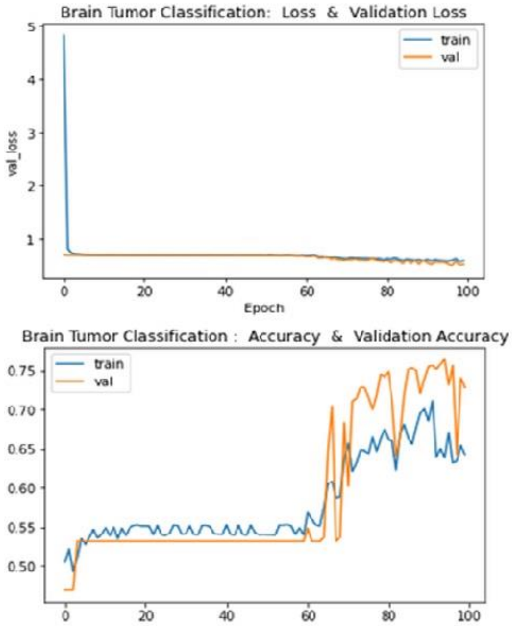


Figure 8. The best training performance for DNN model.

Figure 9 demonstrates the number (No.) of hidden layers, where the No. of nodes in hidden layer2 is equal to 2048, in layer3 is equal to 1024, in layer4 is equal to 512, in layer5 is equal to 256, in layer6 is equal to 128, in layer7 is equal to 64, and in layer8 is equal to 32. Finally, the weights that are obtained from the training stage are stored in the database making the network efficient and effective at the testing stage.

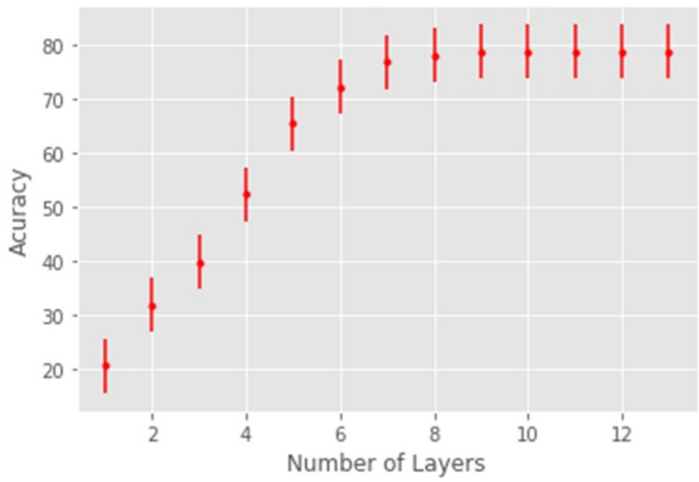


Figure 9. The effect of layers number on recognition accuracy for DNN model.

The examination of the DNN-based classification system is accomplished by testing it with the remainder of the data that is not labelled to classify the cancer images. At this stage, the results are also presented in the form of a confusion matrix. Figure 10 demonstrates the attained results using the confusion matrix.

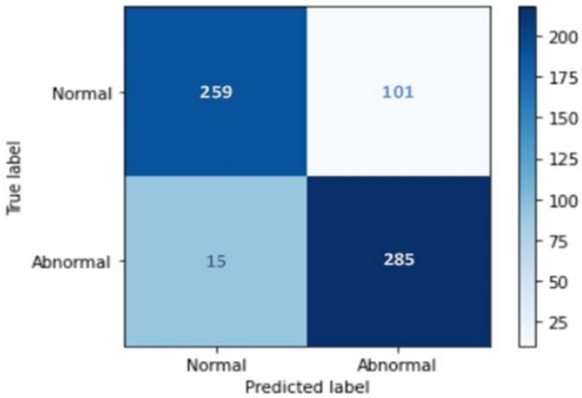


Figure 10. The of Values Confusion Matrix using DNN model.

Using the equations 1, 2, 3, and 4:
Accuracy (Skin) = $TP+TN/TP+TN+FP+FN\times100$ = 544/660×100 = 0.82%
Recall (Skin) = $TP/TP+FN$ = 259/274 = 0.95%
Precision (Skin) == $TP/TP+FP$ = 259/360 = 0.72%
F1-score (Skin) == 2×P×R/P+R =1.368/1.670 = 0.82%

The proposed system is implemented by two types of classification models and compared with related works. Table 3 illustrates a comparison between the proposed system and the existing works.

Table 3. Comparison between other existing works and the proposed work.

Researchers	Methodology	Accuracy
Alwan and Abdula (2020)	CNN (layers # 12)	85.0%
Dubai, Bhatt, Joglekar, and Patii (2018)	Artificial Neural Network	76.9%
Lau and Al-Jumaily (2009)	Artificial Neural Network	89.9%
Refianti, Mutiara, and Priyandini (2019)	CNN	93.0%
Zhang, Gao, Zhang, and Badami (2020)	CNN	91.0%
Our 1st proposed Technique	CNN (layers # 15)	98.5%
Our 2nd proposed Technique	MLNN (layers # 9)	80.0%

Conclusion

In this paper, the CNN-based skin cancer classification was presented, which is considered a good feature extractor algorithm compared to the DNN. The proposed models do not need manual feature extraction. Not always an increase in the number of layers improves the accuracy ratio. During the construction of both networks, a certain number of layers is reached that gives the best value of accuracy, and then increasing the layers may lead to negative performance. Each presented model has a different set of hyper-parameters, however, the parameter space is searched comprehensively to provide a fair comparison among the methods.

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