# Skin Lesion Classification using Deep Learning Methods

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**Abstract**

The incidence of cancer cases has been rising rapidly over the last few decades. Skin cancer is one of the widely found types of cancer, is further classified into two main types, Melanoma and Non-Melanoma. Though Melanoma is less common than other types of skin cancer, it can be lethal if not treated promptly. But it is not the only type of skin lesion that needs attention. It becomes necessary to promptly identify and classify the skin lesions for the recovery of the patient. The machine learning models of Deep Learning prove to be very efficient in this regard. Hence, we developed a deep learning model which is an ensemble of InceptionV3, Xception and ResNet152 models. It can classify the skin lesions into seven main types -Melanoma, Melanocytic Nevi, Benign Keratosis-like lesions, Basal cell carcinoma, actinic keratosis, vascular lesions, Dermatofibroma. The method was applied to dermoscopic images from the HAM10000 dataset. The presence of noise and artifacts in the images makes it difficult to classify. So, as a preprocessing step, we performed hair removal on the dermoscopic images which is a series of methods that starts with blackhat filtering, subsequently creating a mask for inpainting and then applying the inpainting algorithm. Further Contrast enhancement was performed by applying the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm on the luminance channel of HSV image to improve the contrast of the image and also makes sure that it is not over-amplified. It is then followed by Skin Lesion Segmentation where a grabcut algorithm is applied on the enhanced image which segments the image. Thus, the segmented images are produced which are fed to the Model for training and testing. To cope up with the unbalanced dermoscopy image dataset available, we performed Image augmentation on the images generated in the previous step which alters the existing images to create some more images for the model training process, thus solving the problem of paucity of dataset and substantially increases the performance of the model. The final dataset generated is fed to the three deep learning models InceptionV3, Xception and Resnet152 which achieved an accuracy of 84.6%, 86.5% and 86.7% respectively. These were later given to two different ensemble models - Stacking and Random Forest. The Stacking model achieved an accuracy of 88.6% and Random Forest achieved an accuracy of 92.59%. The proposed system includes a GUI for a good user experience.

**Keywords:** Cancer; Prediction; Deep learning; Dermoscopic images; Augmentation

## 1. Introduction

Cancer is a life-threatening disease which is caused due to abnormal and uncontrolled growth of body cells and skin cancer is one of the types. It can be broadly divided into melanoma and non-melanoma, where melanoma ranks 19th in the occurrence while non-melanoma 5th. Non melanoma can also be referred to as Keratinocyte carcinoma while it is considered as the most common form of skin cancer, it is far less capable of spreading and then becoming life-threatening in comparison to its counterparts. They can, however, get larger and spread to other parts of your body if left untreated. The most unfortunate part is that the most widely prevalent non melanoma goes underestimated and unrecognized. Whereas melanoma



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is the benign moles formed by melanocytes and can become cancerous. If they are detected and treated early enough, they can be cured. They have the potential to spread to other places of your body and become more difficult to treat if ignored Several additional skin lesions, on the other hand, are regarded to be part of a bigger skin cancer umbrella. These aren't all skin cancers, but they all have the potential to become malignant. Major types of skin lesions are Melanocytic nevi, Melanoma, Benign keratosis-like lesions, Basal cell carcinoma, actinic keratosis, Vascular lesions, Dermatofibroma Although these red or pink spots of skin aren't malignant, they are a type of precancer. Squamous cell carcinoma can develop from these skin tumors if they are not treated. Basal cell carcinomas are the most frequent type of skin cancer, accounting for 90% of all cases. It is formed mostly in the lower epidermis.

Squamous cell carcinoma: This type of skin cancer develops in the skin's outer layer and is usually more severe than basal cell carcinoma. It develops in top layer of epithelium.

Melanoma: Though it is less common, it is the most dangerous type of skin cancer. Despite accounting for only 1% of all skin malignancies, melanoma is the leading cause of death from skin cancer each year.

A dermatologist's ocular examination is the standard clinical strategy for melanoma diagnosis, however clinical diagnostic accuracy is poor. When compared to the naked eye, dermoscopy improves diagnostic sensitivity by 10–30 percent. It's a common screening approach that act as a bridge between clinical dermatology and dermatopathology by allowing the viewing of morphological traits that aren't visible to the naked eye. Unfortunately, dermoscopy has been proven to diminish diagnosis accuracy in the hands of amateur dermatologists, as this technology necessitates a high level of knowledge to detect skin lesions. Only the experts could reach a sensitivity of 90% and specificity of 59% and when used by less trained doctors, there is a significant drop to 62%-63%. As a result, there has been a surge in interest in employing automated image analysis to help doctors distinguish between early malignant and benign skin lesions in the last couple of decades. The use of computational intelligence approaches aids physicians and dermatologists in speedier data processing, resulting in more accurate and reliable diagnosis, which could in turn save many lives. Many attempts have been made to apply different computational methods to diagnose the skin lesions, but again the main focus area was the Melanoma and ignoring the non-melanoma type. Even in the available works there have been few limitations due to the low availability of the data related to the skin cancer patients (which is again due to poor reporting and diagnosis), varied skin color types, poor pre-processing of the skin lesion images as less or no work on hair removal and scars, etc.

## 2. Related works

U. Saghir and V. Devendran proposed various feature extraction methods for detecting Melanoma [1]. This paper primarily focuses on the best methods for efficient feature extraction. As dermoscopic images are used for analysis, feature extraction i.e, selecting most appropriate features is very important. The methods proposed in this paper are Pattern Analysis, ABCD rule, Seven-point Checklist, Menzies's Method, CASH algorithm. These are some of the most prevalent and effective melanoma detection feature extraction approaches. Di Biasi, Luigi and Risi, Michele, in this paper proposed two essential points that are underlined for Melanoma Detection research [2]. The first point emphasizes on how a small change in parameters in the dataset affects the accuracy of classifiers. The second point is to have a flexible system architecture. For the first point Transfer learning methods are proposed and for the second point three layer architecture is designed. For analysis the MED- NODE dataset is used which consists of 70 melanoma images and 100 nevi images. The three methods used are AlexNet, Google InceptionV3 and GoogleNet out of which GoogleNet performed better. Here it is concluded that the Transfer learning approach is not that reliable despite its high performance.

S. Vinod and M. V. Thomas through this paper proposes analysis of various deep learning techniques recently employed by many studies for skin lesion segmentation and skin cancer detection tasks [3]. Each deep learning approach is evaluated and verified in terms of skin cancer diagnosis and segmentation accuracy. Other models, such as FrCN, Deeplab V3+ ensemble techniques, and Mask RCNN, produce better segmentation results. The usage of big data sets made up of various types of skin lesion photos can improve accuracy even more. Additionally, training the model with augmentation approaches on tiny datasets provides a broad variety of data. As a result, the model's accuracy on unknown data will improve. B. Sreedhar, M. Swamy B.E and M. S. Kumar [4] in this mainly focuses on projecting the comparative stud y on traditional image processing techniques for skin cancer image classification, pre-processing techniques, Feature extraction, and image segmentation datasets. The traditional methods include Gaussian filtering, Pixel, Edge, Region based segmentation, Artificial neural Networks, Convolutional Neural Networks, Support Vector Machine. A proper literature review is presented which consists of the performance of each technique and their accuracies are compared. Rasul, Md. Fazle, Kumar Dey, Nahin & Hashem [5] shown how deep learning can be used in conjunction with augmentation to simplify difficult preprocessing procedures. They also looked at alternative neural network architectures for lesion segmentation and then used transfer learning to



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evaluate network design for melanoma identification in dermoscopy images. SegNet, BCDU-Net, U-Net, ResNet50, InceptionV3, Xception and VGG16 were the approaches employed. The investigation concludes that SegNet and BCDU-Net perform admirably and produce identical outcomes, and that all the deep neural networks perform well. A. K. Waweru and K. Ahmed has proposed a DCNN model [6] that can classify around eight classes of skin lesions and also implemented techniques like Data Augmentation, Minority Oversampling to balance the imbalanced dataset classes. HAM10000 public dataset is used, minority oversampling technique is implemented, DenseNet 201 model is considered. The accuracy can be improved and also size of the dataset is smaller which are considered as the drawbacks.

Kaur R, GholamHoss eini H and Sinha R in this paper [7] proposed a DCNN model to classify for automated detection of melanoma or not. They implemented 31 layered CNN to classify two kinds of skin cancer: malignant, benign. Their proposed system shows 82.95 % accuracy. Data Augmentation technique was implemented to avoid overfitting problems. The drawback here is that only two kinds of lesions are classified. V. Mishra, A. K. V and M. Arora have proposed pre-trained DCNN models [8] to classify melanoma skin cancer types via transfer learning techniques. The optimizer that they used is stochastic gradient descent algorithm. The accuracy of their proposed work is 97.9%. The disadvantage here is that the size of the dataset is smaller as it contains only 3220 images. K. C. Shahana Sherin and R. Shayini [9] worked on image processing techniques to classify skin lesions into melanoma or nevus. They are using a multi thresholding approach to segment the lesion and to extract the features they are using an 18-feature vector and pre-trained ANN model to classify the lesions. K. M. Hosny and M. A. Kassem [10] implemented image augmentation techniques and proposed a DCNN model via transfer learning to classify lesions into three types and obtained a model of 98.16%. L. Wei, K. Ding and H. Hu in this paper [11] For feature extraction a lightweight pre-trained network is used. This model can extract strong lesion features, as it achieves lesion type classification and lesion features similarity at the same time. This model achieves higher performance even with fewer model parameters when compared with existing fusion CNN methods.

A. Galal, N. Fayez and M. El-Seddek [12] proposed a model to classify image provided is cancerous or noncancerous by providing ABCD features to ANN classifier. This model uses Bayesian Regularization algorithm to classify the image. This method is more effective when compared to traditional biopsy methods. It includes various pre-processing steps like noise removal to remove noise and artifacts, contrast enhancement to improve the contrast of the image, lesion segmentation and feature extraction. This method is noise resistant and can also classify complex skin lesions effectively. It gives 98% accuracy for melanoma classification. R. Zhang proposed an automated melanoma detection model using EfficientNet-B6 and transfer learning [13]. The use of EfficientNet enhances the ability to capture complex features for recognizing melanoma. Transfer learning the model in identifying a superior inference convergence state and speeds up the training process. This model achieved an AUC-ROC score of 0.917 which is 3% higher than the VGG-based model (0.819). This model is limited to the binary classification of melanoma. J. Daghrir, L. Tlig, M. Bouchouicha and M. Sayadi [14] worked on pre-processing techniques like image segmentation, hair removal that are applied to the dataset. Three methods SVM, CNN, KNN are considered for

Majority voting. An accuracy of 57.3%, 71.8%, 85.5% are obtained from KNN, SVM, CNN respectively. Combined accuracy obtained through majority voting was 88.4%. This model is limited to a binary classification of melanoma and accuracy can be improved.

R. R. Subramanian, D. Achuth and P. S. Kumar [15] focused on skin cancer classification using CNN. Image augmentation is the first step in this process as the HAM10000 dataset has two-third of its images belonging to the Melanocytic nevi class. Image augmentation involved rotations and random shifts to the images. Later, all the images were resized and normalized to improve the efficiency of the model. Then CNN model is applied. An accuracy of 83.11% is obtained on training data and 83.04% on testing data with a precision of 0.818. Abd ElGhany and Sameh & Ramadan [16] used HAM10000 Dataset, Fine-tuned ResNet50 model using Regularisation, hyper parameter optimization and batch normalization to classify up-to seven different types of skin lesions. The obtained precision is 86% which is higher than that of InceptionV3 and VGG16 models. There is a scope for further improvement of precision. (89%). C. K, P. C. Siddalingaswamy, S. Pathan and N. D'souza proposed a model [17] which is built by blending method is capable of classifying the lesions into eight different types and is an ensemble model of four transfer learning sub models. The resultant large model has an accuracy of 81.2%. Here the accuracy can be improved. M. Babar, R. T. Butt and H. Batool [18] proposed a model that performs feature extraction through DNN GoogLeNetlevel model and SVM, k-NN and ensemble methods that are used for classification. Cubic Kernel of SVM achieves best accuracy of 86.6%. The drawback here are, only melanoma type of skin lesion is classified, there is scope for higher accuracy (current: 86%), SVM does not perform well when the number of features per data point are greater than the number of data samples given for training and KNN also lags behind in case of excessive dimensions. Deep learning was used by [19] to extract relevant characteristics, and a sparse autoencoder was used to extract features. The SVM classifier obtains a 94 percent classification rate, categorizing them into three categories: melanoma,



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suspicious instances, and non-melanoma. Thus, the data is divided into three categories: melanoma, suspicious instances, and non-melanoma cases only and does not specify about any other skin lesion types. A. Huq and M. T. Pervin [20] improved adversarial the robustness of two prominent deep learning models, MobileNet and VGG16, against PGD and FGSM whitebox attacks using adversial training based on Projected Gradient Descent (PGD) has been discovered to provide strong generalization value in guarding against numerous threats.

## 3. Methodology

In order to build a model with good precision and accuracy, firstly the dataset to be fed to the training module is cleaned and enhanced by hair removal, contrast enhancement and then Lesion Segmentation is performed to neatly demarcate the skin lesion. Then Image Augmentation is performed on the above images generated. Next in the training module, ensembling of the three transfer learning models is performed.

### a) Hair removal

Steps involved in Hair removal are as follows - first the color image is converted to a grayscale version then, upon it Morphological Black-Hat transformation is applied. Further the mask is created for the InPainting task, following which an inpainting algorithm is applied on the original image using the mask prepared from the grayscale image.

### b) Contrast Enhancement

For this purpose, Adaptive histogram equalization - an inpainted image is converted to HSV and CLAHE algorithm is applied on the luminance channel to improve the contrast of the image. Then this image is converted back to RGB.

### c) Segmentation

Image segmentation can be simply seen as a process of dividing the Image into portions by allocating labels to the pixels. Thus, it can demarcate the specific area to be fed to the models during further processing.

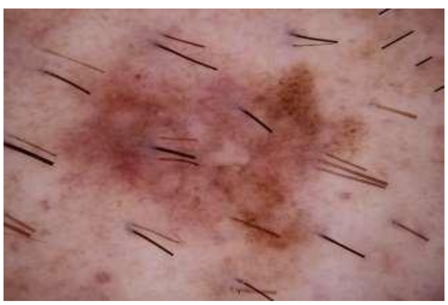

**Figure 1.** Original Image

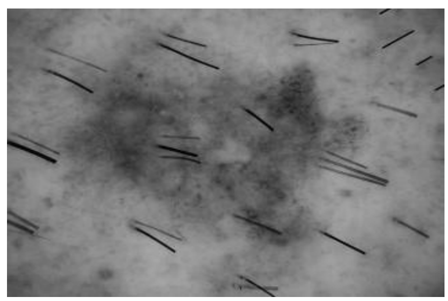

**Figure 2.** Gray Image

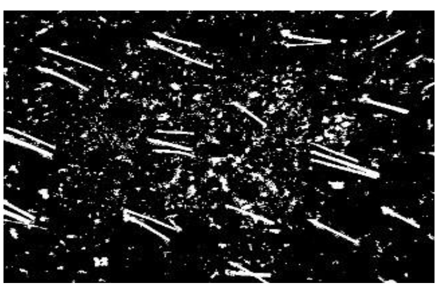

**Figure 3.** Blackhat filtered Image

**Figure 4**. Inpainted Image



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**Figure 5.** Image Segmentation

In the proposed method, we have chosen GrabCut Algorithm for Skin Lesion Segmentation. It involves following steps: A mask is created and a grabcut algorithm is applied on the enhanced image which generates a segmented image. It performs better than other segmentation methods like Magic Wand, Intelligent Scissors, Bayes Matte, Knockout 2, Graph cut and also generates better masks than Mask R-CNN and U-Net.

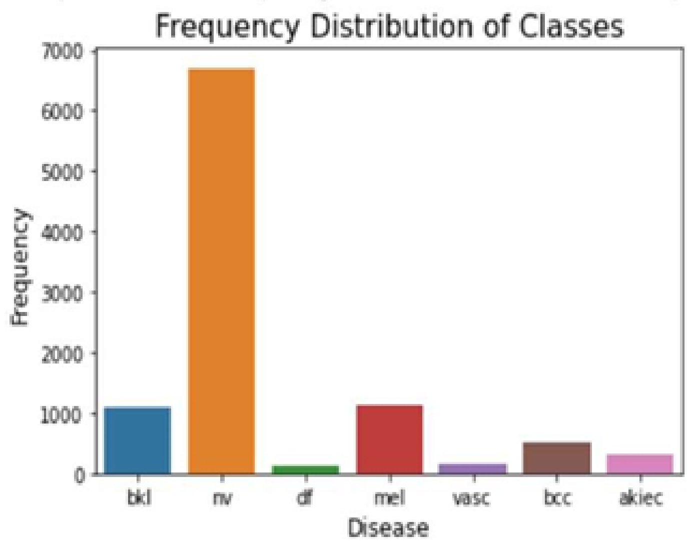


**Figure 6.** Frequency Distribution of Classes

As shown in the above graph, the melanocytic nevi is comparatively over- represented and this skewed representation may lead to inconsistency during classification. Thus in order to generate a high accuracy model with balanced detection rate, the dataset has been balanced.

**d) Image Augmentation**

Though in the above step the data set is balanced, to make the dataset even richer and ample image augmentation comprising of different processes is performed. All these processes differ in the parameter and degrees of change that they introduce to the image dataset. For instance, the horizontal flip, as the name suggests, flips the image horizontally and its counterpart - vertical flip, flips it vertically when the parameter argument is given as true. Other methods of Image Augmentation have been tabulated below.

**Table 1:** Image Augmentation



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| Image Augmentation | | Process |
|---|---|---|
| Horizontal Flip | True | Horizontal image flipping |
| Vertical Flip | True | Vertical image flipping |
| Shear Range | 10 | Images are distorted along an axis with an angle of 10 degrees |
| Zoom Range | 0.1 | Images from zoomed by 0.1 from center |
| Width Range Shift | 0.1 | Images are horizontally moved by a tenth of their original width |
| Height Range Shift | 0.1 | Images are moved vertically by a factor of one tenth of their original height |
| Rotation Range | 90 | Images are rotated by degrees, i.e from -90 to +90 90 |

**e) Classification**

The final model is the ensemble of three pre-trained models namely - ResNet152, InceptionV3 and Xception. A model which has been trained in prior on a dataset is referred to as a pre-trained model. Hence by nature it is aware of the weights and biases representing the features of the dataset. These three models are trained on ImageNet dataset -

**i) InceptionV3**

Inception v3 is a classical deep learning image recognition model, which has earned an accuracy greater than 78.1% on the standard dataset - ImageNet which it is trained in prior. It falls under the category of convolutional neural networks and is 48 layers deep. It built with both symmetric and asymmetric type of blocks, consisting of convolutions, max pooling, average pooling, dropouts, concatenations and fully connected layers. Batch normalization is extensively used in the model to apply to the activation inputs whereas Softmax is used to compute the losses. It is the optimized version of the inception V1 model, is deeper than the former and consists of techniques which help in finer model adaptation and thus produces greater efficiency. The presence of auxiliary classifiers which are used as regularizes, give it higher accuracy. Another differentiator from the former one is that the larger Convolutions in the model are factored into smaller Convolutions. This model has been trained for 15 epochs.

**ii) Xception**

The name itself suggests that it takes the principles of Inception to an extreme. It is similar to depth wise separable convolution as it initially applies the filters on each of the depth map and then compresses the input space using 1X1 convolution by applying it across the depth and thus it is works contrary to the Inception model. The absence of non-linearity is another variation. Here the separable convolution layers are treated as Inception modules and are placed all over the network. The Xception model has been trained for 12 epochs.

**iii) ResNet152**

Compared to the prior frameworks it has a very deep network of 152 layers. It learns the residual representation functions rather than the signal representation directly which is the reason for its depth. Another feature is that it also introduces a skip connection, otherwise known as a shortcut connection which forwards the input to the consequent layers without any moderation of the input. With the use of residual learning, it tackles the problem of decreased accuracy in deep networks, while simultaneously improving model training performance. The Resnet152 model has been trained for 25 epochs. ReduceLROnPlateau callback has been used for all the 3 models, when no further improvement was seen even after certain number of epochs. This reduces the learning rate which will help the model to perform better.

**iv) Ensemble**



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To bring together the best of all the models, ensemble methods are being performed by taking the above 3 models as base estimators.

In both the ensemble models, the stacking method is employed as it is suitable for classification type of models. It uses a meta-model to combine multiple classes and in this case, it acts as a meta-classifier. This Meta model is trained on the features or outputs produced by the 3 transfer learning models. Thus it enables the meta-classifier which is a second-level model to exploit the best from all the first- level models i.e., from the base estimators. In the first Stacking model, model averaging technique is used. It is called the Stacked Generalization approach in which the sub models or first-level models contribute equally in the building of the final classifier. In the second model i.e., in the Stacking model which uses Random forest as the meta-classifier, the sample is drawn with replacement. This results in variance reduction and thus generates a better model.

## 4. Results and discussion

The InceptionV3 model with a batch size of 64 and 15 epochs has resulted in an accuracy of 84.6% whereas Xception model has produced an accuracy of 86.5% when trained on a batch size of 64 for 12 epochs and Resnet152 model generated an accuracy of 86.7% which is a result of 25 epochs with batch size 64 when evaluated on validation dataset. The accuracy vs. epochs graph indicates that while training accuracy approaches 100%, validation accuracy begins to decline after a certain number of epochs, indicating that the model is over fitted, whereas the loss vs. epochs graph shows increase in validation loss. For the InceptionV3 model, the accuracy vs. epochs graph is shown below. Validation accuracy appears to be declining after 15 epochs. For the Xception model, the accuracy vs. epochs graph is shown below. Validation accuracy appears to be declining after 12 epochs. For the Xception model, the loss vs. epochs graph is shown below. Validation loss appears to be inclining after 12 epochs. For the InceptionV3 model, the loss vs. epochs graph is shown below. Validation loss appears to be inclining after 15 epochs. For the ResNet152 model, the accuracy vs. epochs graph is shown below. Validation accuracy appears to be declining after 25 epochs. The confusion matrix of the Stacking ensemble over the validation dataset is shown below. It has been seen that more than 85% of the images are accurately anticipated. For the ResNet152 model, the loss vs. epochs graph is shown below. Validation loss appears to be inclining after 25 epochs.

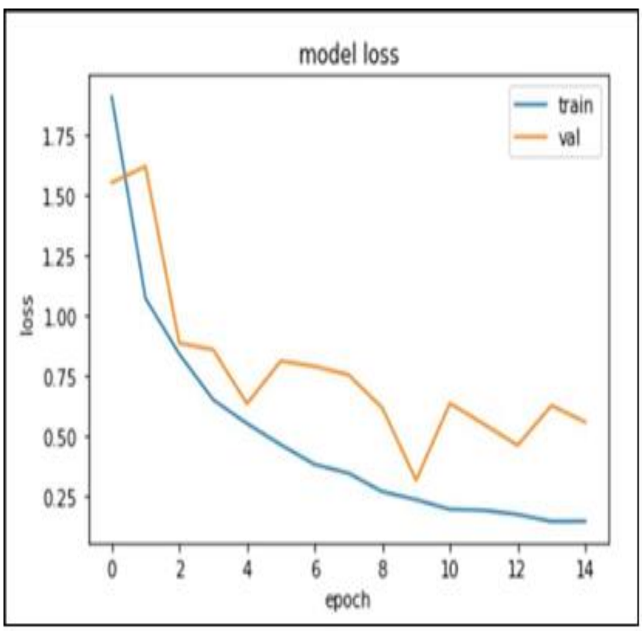


**Figure 8.** Loss vs epochs - InceptionV3

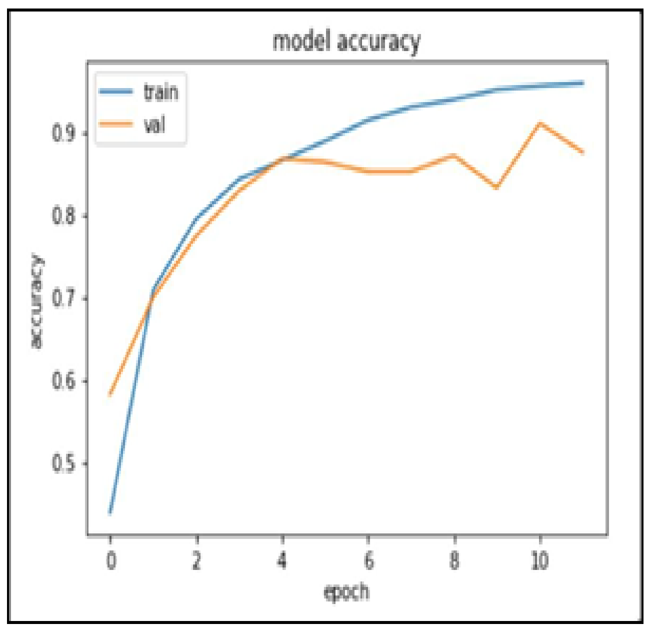


**Figure 9.** Accuracy vs epochs - Xception



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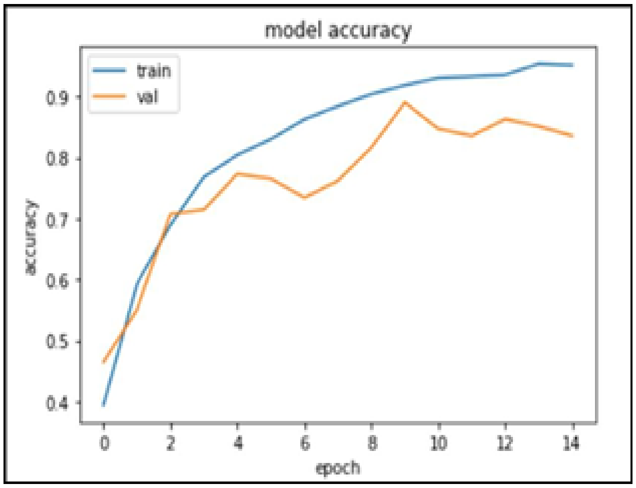


**Figure 10.** Accuracy vs epochs - InceptionV3

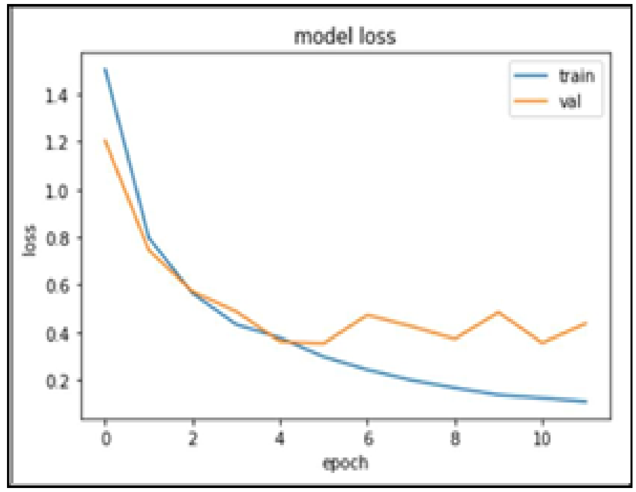


**Figure 11.** Loss vs epochs - Xception

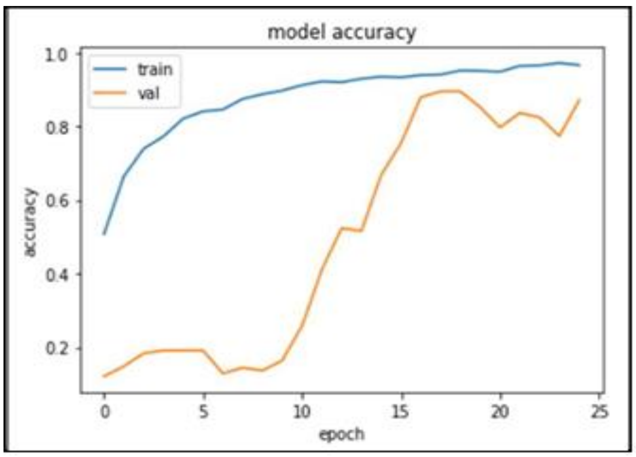


**Figure 12.** Accuracy vs epochs – Resnet152

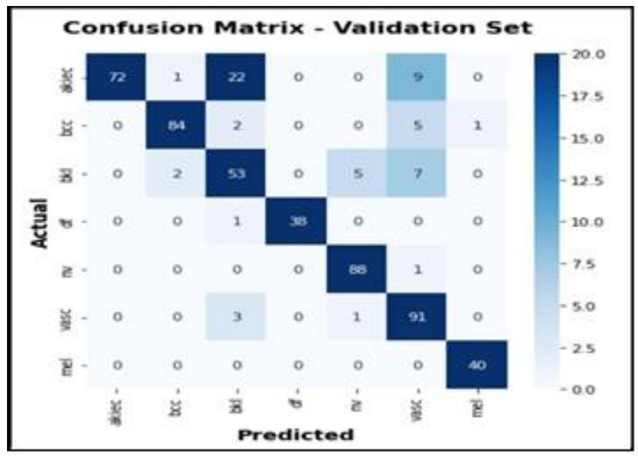


**Figure 13.** Confusion Matrix – Validation Dataset - Stacking

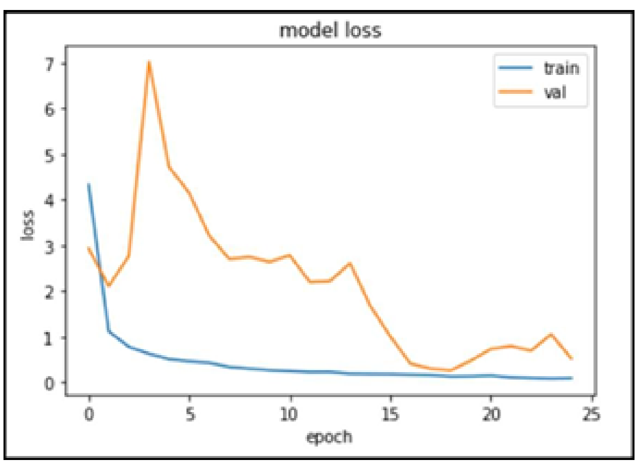


**Figure 12.** Loss vs epochs – Resnet152

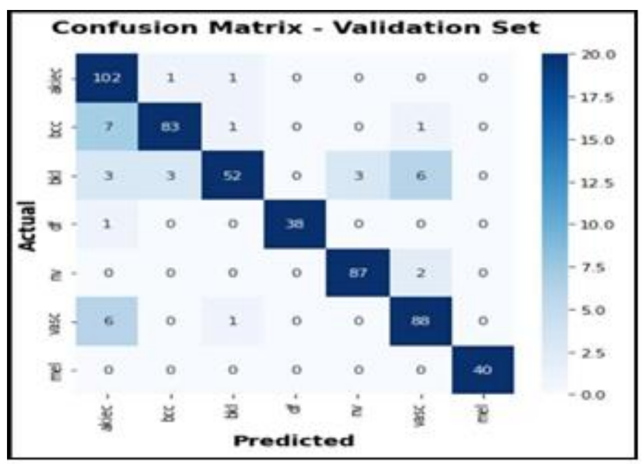


**Figure 13.** Confusion Matrix – Validation Dataset – Random Forest



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In the second ensemble technique, each model's predicted outputs are stacked on one another and a Meta classifier is applied which is Random Forest Classifier in this case. This model generated an accuracy of 90.58% on the test dataset and 92.59% on the validation dataset. The confusion matrix of the Random Forest ensemble over the validation dataset is shown below. It has been discovered that more than 90% of the images are accurately anticipated. Two ensemble techniques were performed on these three models. In the first ensemble technique, layers of each model are stacked on one another and finally a new Average layer which averages the final layer of each model i.e. a dense layer. This model generated an accuracy of 88.6% on the validation dataset and 88.75% on the test dataset. The confusion matrix of the Stacking ensemble over the test dataset is shown below. It has been discovered that more than 85% of the images are accurately anticipated. The confusion matrix of the Random Forest ensemble over the test dataset is shown below. It has been discovered that more than 90% of the images are accurately anticipated.

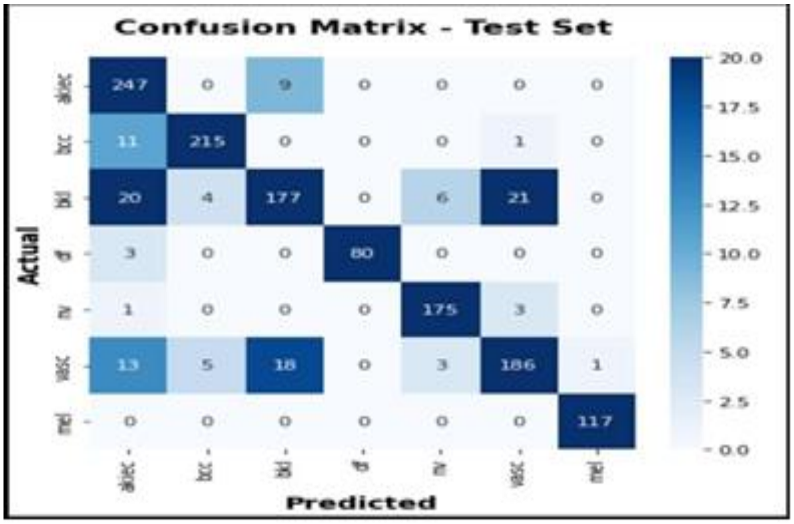


**Figure 14.** Confusion Matrix – Test Dataset – Stacking

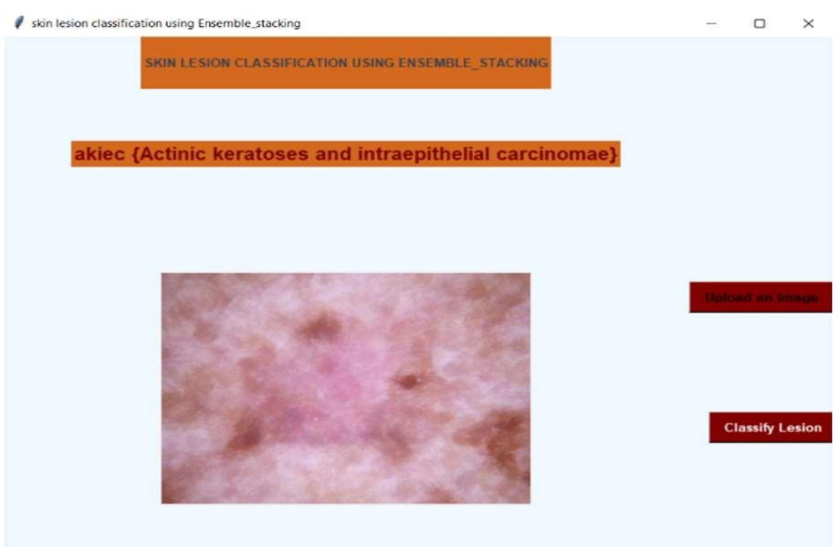


**Figure 15.** Stacking Prediction



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**Figure 16.** Random Forest Prediction

Enhancement, and lesion segmentation are performed to remove any artefacts such as hair and scars. While the first two techniques remove artefacts and enhance the image, the segmentation technique differentiates and extracts the foreground i.e., the lesion from the background image. For this extraction of region of interest, it uses k-means clustering. The resulting dataset is further balanced for better performance. This is achieved through Normalization and image augmentation. Below images are predictions of Stacking and Random Forest ensemble methods respectively.

## 5. Conclusion

HAM10000 Dataset has been used which is a collection of dermoscopic images of seven different classes of skin lesions. On this dataset, hair removal, contrast. Finally the aim of the training module is to efficiently classify the skin lesion into one of the seven types. This module is based on three deep learning models: InceptionV3, Xception, and ResNet152. All the three models generated an accuracy of around 84-85% on the test dataset. In an attempt to yield the best of them, ensembling is proposed which takes the outputs of the three models as input. The first ensemble model, which implements stacking and averaging, achieves an accuracy of 88.6 percent on the validation dataset and 88.75 percent on the test dataset. In the second model, which is also a stacking approach, the Random Forest Classifier is used as the meta- classifier. The accuracy of this model was 90.58 percent on the test dataset and 92.59 percent on the validation dataset. Many evaluation metrics were used to assess the performance of various deep learning models, and findings revealed that a combination of transfer learning and data augmentation techniques produced significant results. While Deep learning models can extract complex characteristics from dermoscopic images automatically, eliminating the need for manual feature extraction, ensemble methods help enhance model accuracy. In this case, Random Forest Classifier outperformed in terms of precision, recall, and accuracy. Finally, a web application is created to serve as a user interface for the model.

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