

Classification of Benign and Melanoma Skin Tumors Using Modified CNN with Transfer Learning

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Abstract

One of the most dangerous and deadly illnesses that people can face in their lives is cancer. Among all cancers, skin cancer is one of the most damaging, hazardous, and potentially fatal to a person's life. If not detected and treated initially, it will extend to other body parts soon and lead to the deadliest situation. It will spread quickly when the skin tissue areas are exposed to sunlight, mostly because skin cells in the designated location develop quickly. An automated skin tumor recognition system is the main requirement in order to detect skin cancer early, minimize time and effort, and save human lives. The most popular and successful methods for classifying skin cancer are the techniques of image processing and deep learning models. So, there is a need for an automated healthcare system to detect and classify skin lesions. We proposed a CNN model for classifying skin tumor images in our work. We have trained CNN models like AlexNet, VGG16, ResNet50, and Inceptionv3 using transfer learning techniques and observed the performance accuracies of all the models. The dataset used in our work contains two types of benign and melanoma skin tumor images, which are classified into two kinds through the Convolution Neural Network models. We used preprocessing techniques to clean our data, and data augmentation was also used to generate more data. As we know, deep learning models need more data to train and test the models. In all our model implementations, we have used all the features from the image while training the models for classification. Finally, we used the transfer learning techniques in our implementation models to improve the accuracy of each Image classification model. We trained the three models with different optimizers: Adam, Adadelta, and SGD. The proposed model (Modified AlexNet) provides better results, with approximately 96.75% for Training accuracy, 94.43% for Validation accuracy, and 94.11% for Testing Accuracy. The proposed model's performance results are compared with the state-of-the-art models like AlexNet, InceptionV3, VGG16, and ResNet50.

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1. Introduction

Cancer is one of the most life-threatening diseases that people commonly suffer from. One of the most common forms of cancer is skin cancer. If we can't identify it in its early stage and it will increase day by day gradually and soon may lead it to the death of a person [1]. Thus, skin cancer is the deadliest and most serious illness. 1 out of 5 Americans is suffering from this type of cancer by the age of 70 or older. More than two people are dying due to skin cancer in the U.S. every hour, according to the survey. It is found that it doubles the risk of melanoma skin cancer if having five or more sunburns. When it is detected early, the survival rate is high. The survival rate for people with melanoma skin cancer is 99 percent and will increase by five years of lifespan. Additionally, it has been noted that throughout the past few years, the number of skin cancers, both melanoma and non-melanoma, has increased. At present, every year, 2 to 3 million non-melanoma type and 1,32,000 melanoma type skin cancers occur worldwide [2]. Skin cancer accounts

for one out of every three cancers that are diagnosed. One in five Americans may experience some form of skin cancer over their lifetime, according to statistics from the Skin Cancer Foundation. Additionally, it has been noted that when ozone levels decline, the atmosphere's protective filtering role gradually diminishes, and UV radiation will be allowed to directly reach the Earth's surface. Therefore, a 10% drop in ozone levels is predicted to cause an extra 3,00,000 and 4,500 skin cancer cases of each class of non-melanoma and melanoma cases. The number of melanoma cases steadily rises due to its ongoing global incidence [2].

The recovery rate can also reach over 90% if physicians detect these skin lesions as early as possible; this would save patients' lives. In general, it is difficult to diagnose this sort of skin cancer from images, and occasionally this might result in inaccurate results because many types of skin lesions can look the same. Additionally, manually analysing the image data will take more time. We also need more expertise and experienced people in the field. Therefore, there is a need for an automatic classification system to be developed so that the automatic system will do the skin lesion image classification automatically by digital methods directly from the images in a visual examination way. According to the statistics, around 3 out of 4 deaths were related to skin cancer, which comes from the Melanoma type [3]. If melanoma were identified more effectively without errors in its early stage, then the recovery rate of melanoma patients would increase further. It takes skilled professionals or experts to manually identify and diagnose melanoma in order to overcome inter-observational variances. Therefore, if melanoma detection is automated, it will be simpler to diagnose patients and improve their chances of survival. Many techniques were developed to classify melanoma and nonmelanoma images, which gave good results. Generally, as we know, traditional methods are very time-consuming and error-prone, and more experienced persons or experts in the specified field are needed to handle this kind of melanoma case. However, the Digital Technology-based methods will use the automation process to identify melanoma and nonmelanoma skin lesions with rapid results.

This paper presents all the deep learning models, proposed modified AlexNet, AlexNet, VGG16 (Visual Geometry Group), InceptionV3, and ResNet50, used to classify skin lesions from medical images. All these models have recorded better classification performance accuracies with their architectures. Performance accuracies are measured for different values of hyperparameters, such as Adam Optimizer, SGD Optimizer, and Adadelta Optimizer, with various values of learning rates and different sizes of epoch values, 10, 20, ..., 100, 120, and 140. The proposed modified AlexNet with Adam Optimizer attains a better accuracy of 94.11% with epoch size 120, the learning rate, and batch sizes as 0.0001, 32.

2. Literature Review

Dermoscopic skin lesion images will provide more information for a deep insight analysis of any skin lesion for image classification. A customized CNN model was developed to identify and classify skin lesion types from the image dataset [4]. Krizhevsky et al. developed a model called AlexNet for the ImageNet dataset, which won the (ILSVRC) Challenge [5]. The CNNs are the deep neural network models with specific architectures that are powerful models in this domain that handle detection and classification tasks [6][7]. Medical image classification with CNNs is a well-known and familiar technique that is already widely used. Also, it has been observed that skin cancer identification, along with the encouraging results, is in the areas of ophthalmic issues such as clinical epidermal issues, diabetic retinopathy issues, and cervical cell issues for the image classifications [8]. DCNN (Deep Convolution Neural Network) classified skin lesions as benign and melanoma more accurately than board-certified dermatologists [9]. A CNN model with a deep neural network architecture, which has more than 50 layers, was developed and used to extract the rich and more descriptive features from it. By using the ISBI 2016 skin lesion images, the system performs a very accurate skin lesion segmentation on it [10], [11][12]. Bi et al. used a Deep CNN Model, which consists of ResNets with no of residual blocks, used for finding and categorizing skin lesions images, and achieve outstanding, cutting-edge outcomes [13]. Sara Hosseinzadeh Kassani et al. [10] surveyed the identification of melanoma and non-melanoma skin lesions using various kinds of deep learning CNN architectures by using the augmented dataset of HAM 10,000, and they found and achieved the accuracies of 84% for the AlexNet model as least then the other accuracies are recorded as 89% for VGGNet19 and with 90% accuracy for VGGNet16 respectively. In this study, the highest recorded accuracies were observed by state-of-the-art models like ResNet50 and Xception models [14]. Furthermore, transfer learning and data augmentation are still necessary techniques to use for data collection and have not entirely mitigated the problem [15]. From the observation of our literature review, we understood that the lack of data, insufficient data, or less data and imbalanced data of different classes included in the datasets lead to the abysmal performance of the models [16]. Even though machine learning models achieved good efficiency due to their high performance in skin cancer image classification [17], the model has shown poor performance in terms of accuracy. The accuracy of the models leading is deviated for extracting the essential features and sensible information from the images [17]. There are some challenges in detecting and classifying the images of different variations in the image

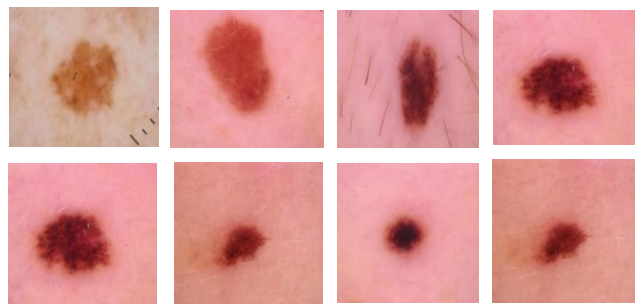
type and other resources available [18]. Additionally, variations in skin color also make the model very hard and complex [19]. Therefore, an internet of health things-driven deep learning approach for identification with classification of skin cancer-based CNN Models using transfer learning are developed. Here, the input skin cancer images are amassed from international Skin Imaging Collaboration (ISIC) image archive dataset [20].

3. Dataset

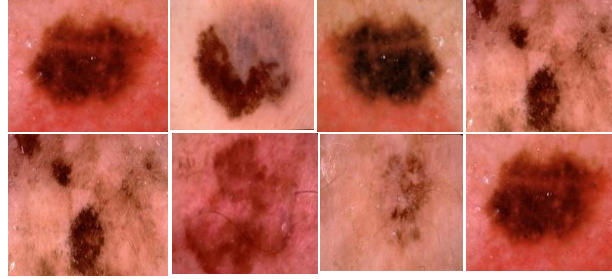
The Skin Cancer Dataset used in our work consists of 3297 images, collected from the Kaggle Datasets is a benchmark Dataset. We used the images for models like for Training Benign Images are 1140, Melanoma Images are 937, so the Total images for Training are 2077, Benign Images are 300, and Melanoma Images are 260 for Validation, so the Total images for Validation are 560, Benign Images are 360, and Melanoma Images are 300 for Testing, so Total images for Testing are 660. Out of 3297 images, 2077 are used in the Training (63%), 560 are used in the validation (17%), and 660 are used in the Testing (20%) process [21]. This is an imbalanced dataset with the number of classes as two, Benign and Melanoma, with unequal numbers of images in each class, and the sample images shown in Figures 1a and 1b.

Table 1: Skin Cancer Dataset Details

Skin Cancer Dataset	Tumor Type	No of Images	Total Images
Train	Benign	1140	2077
	Melanoma	937	
Validation	Benign	300	560
	Melanoma	260	
Test	Benign	360	660
	Melanoma	300	
			3297



a). Benign Tumor Images



b). Melanoma Tumor Images

Figure 1. Sample Benign and Melanoma Skin Tumor Images

4. Methodology

4.1 Proposed Model Architecture (Modified AlexNet)

In our work, we proposed a model, and its architecture is shown in Fig. 2a. The proposed model is the modified version of the AlexNet. The model consists of layers of, 6 are convolutional layers and 3 are fully connected layers forms this structure. In our proposed model we have used a new activation function called ELU (Exponential Linear Unit) in the sixth layer. In ELU, it considers the small negative values also, instead of making the values completely zero or one. So that it can provide the smooth gradient values of the input values and protect the neurons instead of dying completely. An activation functioned called sigmoid is used in the final layer of the model which is a fully connected layer, as our target is to classify two types of skin cancer images: benign and malignant. The steps for implementing image classification using deep learning algorithms are discussed below. First, identify the data required for its implementation. The collected data is then preprocessed using normalization. We can apply the preprocessing techniques for the dataset before we are going to use it for training our proposed model. The processed and collected data of skin lesion images which are used for train our proposed model will give the better and more efficient results [22]. In our work, we used feature extraction, which plays a significant role in image processing. We extracted all features to help us identify and recognize the patterns in the image dataset. It makes use of every feature that has been extracted to reduce the amount of loss while preserving the original dataset images' information. The data was divided into test, validation, and train datasets with varying ratios. Following dataset breakage, the Training Dataset is used to thoroughly train all the CNN models, which are then verified using the Validation Dataset and Tested using the Test Dataset. For each of the processes, we noted the model's results and saved them. The saved models are tested with the Testing dataset for Image Classification. Lastly, the performance measures assess each CNN model's performance individually.

The other models used in our work are AlexNet, Inceptionv3, VGG16, and ResNet50. Table 2 shows the various optimizers used to train each model. The Optimizers used to train the models are Adam, Adadelata, and SGD. There are models currently developing which uses of Transfer Learning and Deep Learning in an IoT system to assist doctors in the diagnosis of common skin lesions, typical nevi, and melanoma [23].

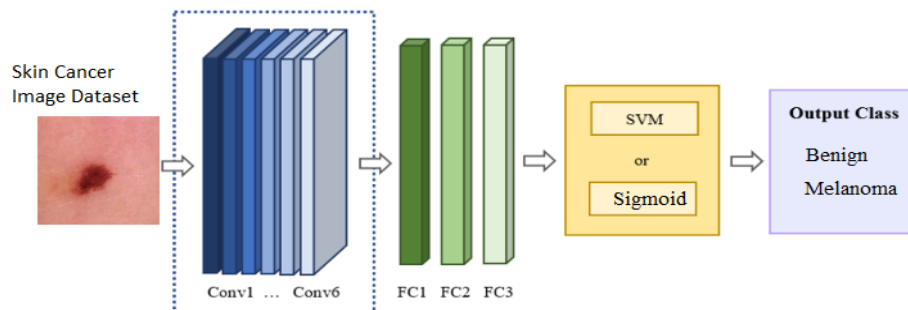


Figure 2a. Proposed Model Architecture of Modified AlexNet

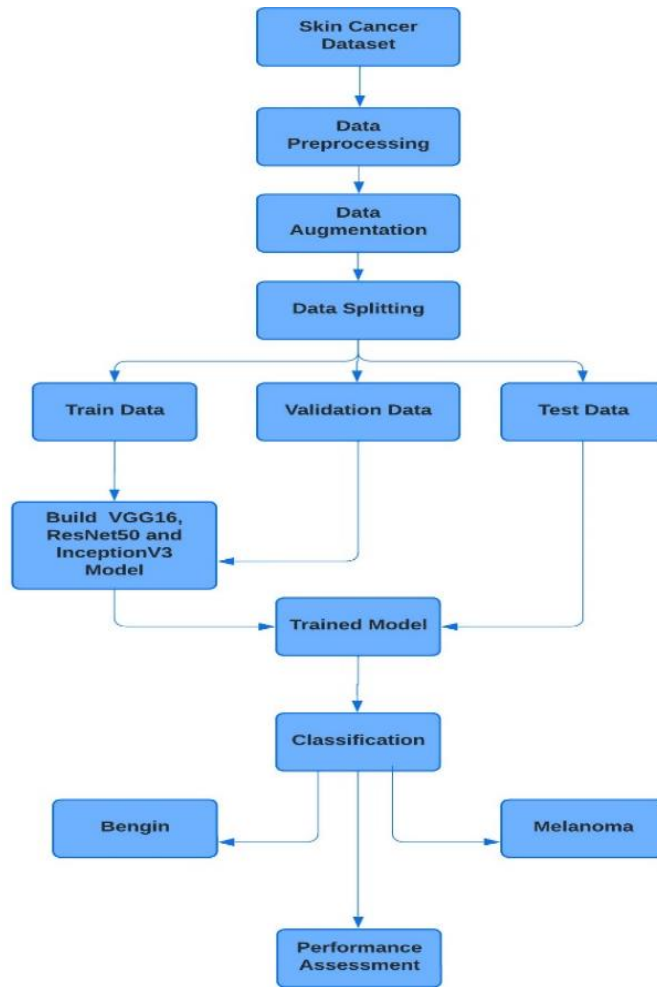


Figure 2b. Process Flow Diagram for Proposed Model

Table 2: Optimizers Used for Models

Model	Optimizers
VGG16	Adam, Adadelata, and SGD
ResNet50	Adam, Adadelata, and SGD
InceptionV3	Adam, Adadelata, and SGD
AlexNet	Adam, Adadelata, and SGD
Proposed Model	Adam, Adadelata, and SGD

4.2 Deep Learning Models

4.2.1 AlexNet

AlexNet is a basic and standard CNN model used for classification of images. It consists of 8 layers in it. Out of these 3 are fully connected layers and 5 are convolutional layers. It also contains the pooling layers and activation functions. The diagram below is the AlexNet model's architecture.

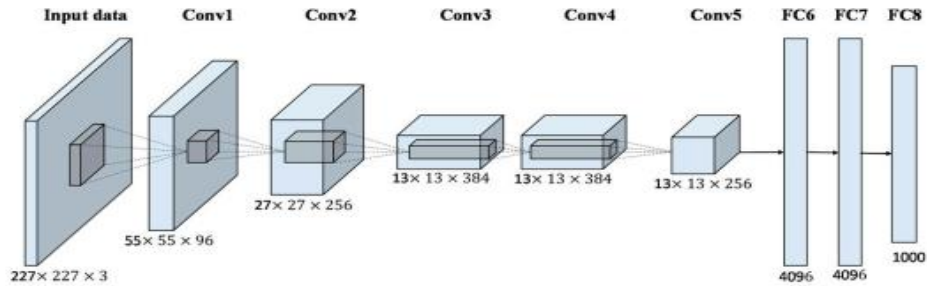


Figure 3. AlexNet Model Architecture

4.2.2 VGG16

VGG16 is one of the best Convolution Neural Net (CNN) architecture models. This model has 16 layers in its architecture. It has a uniform architectural design pattern, as shown in the figure. The VGG16 Model's basic architecture is depicted in Fig. 4. VGG16 can be used here, as it is already a pre-trained model on a specific image dataset, and the parameters are updated for better and better accuracy results.

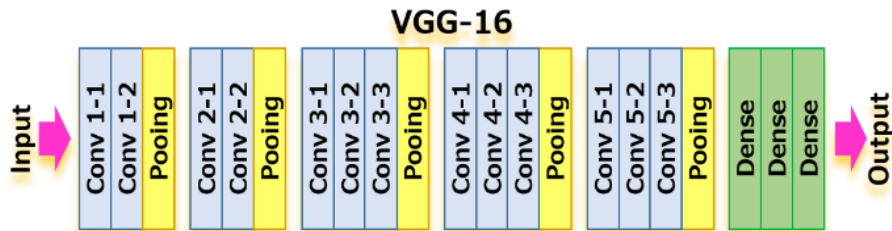


Figure 4. VGG16 Model Architecture [24]

The essential thing about the VGG16 model is that it has more hyperparameters. They focus on the convolutional neural network layers of the 3x3 size filters with a stride value of 1 and always use the same padding and max pooling layers with the 2x2 size filters and with a stride value of 2. Each and every convolutional and max pooling layer is arranged sequentially in its architecture, as shown in Figure 3 above. At the end of the architecture, it consists of two FC layers, and then it follows the SoftMax to produce the output results [24].

4.2.3 InceptionV3

Inception V3 is a Deep CNN model. The model has its depth of 42 layers. A pre-trained version of the InceptionV3 model can also be used to train the model. This pre-trained network model can classify the images into different classes of images. In our work, we used the model for two types of image classifications: Benign and Melanoma. All the convolutional and pooling layers are arranged as shown in Fig. 5.

4.2.5 Training, Validating, and Testing

The whole dataset is split into Train, Validation, and Test datasets with the ratios of 70:10:20. The models in this study were trained using varying ratios of Training, Validation, and Testing. Out of all the selected ratios, 70:10:20 gives better accuracy results than the other ratios. Both the Training and Validation losses are also observed and used to assess the performance of the deep learning models. The training loss assesses the model's error on the training set so that how a CNN model fits the training data. Usually, the training loss is observed by summing all the errors for each sample of the training dataset. It is essential to note that the training loss is pointed out after each training batch is finished. The summation of the errors for each and every sample from the Validation dataset is used to compute the Validation loss. This validation loss is noted after each epoch while validating the model's performance. Based on these, we can understand whether the model requires further fine-tuning or other modifications.

4.2.6 Evaluation Metrics

An evaluation metric, accuracy, evaluates the performance of all the deep learning models. The metrics used for performance analysis are computed with the help of a confusion matrix with index values such as FP, FN, TP, and TN. Here, our trained model's TP-True Positive results correctly classify the cancer image class. Similarly, the TN-True Negative is an outcome where our trained model accurately classifies the non-cancerous image class. In FP-False Positive, our trained model incorrectly classified the cancer class, whereas, in the FN-False Negative, our trained model incorrectly classifies the non-cancer classes. In addition to accuracy, we also used other evaluation metrics, and the equations of all the metrics are mentioned below.

Accuracy: The equation below defines the performance metric derived and calculated from the confusion matrix. Accuracy represents our trained model's ability to correctly classify the positives out of all the positive cancerous tumors.

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \text{ ----- (1)}$$

Precision: It measures the accuracy of optimistic predictions observed by the model. It indicates the ratio of truly predicted positive values to all the true or negative cases predicted as positive. Precision is essential in medical applications, including skin disease classification, where correctly identifying positive cases is crucial to avoid misdiagnosis.

$$\text{Precision} = \frac{(TP)}{(TP) + (FP)} \text{ --- (2)}$$

Recall (Sensitivity): It evaluates the model's ability to locate relevant samples in the dataset, which are referred to as true positives. It displays the proportion of correctly predicted positive events out of all positive occurrences. Recall is crucial in medical diagnostics as it ensures that all the disease cases are correctly identified, minimizing false negatives.

$$\text{Recall} = \frac{(TP)}{(TP) + (FN)} \text{ ----- (3)}$$

F1-score: We can calculate the F1-score from the above metrics: precision and recall. It is the harmonic mean of these two metrics. This can be beneficial for the distribution of uneven classes.

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \text{ ----- (4)}$$

These measures are essential for assessing how well the model performs in identifying various skin diseases correctly, aiding in refining the model's design and training approach [27].

Specificity: It is the true negative rate where the probability of a test result is negative means identification of negative instances out of all actual negative instances.

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positives}} \text{ --- (5)}$$

5. Results and Discussion

All the CNN models' performance results analysis, including the proposed modified AlexNet against the test dataset, is evaluated using transfer learning techniques. The Modified AlexNet, AlexNet, VGG16, ResNet50, and Inceptionv3. VGG16 and ResNet50 are the least-performing models. Modified AlexNet is considered the best-performing model out of all the models. The performance of the remaining two models is also good. Performance accuracies of all the CNN models were observed with three different optimizers, Adam, SGD, and Adadelta, for the various learning rates like 0.01, 0.001, and 0.0001 with different epoch sizes like 10, 20, ..., 100, 120, 140. The proposed modified AlexNet Model gives good training accuracy using the Adam optimizer for 120 epochs, with 0.0001 as a learning rate and a batch size 32. Approximately 96.75% is for training accuracy, 94.43% is for Validation accuracy, and 94.11% is for Testing Accuracy. Fig. 7 shows the comparison of all the CNN models' performance with the training and testing accuracies. Tables 8 and 9 show the performance comparisons of every CNN model using the various evaluation measures that were applied to each trained model.

The proposed modified AlexNet model has the best classification performance compared to the remaining Transfer Learning CNN Models, AlexNet, VGG16, ResNet50, and InceptionV3. The training and validation accuracies and loss results were also observed for each model while training and validating the data. Based on the values of the results, we changed the hyperparameter, and again, we trained and tested the models with different values for each parameter.

5.1 Proposed Model (Modified AlexNet)

Tables 3 and 8 summarize the proposed modified AlexNet models' training, validation, and test results. From this, it is observed that the modified AlexNet has an accuracy of 96.75% for Training, 94.43% for Validation, and 94.11% for Testing. The ROC of the proposed model we can observe in Fig.8.

Table 3: Proposed Model's (Modified AlexNet) performance results

Model	Optimizer	Learning Rate	Epochs	Performance			
				Training		Validation	
				Accuracy	Loss	Accuracy	Loss
Proposed Model	Adam	0.0001	120	0.9675	0.0074	0.9443	0.0711
	SGD	0.0001	120	0.8365	0.0068	0.7147	0.0089
	Adadelta	0.0001	120	0.8273	0.0063	0.7645	0.0067

5.2 AlexNet

Tables 4 and 8 summarize the AlexNet models' training, validation, and test results. From this, it is observed that the VGG16 has an accuracy of 95.07% for Training, 94.62% for Validation, and also 93.39% for Testing.

Table 4: Performance results of AlexNet in summary

Model	Optimizer	Learning Rate	Epochs	Performance			
				Training		Validation	
				Accuracy	Loss	Accuracy	Loss
AlexNet	Adam	0.0001	120	0.9507	0.0074	0.9462	0.0711
	SGD	0.0001	120	0.8365	0.0068	0.7147	0.0089
	Adadelta	0.0001	120	0.8273	0.0063	0.7645	0.0067

5.3 VGG16

Tables 5 and 8 summarize the VGG16 models' training, validation, and test results. From this, it is observed that the VGG16 has been noticed with an accuracy of 84.29% for Training, 74.85% for Validation, and also 71.54% for Testing.

Table 5: Performance results of VGG16 in summary.

Model	Optimizer	Learning Rate	Epochs	Performance			
				Training		Validation	
				Accuracy	Loss	Accuracy	Loss
VGG16	Adam	0.0001	120	0.8429	0.0074	0.7485	0.0711
	SGD	0.0001	120	0.8365	0.0068	0.7147	0.0089
	Adadelta	0.0001	120	0.8273	0.0063	0.7645	0.0067

5.4 ResNet50

Tables 6 and 8 summarize the ResNet50 models' training, validation, and test results. From this, it is observed that the ResNet50 has been noticed with an accuracy of 89.16% for Training, 76.58% for Validation, and also 74.39% for Testing.

Table 6: Performance results of ResNet50 in summary.

Model	Optimizer	Learning Rate	Epochs	Performance			
				Training		Validation	
				Accuracy	Loss	Accuracy	Loss
ResNet50	Adam	0.0001	120	0.8407	0.0085	0.6856	0.0622
	SGD	0.0001	120	0.8916	0.0077	0.7658	0.0095
	Adadelta	0.0001	120	0.8364	0.0074	0.6654	0.0058

5.5 InceptionV3

Tables 7 and 8 summarize the InceptionV3 models' training, validation, and test results. From this, it is observed that the InceptionV3 has been noticed with an accuracy of 94.07% for Training, 81.43% for Validation, and also 78.11% for Testing.

Table 7: Performance results of InceptionV3 in summary.

Model	Optimizer	Learning Rate	Epochs	Performance			
				Training		Validation	
				Accuracy	Loss	Accuracy	Loss
InceptionV3	Adam	0.0001	100	0.9407	0.0075	0.8143	0.0511
	SGD	0.0001	120	0.9365	0.0079	0.7849	0.0086
	Adadelta	0.0001	120	0.9262	0.0054	0.7665	0.0049

Table 8 below shows the overall summary of all five models with their Training, Validation, and Testing Accuracies. The Train, Validation, and Test ratios are 70, 10, and 20 percent, respectively.

Table 8: Comparison of CNN Models with Accuracies (Train 70%, Validation 10%, and Test 20%)

Model	Train Accuracy	Validation Accuracy	Test Accuracy
VGG16	84.29%	74.85%	71.54%
ResNet50	89.16%	76.58%	74.39%
InceptionV3	94.07%	81.43%	78.11%
AlexNet	95.07%	94.62%	93.39%
Proposed Model	96.75%	94.43%	94.11%

Table 9 below shows the overall summary of all CNN models, VGG16, ResNet50, Inceptionv3, and AlexNet, and their performance comparison with different evaluation metrics measured for the Test Dataset.

Table 9: Comparison of all CNN Models with Different Performance Metrics.

Performance Metrics	VGG16	ResNet50	Inceptionv3	AlexNet	Proposed Model
Accuracy	71.54%	74.39%	78.11%	93.39%	94.11%
Precision	71.11%	74.27%	74.59%	92.43%	93.93%
Recall	71.32%	66.56%	75.66%	90.56%	92.12%
F1-Score	72.44%	71.93%	73.23%	91.44%	93.76%
Specificity	73.13%	78.64%	79.10%	91.37%	91.89%

Table 10: Cross-validation (10-fold) results for the proposed Modified AlexNet

Performance Metrics	Accuracy	Precision	Recall	F1-Score
Fold-1	91.54%	92.91%	91.32%	92.84%
Fold-2	93.23%	92.43%	92.23%	93.93%
Fold-3	96.56%	93.83%	91.44%	93.93%
Fold-4	95.66%	93.93%	92.43%	94.23%
Fold-5	94.27%	94.43%	92.43%	93.94%
Fold-6	94.59%	93.83%	91.44%	94.93%

Fold-7	92.43%	93.74%	92.39%	93.84%
Fold-8	94.39%	94.77%	92.56%	92.93%
Fold-9	95.11%	94.59%	93.36%	93.83%
Fold-10	93.39%	94.83%	91.56%	93.74%
Average	94.11%	93.93%	92.12%	93.76%

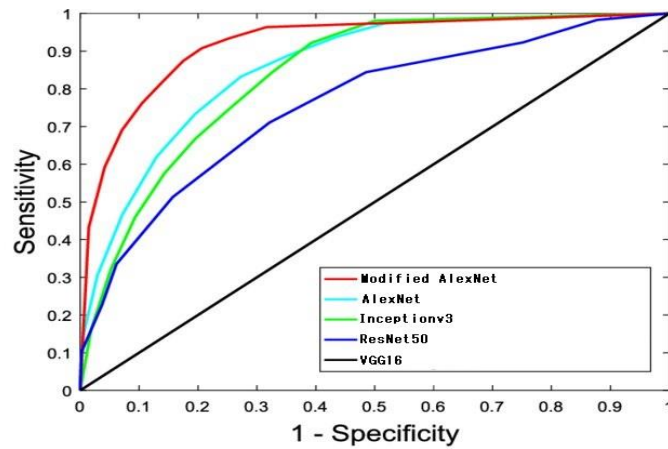


Figure 8. The ROC of the best CNN Model for skin lesion classification.

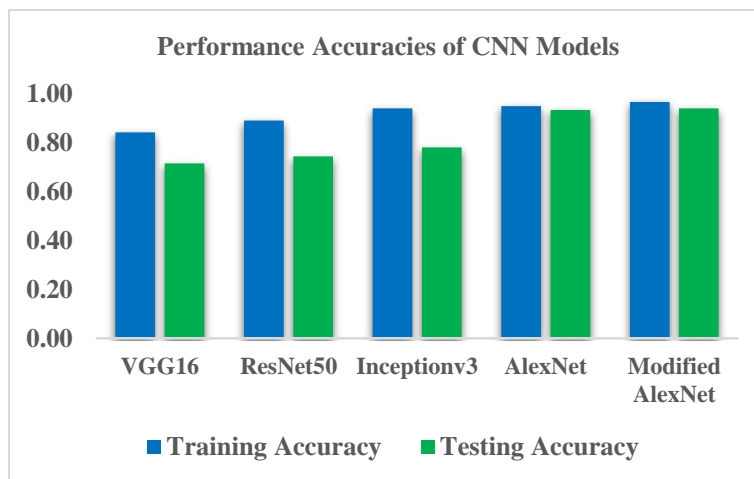


Figure 9. Performance Comparison of Train and Test Accuracies of CNN Models.

6. Conclusion and Future Work

In this work, we present our overall research work and summarize all the CNN models that we have used in our work for the classification of skin cancer types from the given Dataset. Performance metrics used in our work, such as accuracy, precision, recall, F1-score, and specificity, are used to assess all CNN models, including the proposed model. Fig.7 demonstrates the contrast of the performances of all five CNN models for the test dataset. We can also observe the ROC and cross-validation results of the proposed model in Fig.8 and Table.10. By comparing all five deep learning models' performance measures, it is concluded that the proposed model shows the best results among all other models, the AlexNet, VGG16, ResNet50, and InceptionV3 models. The Proposed Model (Modified AlexNet) has 96.75% of training accuracy, 94.43% of validation accuracy, and 94.11% of testing accuracy. In this work, very few inaccuracies are observed, possibly due to the usage of a small dataset. We can also improve this by using large datasets with more classes in future works. If we improve the quality of the images using image enhancement techniques, we can also improve the accuracy of these DL models in future works. We can even work in feature extraction, using different types of optimizers and hyperparameter tuning to improve the models' performance in future works. There are developments in the area skin lesion classification with interpretability in association with the IoT, an End-to-End smart healthcare system through an android application [28].

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