Convolutional Neural Network based Bi-Diverse Activation for Skin Lesion Classification

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Abstract: Melanoma is the most genuine sort of skin malignancy. It is usually caused by high exposure to ultraviolet radiation and damages the skin, and forms pigmented melanin. Early identification of melanoma skin infection can expand the endurance rate. A dermatologist essentially follows a succession of steps for skin lesion appraisal, beginning with independent eye screening of skin lesions, at that point by dermoscopy and next by biopsy. Convolutional neural network manifest potential for better classification of skin lesions. Clinical assessment in dermoscopy images is a tedious errand to the dermatologists because of ancient rarities nearness. In this paper, the bi-diverse activation convolutional neural network model has been developed to classify the skin lesion as benign and malignant by applying different activation functions of the ReLU and Swish process. The proposed approach is tried on the ISIC dataset having an all outnumber of 2637 training parts, and 660 images of testing parts categorize into melanoma and benign skin lesion images. Our proposed model accomplishes empowering results having 84% exactness.CNN with ReLU activation function outperforms the best accuracy compared to CNN's swish.

Keywords: Convolutional Neural network, Melanoma, Skin cancer classification, ReLU, Swish.

1. Introduction

Melanoma is the most dangerous disease which is spreading worldwide extent. Due to high UV (ultraviolet) radiation, it damages the skin's DNA, and the affected cells are melanocytes that produce the pigmented melanin [1]. The first tumor which develops normally will be located in the skin. Two different types of skin lesions - benign: Non-Cancerous; Malignant; Cancerous. Worldwide Caucasian people have the highest probability of developing melanoma. Countries like Brazil, New Zealand, and Australia, are very close to the equator, where sun exposure is high, and also the existence of a thin ozone layer, take a risk of developing melanoma skin cancer. Currently, 100, 350 cases of melanoma skin cancer that is to be diagnosed in the United States in the year 2020 [2].

Early detection of melanoma may enhance the individual endurance rate. Inspecting the highlights of melanoma essentially starts with visual screening, trailed by the investigation, for example, dermoscopy, obtrusive biopsy, and histopathological assessment [3]. Recently, on-intrusive reflectance confocal microscopy has been utilized for skin lesion identification. Assessing the dermoscopy images is a tedious task to the dermatologist due to various artifacts such as poor contrast, irregular border, bubbles, ruler marks, thin hair, color inconstancy, specific location-based information, etc. [4], color inconstancy, specific location-based information, etc. [5]. Features of discrimination for benign and malignant skin lesions [6] are tabulated in Table 1.

The rest of the paper is organized as follows: Section II discusses "Literature Review", Section III clarifies "Proposed Work", Section IV portrays the "Experimental Results" and finally Section V clarifies "Conclusion".

Table 1. Benign and Malignant Features Discrimination

Benign Features	Malignant Features
Symmetry	Asymmetry
Regular Border	Border Irregularity
Shades of brown	Color Invariance (white, Red, light-brown, dark-brown, blue-gray, black)
Diameter≤5mm	Diameter≥5mm
No Evolution	Evolution takes place

2. Literature Review

The Image analysis steps initiate with image acquisition, preprocessing, segmentation, feature extraction, and classification. The clinical image of melanoma is not compatible with the direct step of the classification process. To train a neural network, a huge number of training images are needed to attain accuracy. When there is an insufficient training image, the option of augmentation, flipping, and scaling is done to increase the size of the training images. Image classification can also be done by the concept of transfer learning from a pre-trained neural network.

The preprocessing errands start with denoising. (i.e.) Image data that is no longer needed, to be expelled. This will, in general, enhance the norm of the picture. To evacuate the artifacts such as hair-lines, various methods like filtering, interpolation, and morphological operations [7] -[9] have been utilized.

After preprocessing, the segmentation task initiates. Segmentation is partitioning the input image into similar regions based on color, intensity, etc. Different classes of segmentation such as region-based segmentation [10], pixel-based color segmentation [11], ostu threshold, modified region growing, zack's triangle, quad-tree decomposition, gradient field snake methods [12] used for skin lesion segmentation. Deep learning is also widely used in segmenting skin lesions [13].

Feature extraction focuses on the analysis of the attributes of a skin lesion with techniques such as texture features, color features, etc. In deep learning approaches, feature extraction is done automatically without human intervention. The features such as low-level features, mid-level features, and high-level features are used within a neural network to extract features.

Classification is the most significant task in the method of deep learning. Recent classification techniques of KNN and SVM [14] are used to classify the skin disease. The evaluation step takes place underperformance metrics like sensitivity and specificity. Julie Ann et al.[15] used, deep learning techniques to detect melanoma skin lesion images automatically. The PH^2 dataset of dermoscopy images is used for preprocessing and then make it compatible with alexnet. This pre-trained CNN is used to classify the pre-processed and actual dermoscopy images of melanoma. The overall accuracy of 93% is achieved for the detection of melanoma.

Ni Zhang et.al. [16], proposed a new optimal convolutional neural network for skin lesion diagnosis. To enhance the efficiency of CNN, an improved whale optimization algorithm is used. The algorithm becomes more compatible in the network for choosing apt weights and biases to get the desired output. The performance is evaluated on two different benchmarks (DERMQUEST and DERMIS) and the final output is compared with 10 different methods. The proposed method achieves exemplary performance.

Kemmal [17].et.al, proposed two different methods of CNN to classify the skin lesion automatically (i) Alone CNN (ii) combination of one-versus-all methods. The dataset of HAM10000 contains 7 different skin diseases that were combined for classification. The method of alone CNN classifies the skin with an accuracy of 77%. In one-versus all, each skin disease classes is processed individually and compete with an accuracy of 92.90%.

Lenet architecture [18] is used to classify skin image data. Different level of epochs has been done to train the different amount of data, and check for accuracy. Training and testing under more images with 100 epochs give more accuracy compared to 50 epochs with fewer images.

Keras sequential model [19] is utilized to classify benign and malignant lesions. By increasing the different levels of epochs and convolutional layers, accuracy is achieved.

Khalid et al.[20], applied the concept of transfer learning to the pre-trained alexnet architecture in different ways for an automatic skin lesion classification. By interchanging the classification layer in alexnet, the softmax layer is utilized for skin lesion classification and also by fine-tuning the weight. The performance is evaluated with different datasets (DERMIS-DERMQUEST, MEDNODE, ISIC). The DCNN model achieves good accuracy in classifying the skin image.

In this paper, we aim to utilize the concepts of deep learning to develop an automatic diagnosis system for skin lesion classification. By applying CNN based diverse activation functions such as ReLU and swish in every Conv layer the performance of the model is evaluated.

3. Proposed Work

In this section, the proposed method is to classify the skin lesions images as benign and malignant. The first subsection initiates with the dataset description. The image data training with ReLU CNN and image data training with Swish CNN is described in the second subsection.

3.1   Dataset Description

To attain the best performance with the proposed model, a maximum number of training images are required The accessible dataset is in the type of colored skin lesion images. The dataset is acquired from the ISIC (International Skin Imaging collaboration) archive, which contains malignant and benign skin lesions for dermoscopic assessment. The dataset which is apportioned 2637 images of training images and 660 testing images are used. The balanced dataset is obtained from the archive to train the deep learning framework. The dataset description is illustrated in Table 2:

| Skin Type	Image Type	Training	Testing	Architecture
Benign	RGB	1440	360	CNN
Malignant	RGB	1197	300	CNN

Table 2: Dataset Description

Each skin cancerous and non-skin cancerous RGB image is in the form of a JPG format with a resolution of 224x224 pixels. A sample training of benign and malignant images is displayed in Fig 1:
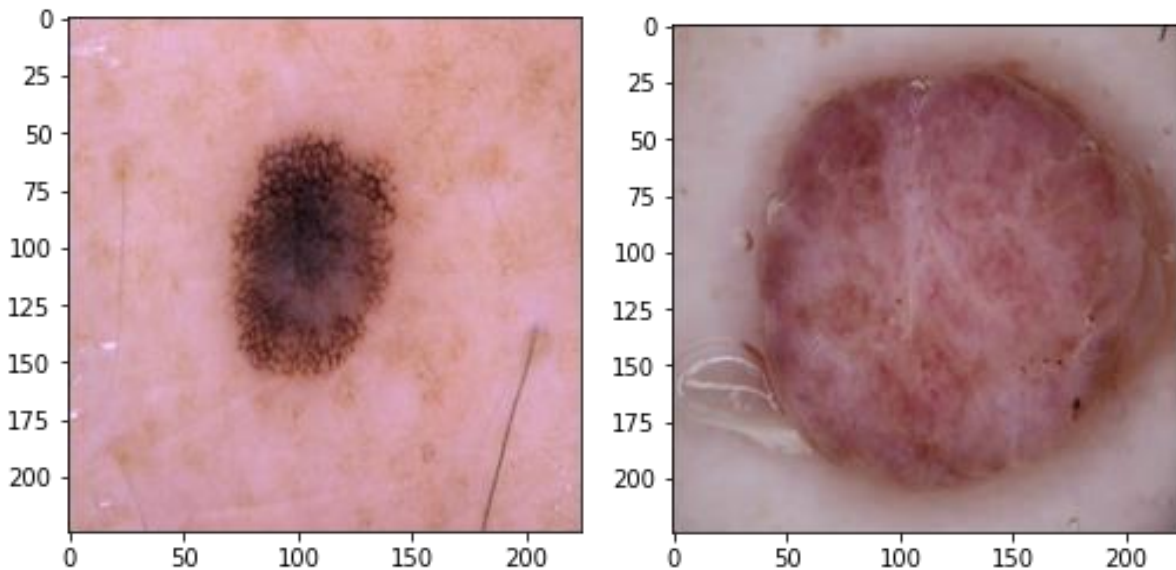
Fig.1.(a)Malignant Training Image   (b)Benign Training Image

Each RGB(Red, Green, and Blue) image is shown in the type of pixels and it is sorted out into width, height, and depth, and then their profundity will be 3. The depth-wise RGB image visualization is delineated in Fig. 2.
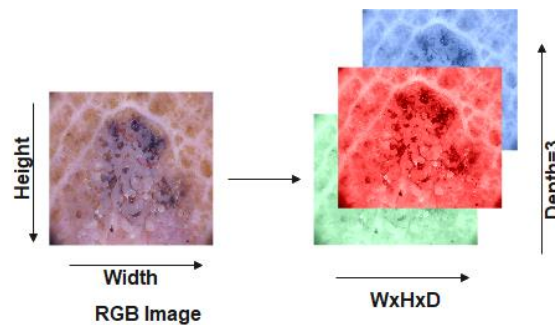

Fig.2.Depthwise RGB Convolutions

3.2   Bi-Diverse Activation CNN Working Methodology

In the proposed model of the Bi-Diverse activation CNN approach, the Convolutional neural network (CNN) plays a prominent role, it also addresses a colossal progression in image classification. Each pixel of skin lesions is fed as input (x_i) as nodes to the input layer in the neural network. Each node in the first layer is connected to the nodes of the next layer via channels. Each of these channels is assigned with a novel weight (W_i). Weights can be either positive or negative value. The given input is multiplied into the respective weights and their summation is sent as input to the nodes in the hidden layer. Each of these neurons is bound with a bias. Each input of data is altered by a lot of weights and biases. Each edge has a novel weight and every node has an exceptional bias. The prediction accuracy of a neural network relies upon its weights and bias. The bias (B_o) is then added to the input sum. The result of the sum is then traversed via a threshold function(activation function). The output of the activation function always decides if the particular neuron to be activated or not be activated. At that point, not enacted neurons will pass data to the neurons in the succeeding layer. Mathematically, the perceptron model is computed by

$$f(x) = B_o + \sum_{i=0}^{n} X_i W_i \qquad (1)$$

Among other activation functions, ReLU has the unique advantage that it does not activate all the neurons at the equivalent time.ReLU function is all the more computationally efficient and also converges faster. Swish

was found to be self gated activation function dispatched by Google, its computational effectiveness discovered to be higher than ReLU. Swish performs well in deeper models than ReLU[21]. The architecture of the proposed Bi-Diverse Activation CNN is depicted in Fig 3:
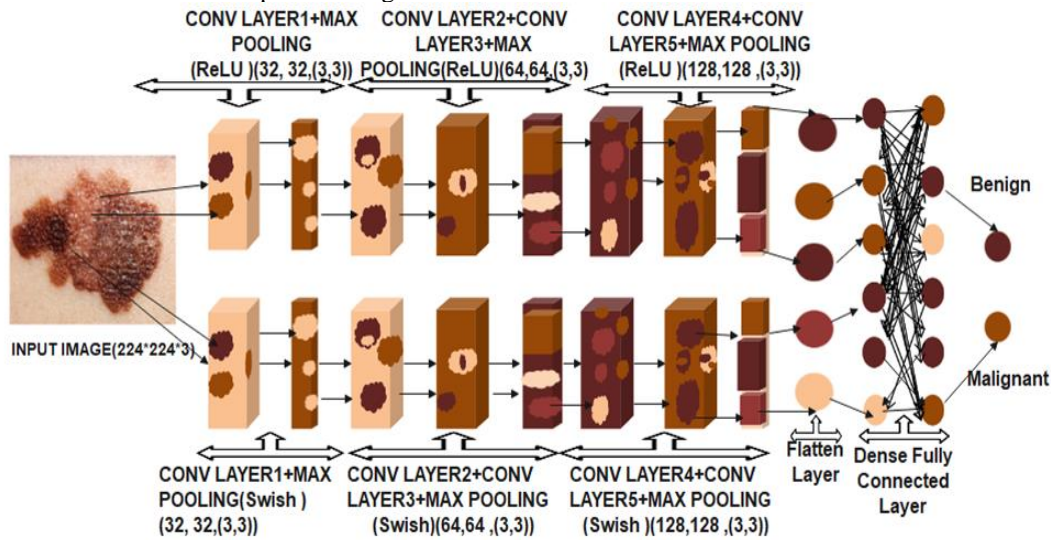
Fig.3. Architecture of proposed Bi-Diverse Activation CNN Model

3.2.1 Image Data Training With ReLU CNN

In our proposed work, training methodology with ReLU (Rectified Linear Unit) CNN activation aims to classify the skin lesions as benign and malignant. The process initiates with dataset load on the drive and then importing necessary Keras libraries and modules from Tensor Flow for CNN model development. The input (224*224*3) will hold the raw pixel values of images with 224 widths, 224 as height, and 3 RGB color channels as depth. To verify the training image fit, the plotting of the image process has been done. To build the linear stack of layers, the sequential model is utilized. Creating a convolutional base utilizing a typical format, with a stack of conv2D, the parameters have been fine-tuned. The CNN's model designed in a form of 5 convolutional layers with a first conv2D with 32 filters and a kernel size of (3,3) followed by max-pooling and the next two conv2D layers by using each of which is 64 filters, with a kernel size of (3,3), and then succeeding by max-pooling and then designed by two conv2D with 128 filters and a kernel size of (3,3). The activation function ReLU is implemented in all the convolutional layers. After each conv layers, the max-pooling layer is defined subsequently with a stride of (2,2) this tends to reduce the spatial output volume. Max pooling partition the outcome of the convolution layer into several small batches and then the largest value is obtained from each batch of each feature map. The max-pooling process delineated in Fig 4.
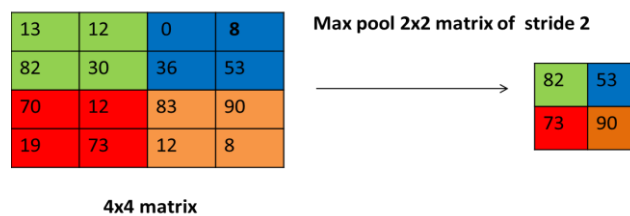
Fig.4. Max pooling process

By increasing the size of the filter in series of conv2D the spatial volume gets decreasing to develop the best CNN model. To create a single long feature vector flatter layer is used afore, inputting to a fully connected layer. This helps for the dense layer in the fully connected neural network for classifying the final output. The sigmoid activation is used for a binary outcome. Compiling the composed CNN model by tuning parameters such as optimizer, metrics, and loss is defined, to evaluate performance. By fitting the model to the training dataset and predict the outcome using the test dataset. After the model fit, the prediction process takes place with new images. To learn more complex skin lesion features of non-linear data in the proposed network model, the ReLU (Rectified Linear Units) activation function is more compatible.ReLU consistently partakes just in the hidden layers. Mathematically, ReLU is processed by

$$f(x) = \max(0,x). \qquad (2)$$

3.2.2. Image Data Training With Swish CNN

Our proposed model of Swish activation CNN is made in the structure out of five convolutional layers with the same kernel size of (3x3) is applied with various input sizes in expanding order. By importing a sigmoid function from Keras backend. Creating a sequential model with Keras. The input volume size of W1xH1xD1 is procured and each pixel of skin lesions is fed as input to the convolutional layer. The input image data is with a

progression of 0's and 1's. The first convolutional layer with input size of 32x32 and next two convolutional layers succeeded with the size of 64x64 followed by max-pooling of size (2,2) than last two convolutional layers is tethered with 128x128 with the same channel size of all convolutional layers (3x3) and proceeded with the max-pooling layer (2,2) at the end. In each conv layer, the swish activation function is manipulated. By applying the same filter consistently and slides over the width and height of an input data that outcomes in a map of 2D activations as a feature map, which recognizes the significant key spatial features of an input image. The convolution (*) operation is processed on the local receptive field of the same size(W_i) by utilizing filter (f) (3x3) to deliver a feature map(f_m). Mathematically evaluated by

$$f_m = W_i * f \qquad (3)$$

The output of the last Conv layer is fed as input to the fully connected layer for evaluation. The classification of a fully connected layer will rely on the features extracted by the previous convolution layer and applies weights to anticipate the right label and then converts it into 1D data. The sigmoid function is used in the last layer of the neural network to determine the probability of output. To assess the performance of swish, the loss, and metrics are calculated. Swish was found to be monotonic and soft function. Mathematically, this is processed by

$$f(x)= x*sigmoid(x). \qquad (4)$$

$$f(x) = \begin{cases} x \text{ for } x \geq 0 \\ 0 \text{ for } x < 0 \end{cases} \qquad (5)$$

and for the positive value function brings x back. The sigmoid function helps to predict the probability of output in the neural network model. Two class logistic regression of the sigmoid function is used for classifying the skin lesions as malignant and benign in our proposed work. The value always lies in the range between 0 to 1. Mathematically, it is computed by

$$y = \frac{1}{(1+e^{-x})} \qquad (6)$$

4. Experimental Results

The proposed model attains the accuracy of the trained and tests part of two different CNN models with different activation functions such as ReLU and swish. The training dataset contains 2637 images belonging to 2 different classes and the testing dataset with 660 images belongs to 2 classes as benign and malignant. The model was performed in python (Jupyter Notebook) by importing necessary Keras and TensorFlow libraries and precision and recall have been evaluated from the results of the proposed model which is as follows:

$$\text{Precision: } \frac{TP}{TP+FP} \times 100\% \qquad (7)$$

$$\text{Recall: } \frac{TP}{TP+FN} \times 100\% \qquad (8)$$

4.1. Evaluation with ReLU CNN

The ReLU CNN model has been trained and checked for loss and accuracy. The fit() function is used to train the model .The training and validation loss should be going lower and accuracy should be going higher in a learning network cycle. The CNN ReLU model obtained an accuracy of 86% in training and 81% in validation with epoch 30. The training and validation accuracy of the model depicted below in Fig 5:
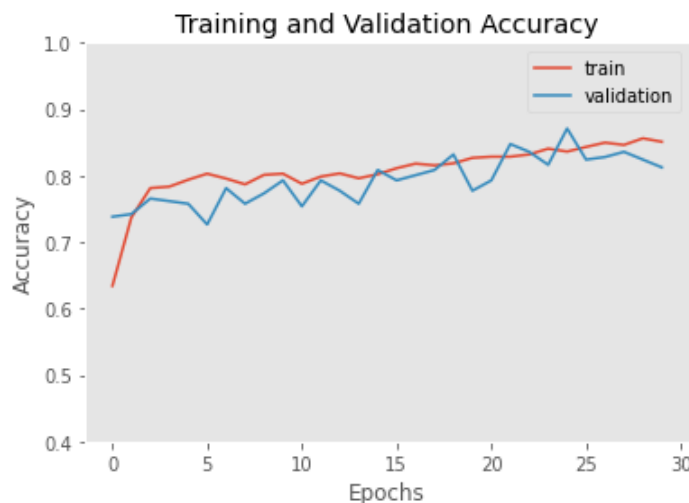

Fig 5. Training and Validation Accuracy –ReLU CNN

From the plot of the graph that the trained and validated data model accuracy has been increased with every epoch its shows that the ReLU CNN seems to be efficient.. The training and validation loss for CNN ReLU with epoch 30 model in Fig 6:
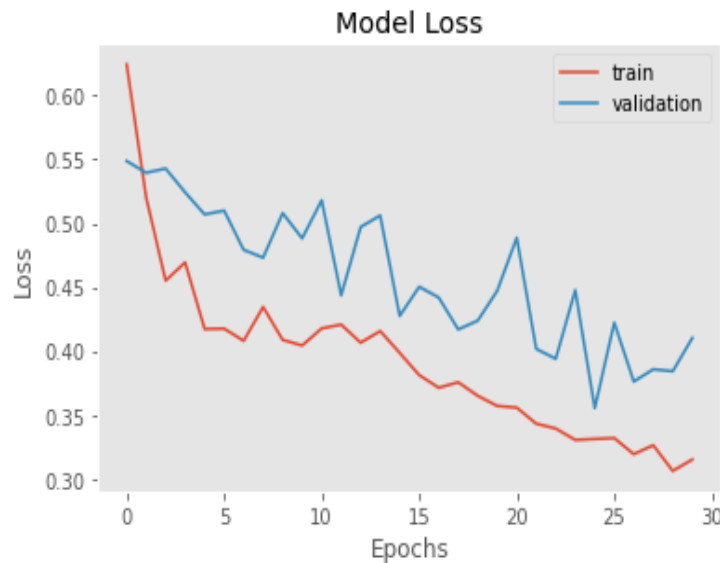

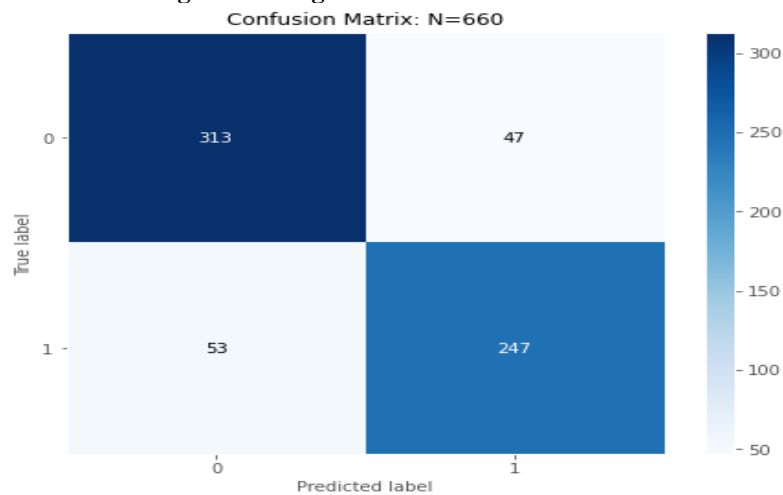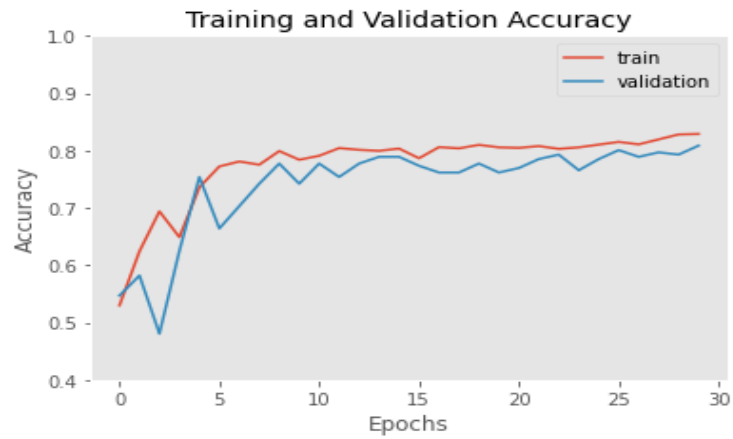**Fig 6. Training and Validation Loss –ReLU CNN**

Fig 7: Confusion Matrix- CNN ReLU

The proposed model of ReLU CNN returns numerous pertinent outcomes and also indicates the outcomes are named accurately. In total of 660 images 560 images are found to be true positive and true negative and 100 images are noted as false positive and false negative .The ReLU CNN accuracy score of 84% is obtained.The confusion matrix of ReLU is displayed in Fig 7:

4.2. Evaluation with Swish CNN

The Swish CNN model has been trained and evaluated for the exactness of the model. From the plot of the accuracy-loss graph, it is found that val_loss starts decreasing and val_accuracy starts increasing .The swish CNN model obtained an accuracy of 83% in training and 80% in testing with epochs 30. The training and validated accuracy of the model depicted below in Fig 8:

Fig 8.Training and Validation Accuracy –Swish CNN

In the accuracy plot graph, the training accuracy increases the validation accuracy also.The training and validation loss for Swish CNN model in Fig 9:

Fig 9.Training and Validation Loss- Swish CNN

The proposed model of Swish CNN model returns relevant outcomes than unessential ones by evaluating the performance of the classifier. In total of 660 images 537 images are found to be true positive and true negative and 123 images are noted as false positive and false negative .The overall accuracy score for the proposed model of 81% is obtained.The confusion matrix of Swish CNN is displayed in Fig 10:
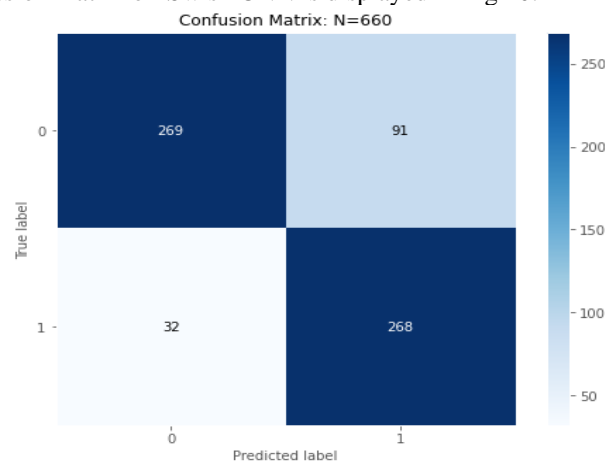
Fig 10. Confusion Matrix- CNN Swish

The performance evaluation of the proposed bi-diverse CNN activation model shows that ReLU CNN outperforms exemplary results .The developed RELU CNN model training accuracy and testing accuracy of ReLU CNN shows higher results than swish.

Bi-Diverse CNN Activation	Training Accuracy	Testing Accuracy	Epochs

ReLU	**86%**	**81%**	**30**
Swish	**83%**	**80%**	**30**

Table 3:Performance Evaluation Of The Proposed Model

5. Conclusion

The convolutional neural network plays a major role in classifying the skin lesion image. Two different CNN models have been developed with various filter size, the different activation function such as ReLU and Swish is applied in each convolutional layer and compared for best classification accuracy. The CNN model with ReLU achieved the accuracy as 84% .The CNN model with swish achieved the accuracy as 81% .The CNN with ReLU activation function outperforms the best accuracy compared to CNN's swish. The proposed Bi-Diverse activation CNN model has the potential to classify the skin lesion as benign and malignant. Future advancements will be with deep learning based on the color prediction of skin disease.

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