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Evaluation of deep learning models for melanoma image classification

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ABSTRACT

Melanin-producing cells are the origin of melanoma, the worst form of skin cancer (Melanocytes). If this cancer is not caught early, it might spread to other organs. With automated diagnostic technologies, clinicians and non-professionals may better diagnose diseases. Dermoscopic analysis, biopsy, and histological tests may be needed starting with a clinical assessment. Photo-based skin lesion categorization is challenging due to the fine-grained variability of skin lesions. We provide a more reliable melanoma detection model for each suspicious lesion in this paper. A set of characteristics characterizing a skin lesion's borders, texture, and coloursis used to educate convolutional neural networks. The deep learning models were generated using a standard dataset. To know the model's performance, consider the metrics like accuracy, sensitivity, specificity, Jaccard index and Dice coefficient. Transfer learning is used to categorize normal and diseased skin pictures automatically. This model-driven design helps doctors swiftly assess lesions.

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1. INTRODUCTION

Regarding surface area, the skin (which covers the whole body) is the body's biggest organ. Muscles, bones, ligaments, and internal organs are protected by upto seven layers of epithelial tissue in the skin. The skin protects the body, regulates temperature, and allows cold, heat, and touch sensations. A skin lesion develops when a portion of the skin exhibits abnormalities compared to other areas of the skin. Both primary (present at birth or developed over time) and secondary (caused by mishandling the original skin disease) skin lesions may cause skin cancer. Figures 1 and 2 are images of melanoma on the skin.

Over 4,000 Indian skin cancer sufferers die each year. Malignant skin tumours are cancerous because they form fast and spread to other body parts. A benign tumour, on the other hand, forms but does not spread [1]. Melanoma risk rises with UV exposure from the sun, tanning lights, and beds. Those under 40, particularly women, seem at a higher risk of melanoma [2]. Figure 3 displays melanoma statistics by gender. Developing a dependable automated melanoma identification system that improves pathologists' accuracy and efficiency is worth developing. Dermoscopy createsto enhance melanoma diagnosis. Dermoscopy is a non-invasive skin imaging technology that magnifies and illuminates skin regions to improve spot clarity. It removes surface reflection to enhance the skin lesion's visual impression. However, automated melanoma detection from dermoscopy pictures remains problematic [3].

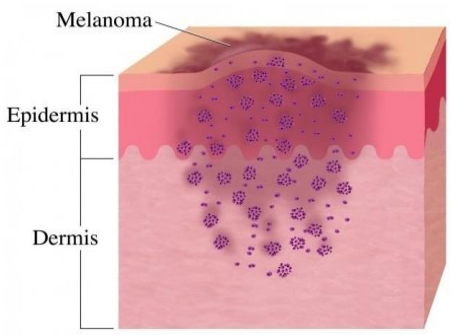


Figure 1. Image of melanoma

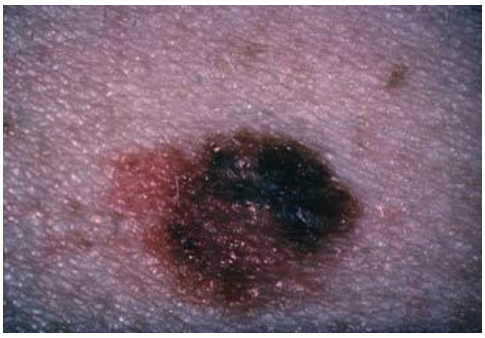


Figure 2. Image of melanoma on the skin

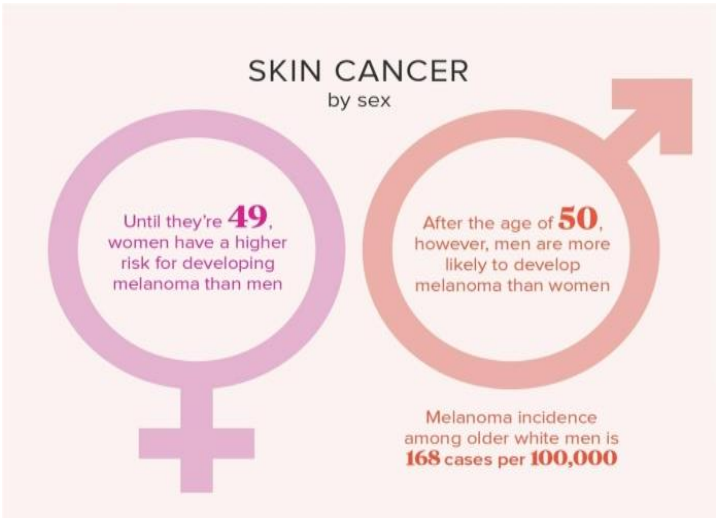


Figure 3. Statistics of melanoma in male and female

Before men reach the age of 49, women have a lower risk of developing melanoma than men. Before they reach the age of 49, women have a more significant chance of developing melanoma than any other cancer, as stated by the skin cancer foundation. According to the existing data, beyond the age of 50, the risk of developing melanoma is much higher for males than it is for women. Males are twice as likely as females to get melanoma after 60. On the other hand, the tendency began to shift significantly before the age of 60. The largest category of melanoma patients is older white males [4].

2. RELATED WORK

Subramanian *et al.* [5] presented a technique based on statistics of medical images employing Convolution neural networks to identify and categorize cancer classes. The model is used to diagnose skin cancer with an accuracy of better than 80%, keeping the false negativity rate in the prognosis to below 10%, achieving a higher than 80% precision, and performing data visualization are some of the goals of this Research. Computational results reveal that the suggested strategy outperforms the other methods under consideration. Mishra *et al.* [6] detected deep convolutional neural network (D-CNN) model and classified the skin cancer with 97.9% accuracy. Janoria *et al.* [7] used the visual geometry group (VGG16) model and found 99% accuracy for classification. Mustafa [8] employ image processing techniques to extract characteristics that allow machine learning algorithms to discriminate cancer from non-cancerous skin. This work proposes utilizing a sequential backward selection strategy to discover the most miniaturefeatures to achieve high accuracy in machine learning classification using the k-Nearest Neighbors algorithm.

Ashraf *et al.* [9] were reported to distinguish melanoma from nevus malignancy. An enhanced k-mean method extracts region of interests (ROIs) from images and identifies discriminative traits by training the algorithm with melanoma cells. ROI-based transfer learning beats whole-picture classification methods.

Subha *et al.* [10] research aims to identify skin cancer from rashes and help diagnose it in people. This model employs convolutional neural network (CNN) to locate and classify skin cancer and rash photos. Previous models used image classification to detect skin cancer types. After 20 iterations, the system accurately identified the image as having rashes or skin cancer, with an average accuracy of 80.2%.

Islam *et al.* [3] created a deep learning algorithm with photo preprocessing that classifies skin lesions better than existing methods. The proposed model exhibits 96.10% training accuracy and 90.93% testing accuracy. Layode *et al.* [11] present a combined classification and retrieval for skin by using decision support systems (DSS). Dermoscopic image characteristics must be descriptive and discriminative for good classification and retrieval outcomes. By supplying pertinent images of pigmented skin lesions from prior instances and classifying the images as different types of skin cancer, this system would respond to dermatologists' picture-based visual questions. Waheed *et al.* [12] objective are to provide an effective machine learning (ML) technique for melanoma detection using dermoscopic photos. It detects melanoma skin lesions using their distinguishing traits. Based on melanoma lesion shapes and degrees, picture data was retrieved for colour and texture features. The classifier detects melanoma from dermoscopic images using the obtained features. Extracted feature findings show the technique's reliability.

Demir *et al.* [13] classifiedthe dataset as benign or malignant to build an early skin cancer detection approach. They used InceptionV3 for classification and got 87.42%, and the ResNet-101 model got 84.09%. Jusman *et al.* [14] trained Multi-layer Perceptron, a proprietary CNN, and VGG-16 to classify skin cancer on HAM10000, a massive dataset. After that, each trained model's accuracy and computational time are compared and analyzed. VGG-16 and custom CNN models test faster than the Multi-layer Perceptron and have the highest classification accuracy. This data compares and analyses several neural networks for skin cancer classification. Hasan *et al.* [15] suggested using image processing and convolutional neural networks to diagnose skin cancer faster. The collection contains roughly 3,000 pictures of malignant and benign skin diseases. CNN and its seven designs were used to evaluate skin cancer photos, and a comparative study determined the best architecture for this issue. ResNet50, VGG16, InceptionV3, VGG19, Xception, MobileNetV2, and MobileNetmodels were tested to evaluate which worked best with our dataset. MobilenetV2 has the lowest model accuracy at 54.545%. Reddy *et al.* [16] haveworked on liver metastasis and hepatic disease [17] by using various DL models and classifying whether the patient suffered from the disease.

Rahi *et al.* [18] used multiple neural network methods to identify five major skin diseases and select the best accurate way. CNN's new model uses Keras sequential application programming interface (API) to achieve 80% accuracy. Later, they used designs that compared and improved accuracy with pre-trained data. Rokhana *et al.* [19] built a deep convolutional neural network to sort melanoma pictures into benign and malignant categories (CNN). They suggested network architecture, including a dropout and fullyconnected layer after several convolutional and max-pooling layers. Sriwong *et al.* [20] constructed a CNN model for autonomous skin disease identification. According to experimental findings using a public dataset, the CNN model with 79.29%, while adding patient history information in the modelling phase may increase accuracy to 80.39%. Nasr-Esfahani *et al.* [21] suggested a graphics processing unit (GPU)-based deep learning system indicated for melanoma lesion detection.

They recommended a method that uses clinical (non-dermoscopic) photographs. The proposed method preprocesses them to eliminate illumination and noise artefacts from clinical images. Shankar *et al.* [22] have done their work on gestational diabetes. Attia *et al.* [23] employed hybrid convolutional-recurrent neural networks and proposed a technique to test on 375 photographs after training on 900 images. The ISBI 2016 conference's "skin lesion analysis toward melanoma detection" competition contributed to the pictures. 0.93 Jaccard index and 0.98 average segmentation accuracy. Moldovan [24] identified skin cancer photos in two phases using transfer learning and deep learning. Masood *et al.* [25] provide a semi-advised training and classification technique that successfully employs limited labelled and massive unlabeled data. It acquires many unlabeled data to train an algorithm using a guided and partially supervised approach. Skin cancer histology and dermatological pictures compared. Reddy *et al.* [26] did their work on foot ulcers using the image dataset with different deep learning models [27].

A technique for classifying skin lesions extremely well is provided by Kassem *et al.* [28]. The suggested model's ability to classify skin lesions was tested using international skin imaging collaboration (ISIC) in 2019, the latest public challenge dataset. They achieved 94.92%, 79.8%, 97%, and 80.36% for the models' accuracy, sensitivity, specificity, and precision percentages. The model can identify unknown pictures that don't fall into the eight categories. Swetter *et al.* [29] developed a method that employs asymmetry, border, color, diameter and evolving (ABCD), gray level co-occurrence matrix (GLCM), histogram of gradient (HOG) feature extraction to diagnose skin lesions early. Geodesic active contour (GAC) segmentation separated lesion portions for feature extraction. Support vector machine (SVM), k-nearest neighbor (KNN), and Naive Bayes classifiers use recovered attributes to classify skin lesions as benign or malignant. SVM classifiers ranked 97.8% with 0.94 area under the curve.

Pham *et al.* [30] proposedan EfficientNetB4-CLF model and got the highest accuracy of 89.97%, the highest mean recall of 86.13%, and the lowest standard deviation of 7.60%. Daghrir *et al.* [31] presented a hybrid screening method for suspicious lesions. These systems' results are merged using a majority vote to increase performance. Integrating the three approaches yields the most accuracy, according to experiments.

Munia *et al.* [32] used digital camera pictures to construct an autonomous melanoma diagnosis system. Nonlinear properties, colour, and texture parameters were also analyzed and obtained from the lesion mole. With 89.7% accuracy, the model predicted the diagnosis of a mole. Ibraheem *et al.* [33] proposed using pixel-based characteristics to identify benign keratosis (BKL) from malignant melanoma (MEL). Experimental dice measures 98.5%, sensitivity 98.3%, and specificity 92.1%. Aggarwal *et al.* [34] employ the attention mechanism to concentrate on relevant picture areas to improve D-CNN performance. They proposed an attention-guided D-CNN for skin cancer classification. According to the classification results, an attention-based model boosts a regular D-CNN architecture's accuracy by roughly 12%. This work improves D-CNN performance and identifies skin cancer early, significantly contributing to biomedical image processing. Wang *et al.* [35] used ML methods to automate melanoma detectionusing polarisation speckle imaging based on depolarization rate. The SVM has the highest classification accuracy of 86.31% and the most incredible sensitivity and specificity. All techniques showed that the blue light source depolarized faster than the red-light source.

3. METHOD

Melanoma, a kind of skin cancer, is rarer than basal cell and squamous carcinoma but more hazardous since it may spread. Hence, if it is found early on, we can cure it quickly; otherwise, it is deadly. The significant steps involved in this section for melanoma classification are Dataset, Data Collection, Dataset Description, Models used, and Image classification.

3.1. Dataset

The source data is from the Human against machine with 10,000 training images dataset (HAM10k). The HAM10k dataset's dermoscopic pictures have been selected and adjusted for brightness, colours, resolution, and other characteristics. More than half of the cases had histopathology confirmation, twice as many as the previously published skin lesion datasets. The rest of the lesions were diagnosed by dermatologists in agreement. Let's limit the challenge to the diagnosis of melanoma vs not melanoma rather than trying to categorize seven skin lesions with a severely skewed dataset. The dataset remains unbalanced even if we divide the categories, as mentioned earlier, into two groups. There are 1,113 melanoma photos and 8,902 non-melanoma photographs.

3.2. Dataset description

The considered dataset consists of 7,396 images, of which 6,277 images are used for training our model, and the rest are used for testing. The data belongs to two classes, and the classes are melanoma and not melanoma. Some dermoscopy images from the HAM10k collection have been enhanced in terms of contrast, saturation, and sharpness.

3.3. Models used

The literature review observed that many researchers have worked in various domains using multiple mining techniques, ML models and deep learning (DL) techniques. Here, we use the DL models like CNN, Inception V3, Xception, VGG16, ResNet50 and compare them with various evalution metrics.

3.3.1. Convolutional neural networks

The essential component of CNN is the convolution layer, which bears the brunt of the computational work. The provided input has shape (224,224,3) when given to the first CONV2D layer. It performs dot product between the kernel, which is of size (3,3) and window matrix, which is a portion of the given image with preset size and sliding here the stride is one, and here we employed relu activation function. Further, the addition of the batch normalization function adds extra layers to the neural network to make it fast and more stable. Because the three in the input shape indicate, three channels (RGB), the kernel and receptive field will be extended to three tracks. The kernel iterates over input photos to generate smaller images that translate input images to the kernel. Here 896 parameters are being trained in this layer. The dropout prevents overfitting the training data; the dropout rate is 0.1. The entire flow is shown in Figure 4.

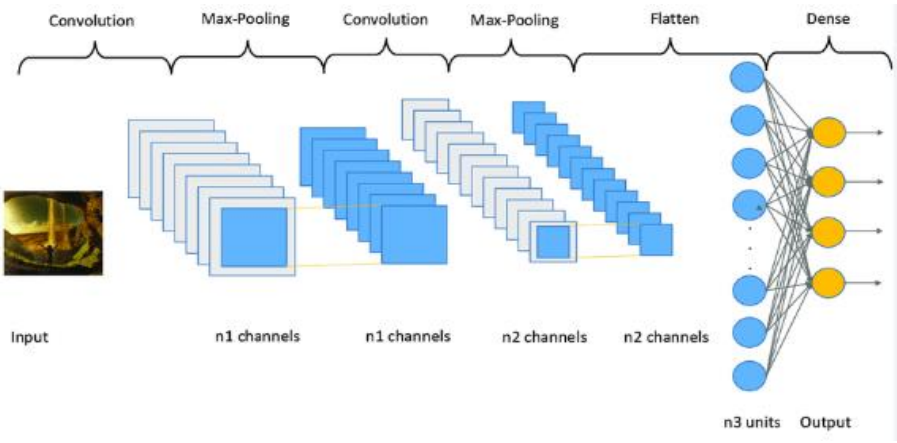


Figure 4. CNN architecture

3.3.2. Inception V3

The architecture was initially known as GoogLeNet, but later iterations have been referred to as Inception vN, where N corresponds to the Google version number, as shown in Figure 5. In the functional inceptionv3 layer, the input shape is (224,224,3), average pooling used, weights taken from imagenet, and a dropout rate of 0.5 used. The softmax activation function is used in the dense layer and some layers are frozen to stop weights from being trained.

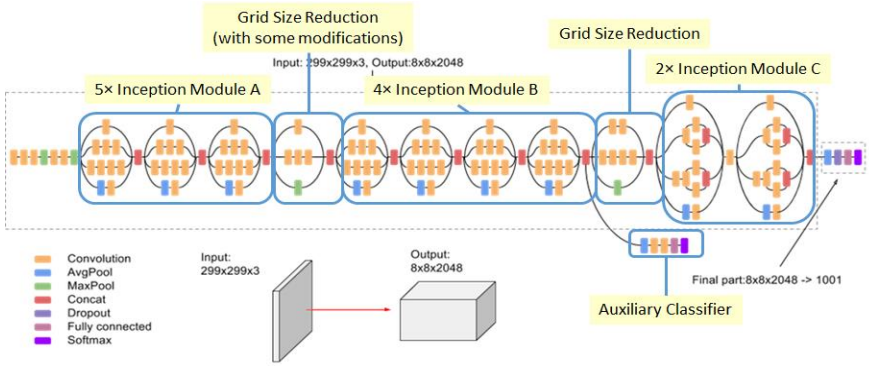


Figure 5. InceptionV3 architecture

3.3.3. Xception

Xception is an Inception architectural enhancement that uses depth-wise separable convolutions to replace the basic Inception modules, as shown in Figure 6. At under 91MB, Xception enables the least weight serialization. The functional Xception layer flattens the input provided and converts it into a single continuous one-dimensional vector of size 2,048. Then this output is passed to the dropout to deal with overfitting,then passed to the dense layer with softmax activation function to classify the images.

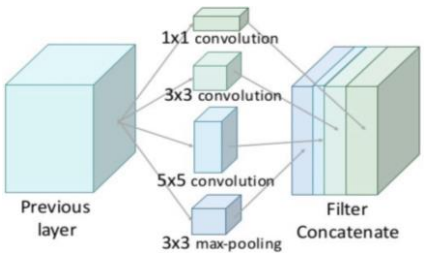


Figure 6. Xception architecture

3.3.4. VGG16

In the first two 2D convolutional layers, the image shape is converted to (224,224,64) with 1792 and 36928 parameters to train. After the max pooling, the shape is reduced to (112,112,64). In the fatten layer, the input from previous layers is converted to a single one-dimensional vector of size 25088. The architecture is shown in Figure 7.

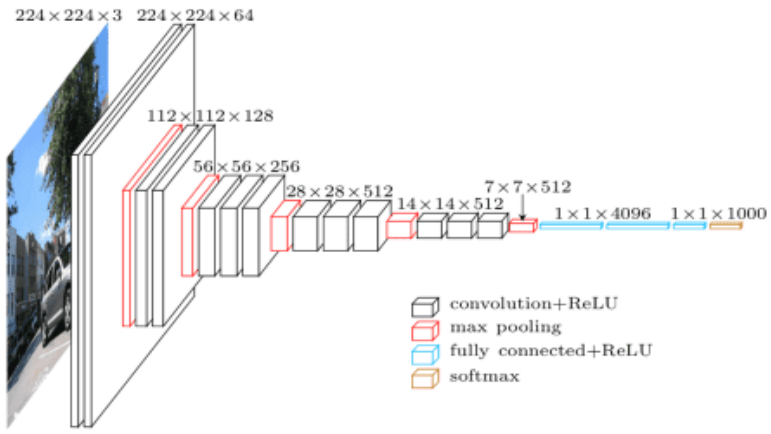


Figure 7. VGG16 architecture

3.3.5. RESNET50

Zero padding is applied to the input layer, adding rows and columns of zeros at an image tensor's top, bottom, left and right side. After using max pooling, the shape reduces to (56,56,64). Batch normalization is applied, and in the next convolution layer, the nonlinear activation function (relu) used, which is advantageous to other activation functions as it does not activate all the neurons simultaneously. architecture is shown in Figure 8.

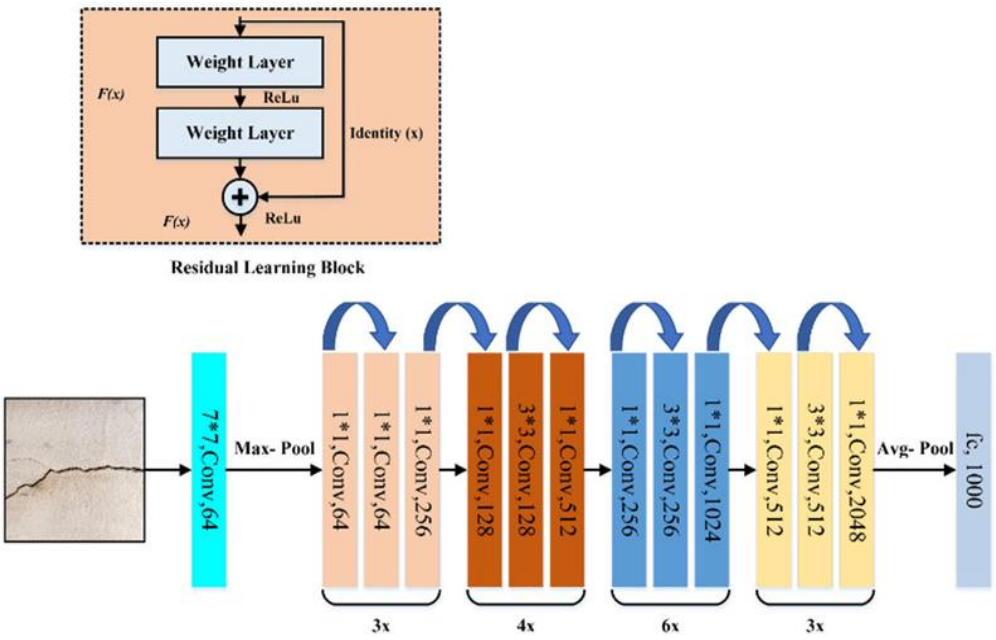


Figure 8. RESNET50 architecture

3.4. Image classification

After selecting the images from the dataset, we have to apply the models to get exact classification of the image. So, here we select the suitable model from the models mentioned above and feed the model with the test data to get the target class to which the lesion belongs, either melanoma or not melanoma. After that evaluation metric were evaluated.

4. RESULTS AND DISCUSSION

In this section, we can analyze the performances of the various models with various evaluation metrics. The metrics aregiven detailed in Table 1. Let K_{tp}, K_{tn}, K_{fp} and K_{fn}be the number of true positive, true negative, false positive and false negative, respectively. Using Table 1, evaluated each model individually was given in detail in Table 2. Using Table 2, we analyzed that ResNet has achieved more accuracy than other models. To build the CNN model, we used five convolutional layers and a batch normalization technique, and we employed max pooling for pooling. The softmax activation function is usedto compile the model with 12 epochs and considered 100 steps per each epoch. Early stopping is monitored based on validation loss. The accuracy obtained through this model is 90.08%.

Table 1. Performance of various evaluation metrics

S. No	Metrics	Equation
1	Accuracy (AC)	$\frac{K_{tp}+K_{tn}}{K_{tp}+K_{fp}+K_{tn}+K_{fn}}$
2	Sensitivity (SY)	$\frac{K_{tp}}{K_{tp}+K_{fn}}$
3	Specificity (SF)	$\frac{K_{tn}}{K_{fp}+K_{tn}}$
4	Jaccard index (JI)	$\frac{K_{tp}}{K_{tp}+K_{fp}+K_{fn}}$
5	Dice coefficient (DI)	$\frac{2*K_{tp}}{2*K_{tp}+K_{fp}+K_{fn}}$

Table 2. Evaluation of various metrics using various models

S.No.	Model	AC(%)	SY	SF	JI	DI
1	CNN	90.08	80.6	92.3	71.6	79.3
2	Inception v3	84.06	82.3	93.7	75.1	78.5
3	Xception	87.02	84.1	95.4	79.9	81.4
4	VGG16	85.08	83.6	96.6	83.7	82.1
5	ResNet	92.07	85.5	97.4	84.4	83.9

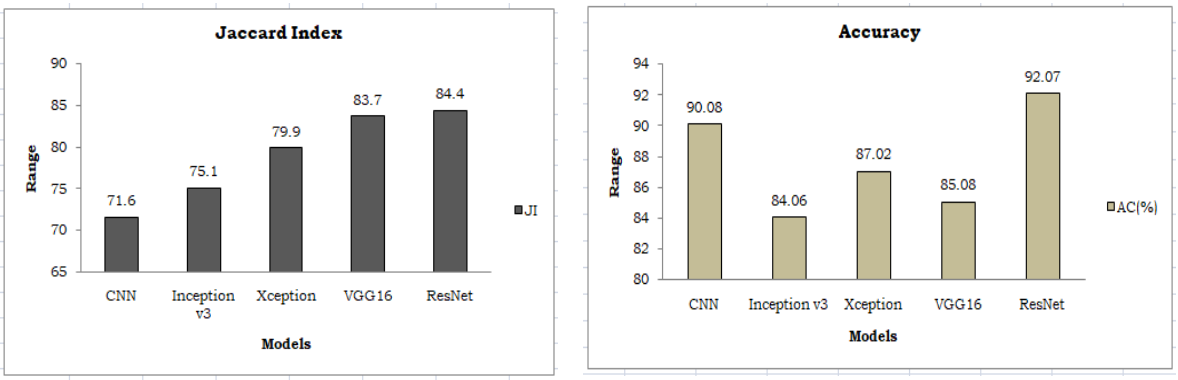
In the Inception V3 model, we have used average pooling and softmax activation functions. For the compilation, adam optimizer is used along with binary cross entropy as a loss function and considering accuracy as a metric. We have taken 20 as batch size, and the number of epochs is 35. This model trains 262,530 parameters. The accuracy obtained in this model is 84.06%.

In the Xception model, we used the Adam optimizer and binary cross entropy loss function with 30 epochs with a batch size of 32 and 100 steps per epoch. The accuracy obtained from this Xception model is 87.02%.In VGG16 model compilation, categorical cross entropy is used alongside the Adam optimizer.A number of epochs is 25, and the number of steps per epoch is 25. Here 50,178 parameters are trained. The accuracy obtained in this model is 85.08%. In the ResNet50 model, 30 epochs are used, and the batch size is 32, with 100 steps per epoch.Here 200,706 parameters are trained.The accuracy is 92.07 %.

From Table 2, Figure 9 was represented with graphs, like Figure 9(a) represents the JI metric with various models and Figure 9(b) was shown the accuracy as we discussed. Figure 10 shows various metrics like sensitivity (SY), specificity (SF), and dice coefficient (DI). Finally, the classification of the target class is shown in Figure 11 and Figure 12. Figure 11 was shown the image of melanoma, and Figure 12 was shown the image of not Melonama.

According to [1], they employed primary ML to determine whether or not a patient had melanoma. In [2], they applied the CNN model to various datasets. In [5], the CNN model achieved more than 80 % accuracy, while assessment metrics [6] such as VGG16, VGG19, ResNet 50, ResNet 101, and Inception V3 achieved lower values. They obtained 99% accuracy using the VGG16 CNN Model combined with the K-NN model [7]. Like [11], they employed DL models on HAM 1,000 dataset and got 96.10% in training and 90.03% in testing. All the DL models [6] were also utilized by Reddy *et al.* [16], along with MobileNetV2

and Xception as additional models. Among those, Xception received 85.303 % accuracy. Also, in [20], they employed D-CNN for image categorization and achieved an 84.76% success rate. CNN with GPU analyzed clinical images in [22]. In [31], the authors employed D-CNN on an imbalanced dataset and obtained 89.97% while customizing the loss function. In [34], they hired a non-invasive automatic skin cancer screening technique for seborrheic keratosis. In this case, they used gradient-boosted decision trees (GBT) and achieved 97.5% accuracy. The proposed model has the highest performance levels, with 92.07%, according to the results compared to the existing models.



(a) (b)

Figure 9. Representation of graphs (a) graph for Jaccard index (b) graph for accuracy

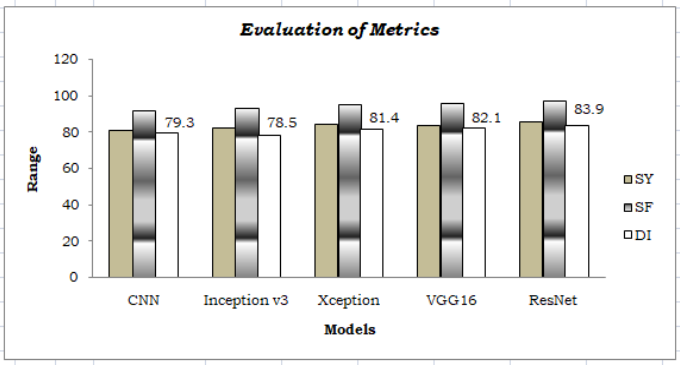


Figure 10. Representation of graph on various metrics

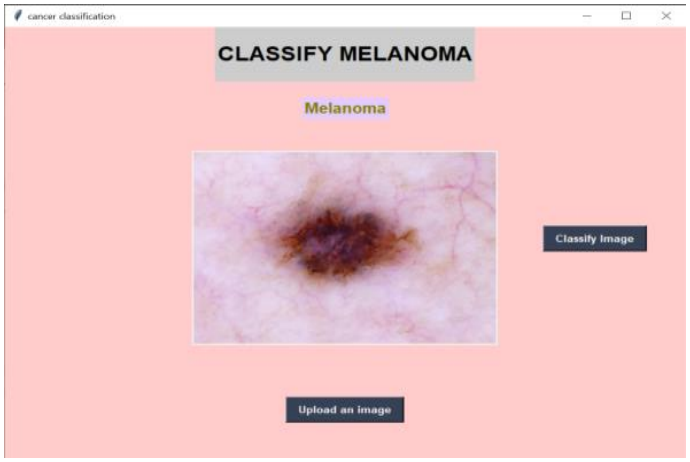


Figure 11. Final classification of images as melanoma

Figure 12. Final classification of images as not melanoma

5. CONCLUSION

Images are used to detect melanoma. We employed CNN and transfer learning to automate the system for increased efficiency. The trained models have performed well, with each model's final accuracy over 90.08%, whereas the ResNet was given the 92.07% in accuracy. As a result, we may be confident that a new image supplied as input is of genuine value. We may go even further by segmenting the skin cancer region, which highlights the cancerous area of the picture. This technology might be a ready-to-use melanoma detector for radiologists and clinical professionals, saving them time and increasing their productivity. We can also integrate our idea with hospitals whereskin cancer will be diagnosed in future images.

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