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Detection and Prediction of Skin Cancer based on Machine Learning

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ABSTRACT

Statistical evidence suggests that skin related deaths were most in number compared to those resulting from other types of skin cancer. However, detection of skin cancer in its early stages is extremely challenging to doctors since as they say cancer is skin-deep. Wrong diagnosis of the disease due to inaccurate methods has prompted study in this field for a while since malignant melanoma implies asymmetrical and irregular borders, notched edges and color variations. Hence, it is extremely vital to analyse each characteristic of the lesion like shape, colour and texture early detection and prevention. In this study, effective detection of skin cancer detection is proposed. Four features are chosen that are trained and tested by using various classification techniques like K-Nearest Neighbor, Decision Tree, Naive Bayes, Random Forest, and XGBoost have been done. The methodology actually has a good result for the various classifiers but still can be improved. The result discusses that XGBoost is a better classifier than K-Nearest Neighbor, Decision Tree, Naive Bayes, Random Forest has the highest accuracy of 68.75%. The results achieved are relatively good when compared. The future work will focus on improving the number of features selected and then classified to improve the accuracy.

1. INTRODUCTION

Skin cancer has emerged as one of the most common types of cancer, rising exponentially worldwide due to malignant tumors [1]. Of the many types of skin cancer, Melanoma is on the rise at a very fast pace, especially in those countries where there is high rate of ozone depletion. Statistical results reveal that the incidence of melanoma cancer has been increasing from 3% to 7% in one year [1]. A recent survey stated that at present there are approximately2 to 3 million non–melanoma skin cancers, and 132,000 melanoma skin cancers diagnosed globally every year. It has also been found that one in every three diagnosed cancers is skin cancer. Interesting research and survey by the Skin Cancer Foundation revealed that one in every five Americans used to suffer from skin cancer during his/her life span. As advanced cutaneous melanoma could not be cured and no any significant diagnosis approach could be achieved till now, early detection through certain approaches, such as precise skin screening and classification, can be of great significance to reduce mortality rate. The task of identifying and classifying early melanoma from other pigmented skin lesions is not a minor one, and is still a complicated procedure for even the most experienced dermatologists. The idea of early detection of melanoma through has automated system has motivated researchers to develop an optimal Computer-Aided Diagnosis System [2].

In the present-day scenario, a majority of dermatologists predominantly depend on their visual perception and analysis-based assessment to distinguish a malign skin lesion from abenign lesion. However, there may be instances when accurate cancer classification can become complicated. For instance, a person who has Cutaneous T-Cell Lymphoma (CTCL), a type of blood cancer, exhibits similar symptoms as that characterized by skin cancer. Moreover, it is extremely vital to arrive at a decision when it comes to melanoma diagnosis in order to initiate a successful life-saving treatment [3].

In traditional approaches, even an experienced dermatologist depends on pattern extraction, which is then followed by laboratory tests. Generally, physicians follow the "ABCD" criteria - Asymmetry, Border irregularity, Color variation, and Diameter - in their assessment [4][5][6][7]. However, particular aspects of the skin (the morphology) cannot be evaluated effectively with the naked eye as the skin is composed of many superimposed layers with different characteristics, properties, and functions; they can be clearly delineated by imaging methods. Advancement in digital dermoscopy technologies and imaging systems has significantly contributed toward efficient and early prediction and analysis, for better diagnosis facilities.

Various new technologies have been developed for swift skin lesion identification and diagnosis, with hand-held magnification approaches and computer-aided imaging systems to name a few. Approaches such as colored imaging techniques have been proposed for melanoma detection [8]. They primarily emphasize non-constant visual information of the skin lesions. Some approaches based on artificial neural networks have also been proposed to classify and extract features of the lesion from dermoscopy images [9]. Many other attempts have been made to automate the detection and classification of melanoma from digital color and surface reflectance images [10]. Those attempts involve initial skin segmentation from its neighboring skin followed by the calculation of classification features. However accurate feature extraction cannot be accomplished without a robust segmentation approach. Therefore, a number of algorithms have been developed for color image segmentation, majorly classified as, pixel-based segmentation, region-based segmentation and edge detection. However, in the case of optical spectral reflectance images, research is still limited due to the recent introduction of imaging technology in dermatology.

Dermoscopy consists of a visual examination of the skin lesion that is optically enlarged and illuminated by halogen light. This is a non–invasive approach called in-vivo that plays a significant role in early melanoma detection. This technique permits the revelation of morphologic features, and in such scenarios enables early prediction and diagnosis. While measurement of these morphologic characteristics is highly recommendable and significant, in practice, it is an extremely complex task [10]. The Second Consensus Meeting on Dermoscopy, organized in 2000, concluded with an agreement to employ four algorithms for the purpose of skin lesion evaluation, vis a pattern analysis, ABCD rule, Menzies method, and the 7–point checklist. Interestingly all these four techniques are similar in function and enable the selection of specific characteristics. The ABCD rule takes into consideration a number of visual features that make up malignant lesions; these are then used to measure a score (the Total Dermoscopic Value or TDV). This approach facilitated clinicians with a significant analytical model but still could not justify its robustness for Clinically Doubtful Lesions (CDL). The predominant reason for this is the complexity involved in the characterization of the features of the lesion area. Providing an efficient decision threshold to the score is also found to be highly intricate. A number of researchers have stated that such thresholds might result in an elevated rate of false detection and diagnosis. Therefore, a computer-aided diagnosis (CAD) system using Histopathological or dermoscopic images can be an enormously significant approach to estimating and detecting sets of characteristics from which dermatologists can arrive at a diagnosis. In addition, it can be of immense significance for primary screening campaigns, elevating the probability of an earlier diagnosis of melanoma.

Skin cancer is an alerting issue and it must be detected as early as possible. The diagnostic is a manual process that is time-consuming as well as expensive. But today's world science has become advanced by using machine learning and it can be helpful in many ways. Hence, machine learning can make it easy for detecting cancerous cells and that is why machine learning especially machine learning techniques is used to detect cancerous cells more quickly, and efficiently.

The main contribution of this paper is

- The main aim of this research is to design a machine learning model for the analysis and detection and prediction of skin cancer.
- To classify skin cancer images using machine learning classifiers with the proposed feature set.
- To proposed a classification algorithm for increasing accuracy and prediction rate.

2. Related Work

S. Sasikala et. al. (2020) proposed Convolutional Neural Network (CNN) algorithm with four different transfer learning techniques are used to classify the images of the skin with dermoscopic analysis which enables fast detection. A CNN model is trained using a dataset of 3700 clinical images and its performance is tested over 660 images which represent the identification of deadliest skin cancer. A considerable improvement in accuracy of skin cancer detection using deep learning architecture ResNet34 provides a reliable approach for early detection and treatment.
M, Vijayalakshmi. (2019) collected 813 images from five different skin diseases namely eczema, psoriasis, impetigo, melanoma, and scleroderma, with the aim of diagnosing it based on the color feature. Images were pre-processed using median filtering, image sharpening, and binary masking methods and then Red, Green, and Blue (RGB) color means were extracted from each image. Later, these color values were analyzed by Artificial Neural Network (ANN) classifier, and 90% classification accuracy was obtained [6].

Omara, (2020), examined herpes, paedures dermatitis, and psoriasis diseases using 10 standard samples and 20 test samples [7]. Gray Level Co-occurrence Matrix (GLCM) texture features were extracted after selecting the region of interest using median filtering and marker-controlled watershed algorithm along with clustering. The four GLCM features were tested using Support Vector Machine (SVM) classification and achieved 85%, 90%, and 95% accuracy respectively for the studied diseases.

Convolutional Neural Network (CNN) algorithm was tested to classify five diverse diseases [8]. The images gathered from online sources, and the Dermnet dataset were rotated in all directions to increase the sample number. The softmax model was used in CNN. The border, edge, and color features were extracted from each image. The features-based classification system gave 70% classification accuracy.

Healthy and diseased skin regions were classified using eczema, impetigo, and psoriasis images by M. Vidya et al., (2020), (54). These disease images were acquired from the Dermnet skin disease atlas database. Initially, images were processed and regions of interest were selected using contrast enhancement, median filtering, and maximum entropy thresholding algorithms. GLCM texture features were extracted and examined in ANN's feedforward method. The overall accuracy rate of this system was 80% with 71.4% sensitivity and 87.5% specificity [9].

An ANN trained with the Non-dominated Sorting Genetic Algorithm – II (NSGA – II) model was tested with the International Skin Imaging Collaboration dataset (ISIC) images [10]. Angioma, basal cell carcinoma, and lentigo simplex diseases were used in this study. The GLCM feature set was created using the Daubechies DB4 filter and then applying Principle Component Analysis (PCA) to it. From that, GLCM image features like mean, standard deviation (SD), entropy, root mean square (RMS), variance, kurtosis, skewness, contrast, correlation, and homogeneity, were extracted. These features were tested in three different models of Neural Network (NN), i.e., ANN trained with Particle Swarm Optimization, ANN trained with Genetic algorithm, ANN trained with NSGA – II. The study concluded with an accuracy rate of 87.92% using ANN-NSGA II.

Hasan, et al., (2020), conducted a study to investigate the performance of a CNN tool for skin disease classification versus skin lesion characterization. In total, 75,665 images were collected from six online databases, i.e., AtlasDerm, Danderm, Derma, Dermanet, and DermQuest. These images were used to train a multi-class CNN for disease targeted and another multi-class CNN for lesion targeted classifications. The results showed 27.6% of top-1, and 57.9% of top-5 accuracy values, with an average precision rate of 0.42 using fine-tuning learning type [11].

Six diverse skin diseases namely chronic dermatitis, lichen planus, pityriasis rosea, pityriasis rubra pilaris, plaque psoriasis, and seborrheic dermatitis were classified based on Sobel edge detection, color homogeneity, and Hue, Saturation, and Value (HSV) color model features [12]. The digital camera and histopathological images were collected from the Department of Dermatology, M. S. Ramaiah College, Mysore, and the learning data repository of the University of California. Before extracting the features, images were converted to grayscale, and the diseased region was segmented using Otsu gradient vector flow, and color-based segmentation methods. After feature extraction, they were analyzed by ANN, K-Nearest Neighbor (KNN), and decision tree algorithms. The study concluded with 95% accuracy.
The Adaboost classification algorithm was used in a study to classify dermatophytosis, melanoma, and psoriasis diseases [13]. A total of 130 images were collected from standard databases and used in this study. The luminance, texture, and entropy features were used by the classifier, and 90% accuracy was achieved.

A tool was developed to detect the different skin conditions using the KNN classification algorithm by Dr. M. Vimaladevi et al. [14]. Bloody skin, burn skin, skin cancer, allergic skin, and normal skin conditions were examined in this study. Images were enhanced using histogram equalization and then useful features were extracted by HSV color histogram and Speeded-Up Robust Features (SURF) blob detection methods. Finally, these feature values were analyzed in the KNN classifier and good diagnostic performance was observed (59).

Sumithra et al., (2015), gathered 141 lesions from five diverse skin diseases namely bullae (n=26), melanoma (n=32), seborrheic keratosis (n=33), shigles (n=20), and squamous cells (n=30) to develop a computer-aided diagnosis tool (60). The internet was the source of these images. After pixel-based segmentation, each lesion was considered as a separate sample and the total number of samples was increased to 726. Once the diseased area was segmented different color models like RGB, HSV, NTSc, Luma component, Blue-difference, and Red-difference (YCbCr), and Commission Internationale de LeClaire's (CIE) L*u*v, and L*a*b were applied and its mean, standard deviation, variance, and skewness were noted. KNN and SVM classifiers were examined with these features in the 70:30 classification rule.

The system's classification accuracy was 61% [15]. Eczema, impetigo, and melanoma disease images were used by Shi Wang et al., (2021), to build a skin disease classification system. Images were segmented using thresholding and morphological transformations, following which, color and shape features were extracted. AdaBoost, BayesNet, Multi-Layer Perceptron (MLP), and Naïve Bayes classification methods were implemented to classify the above-mentioned diseases. The disease identification rates were 85% for eczema, 95% for impetigo, and 85% for melanoma using MLP method [16].

Since skin cancer has a specific rule for diagnosis, it is easy to incorporate into a machine. With this hypothesis, a skin cancer detection device was developed based on geometry features like area, perimeter, greatest diameter, and circularity and irregularity indexes [17]. They used mobile camera images of melanoma, other skin cancer, and normal skin. Good accuracy was achieved using the ABCD classification rule.

Instead of distinguishing psoriasis from other diseases a study differentiated three types of psoriasis, i.e., plaque, guttate, and erythrodermic psoriasis [18]. Around 30 images were acquired by a digital camera in a low flash with the size 1280×960 pixels. Before performing Daubechies wavelet transformation, only the diseased area was cropped with a window size of 64×64 pixels. Based on these feature values error plots was drawn with a 95% confidence rate.

Six diverse skin diseases were analyzed with an accuracy of 94% [19]. This study acquired acne (n=107), eczema (n=102), psoriasis (n=105), tinea corporis (n=105), scabies (n=182), and vitiligo (n=101) images using Panasonic LumixFZ-35 camera, and natural lighting condition. Lesions were cropped and segmented by morphological processing and thresholding methods. After lesion segmentation, GLCM features were extracted and fed to the ANN classifier to make a decision. The overall classification accuracy observed in this procedure was 94%.

Alenezi, et al., (2019), segmented diseased lesions from the normal skin. A total of 45 plaque psoriasis images were captured in a 16-mega pixel camera and cropped manually before the segmentation process. CIE's L*a*b color space was used with K-means clustering for ROI segmentation. Post-processing was done using erosion followed by dilation. This segmentation process was compared with manually selected ground regions, and it achieved 93.83% accuracy [20].

Malignant melanoma lesions were detected by segmenting the area affected in the body [21]. Melanoma and benign nevus images were collected from online databases. Morphological closing, color space transformation, and illumination correction methods were used to remove the noise from images. Later, these images were segmented using Otsu's thresholding, Canny edge detection, Sorensen Similarity Index (SSI), and hole filling algorithms. This segmentation method achieved 93.71% accuracy in lesion segmentation.

Other than skin disease classification, a study had analyzed melanin and hemoglobin in the area of the human hand K. Melbin et al., (2014), Two-dimensional images (n=4,000) were obtained from five hyperspectral images acquired by Specim PFD-V10E camera. The images had covered three areas of the hand, i.e., the fingers, the metacarpus, and the wrist. The regions studied were isolated using the nearest neighbor method, and melanin and hemoglobin values were then determined by analyzing the brightness of the specific wavelengths λ [22].

Srinivasu, et al., (2021), developed a tool to segment the psoriasis lesions in the image. A total of 722 lesions were extracted from 103 images taken using Fuji Pix S2, Nikon D300, and Nikon D3100 cameras, and in an indoor environment. L*a*b color and Gabor texture features were extracted to differentiate the lesion area from the normal region. These features were analyzed with KNN and fuzzy C-means classifiers to segment the psoriasis region. These classifier results were compared with the SVM classifier and showed better performance [23].

3. Proposed Methodology

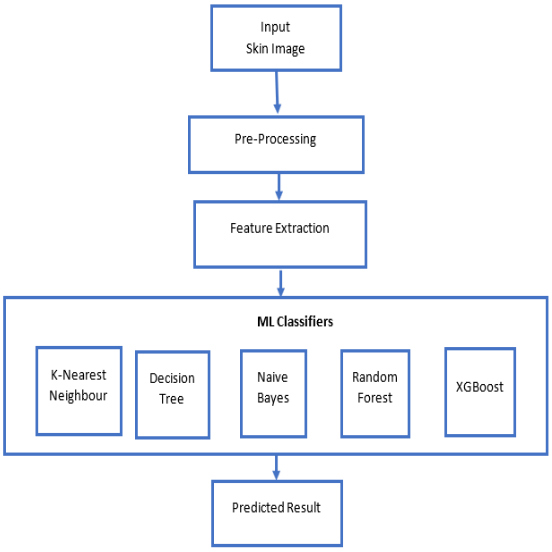

Figure 1: Proposed Skin cancer prediction model

A. Stages of Skin Cancer Detection

Input Skin Image: Image is acquired from dataset of skin cancer. There are moderately barely any informational collections in the general field of dermatology and considerably less datasets of skin sore pictures. The sources of the images and details of the dataset can be found in Kaggle website. A large amount of high-resolution dermoscopy images taken from different conditions are employed in our experiments.

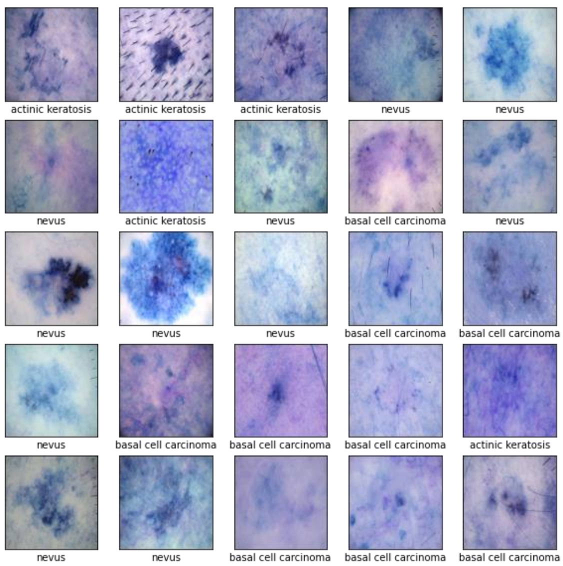

Figure 2: Sample Data Set

Table 1: Number of Images in Dataset

Number of training images	928
Number of testing images	48
Training dataset content	
Actinic keratosis	114
Basal cell carcinoma	376
Nevus	438
Testing dataset content	
Actinic keratosis	16
Basal cell carcinoma	16
Nevus	16

Pre-processing: A necessary action to manage pictures that don't have sufficient quality to be investigated. This absence of value can be because of the nearness of antiquities (e.g., hair) that can adversely influence the exhibition of the resulting steps.

Feature Extraction: A vital step to produce critical representation of skin cancer. Tracking proper features is a heavy task and a ton of research has been performed in this field, causing it conceivable to distinguish an enormous range of highlights that to portray skin cancer.

Classification: The last step of the diagnosis is classification. An algorithm based on classification can be used to predict the class of the cancer. The majority of the machine Learning model center around the differentiation among melanoma and kind or actinic keratosis, basal cell carcinoma, because of high level of danger related with the previous sort of malignancy. In any case, it is additionally conceivable to find machine Learning model that target recognizing melanocytic and non-melanocytic injuries just as distinguishing more than one kind of skin cancer. The machine learning classifiers K-Nearest Neighbor, Decision Tree, Naive Bayes, Random Forest, XGBoost, Multi-layer Perceptron has been used for classification and analyze which classifier gives the best results.

kNN classifier: Skin cancer classification can be done with the identification of his algorithm such that the test samples and the training samples are loaded in the databases. Samples are categorized by evaluating the nearest diameter to the preparation case. Its part then concludes the categorization of the sample. kNN classifier expands this suggestion by captivating the k adjacent position with proclaiming the indication of the mainstream. It is unique to choose k values. Values which are greater in the value of k help in reducing the effects of noisy levels in the pixels rate inside the training data set and opt the value of k is frequently executed during cross-validation. Here the several methods obtainable for this problem is to select a subset of the training data such that classification by the 1-NN rule using the values of many subsets.

Decision Tree: The decision tree is a classifier algorithm in the structure form of a "tree". Decision Trees are simple, but very commonly used methods by moving the inductive logic into a programming environment. It works with discrete valued parameters. The basic intuition about the inductive philosophy on which the decision tree algorithms are based is that a "good" decision tree to be constructed with learning characteristics should be small as possible.

Naïve Bayes Classifier: Naïve Bayes classifier works on the principle of Bayes Theorem which was proposed by Thomas Bayes (1702-1761). It is based on supervised learning and uses probability in determining the group to which a particular object belongs. After normalization of the extracted values, the values are separated into two classes. Using a GPDF function, the probability of the image will be obtained. Naïve Bayes classifier is a simple machine learning classifier algorithm. It makes the classification posterior in Bayesian algorithm. It is represented by the Bayesian network. It is used as a solution for spam and text detection. Naïve Bayes classifier can perform more complicated classification methods. The Bayes rule is,

$$P\left(\frac{K}{L}\right) = \frac{P\left(\frac{L}{K}\right) P(K)}{P(L)}$$

Naïve Bayes classifier performs well for large number of data points because finding the parameters for probability functions can be done quickly.

Random Forest: An RF is established with a numeral of decision trees, and every tree acquires its position arrangement effect by utilizing dissimilar classification. This method permits the evaluation of the sampling allocation utilizing the random sampling technique, also particularly appropriate for some minute models. Essential procedure of classification on basis of RF is as follows. Figure 2 depicts the flowchart for Random Forest.

The unique training illustration set is developed, in which the number of cases is X also the amount of contribution character is Y. This illustration will be the training set for increasing the tree.

2. A secondary training set is arbitrarily created by sampling with the substitution bootstrap technique for n tree times; hence, the subordinate training set for the RF with numeral n tree is created.

3. Ahead of choosing the characters (features) for every non leaf node (internal node), this technique at random chooses a definite number of characteristics from all distinctiveness, utilizes them as divide characteristics of the existing decision tree, and chooses the optimal one to divide the nodes. The number of characters tried at every division is indicated by mtry, mtry ≤ M.

4. Expect pruning, the tree expansion is increased.
5. The created trees are joint with RF. every tree in the RF transmits an entity choice for the mainly accepted group, and the classifier result is resolute by a mass choice of the trees 6. Considering that set S comprises k sorts of attribute principles and every kind of attribute principle creates one sub-node.

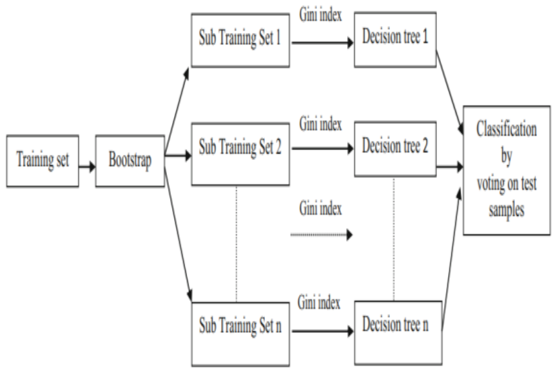

Figure 3: RF classification algorithm Flowchart

XGBoost: XGBoost is a decision tree-based ensemble Machine Learning technique that uses a gradient boosting framework. It was mostly used to categorise unstructured data like text, photos, and so on. In some cases, xgboost algorithms outperform neural networks. When it comes to small to medium data, though, Decision tree-based algorithms are currently the best in class. The model parameters are adjusted when hyperparameter tweaking is completed.

4. RESULT ANALYSIS

A. Performance Metrics

This section presents the experimental results and performance metrics for different models. Accuracy is one of the common performance metrics. It is the measure of all the correctly identified cases. It is mostly used when all the classes are equally important. Accuracy is the proportion of correctly classified examples to the total number of examples, while the error rate is incorrectly classified instead of correctly.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where, TP is True-positive, TN is True-negative, FP is False-positive and FN is False-negative. The six models have yielded different accuracy scores, which are displayed in table 2.

Table 2: Accuracy Score of various Models

Sr. No.	Classifiers	Accuracy in %
1	K-Nearest Neighbor	60.42
2	Decision Tree	56.25
3	Naive Bayes	66.67
4	Random Forest	66.67
5	XGBoost	68.75

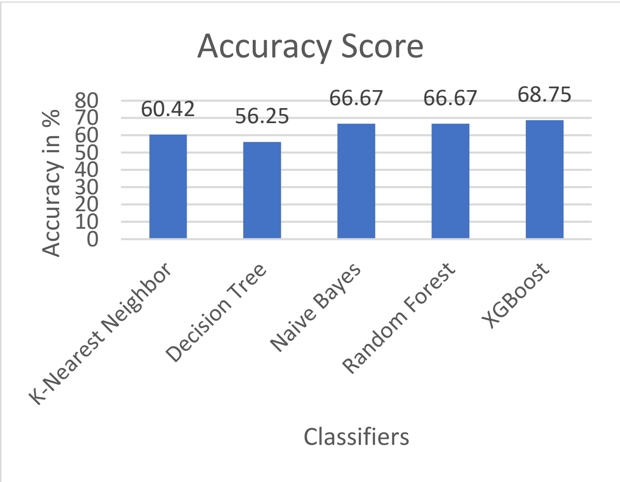

Figure 4: Bar graph of the accuracy measures of different models

Figure 4 shows the Bar graph of the accuracy measures of different models. The methodology actually has a good result for the various classifiers but still can be improved. The result discusses that XGBoost is a better classifier than K-Nearest Neighbor, Decision Tree, Naive Bayes, and Random Forest has the highest accuracy of 68.75%. The results achieved are relatively good when compared.

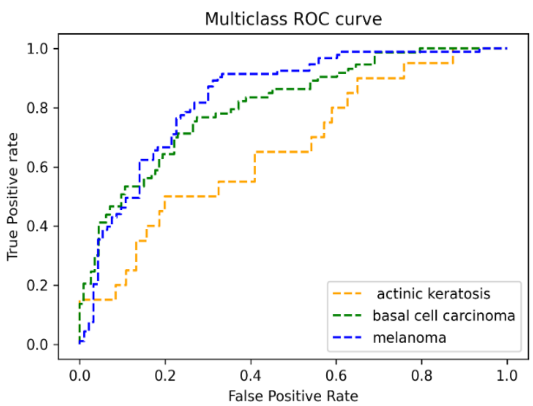

Figure 5: Multiclass ROC of KNN

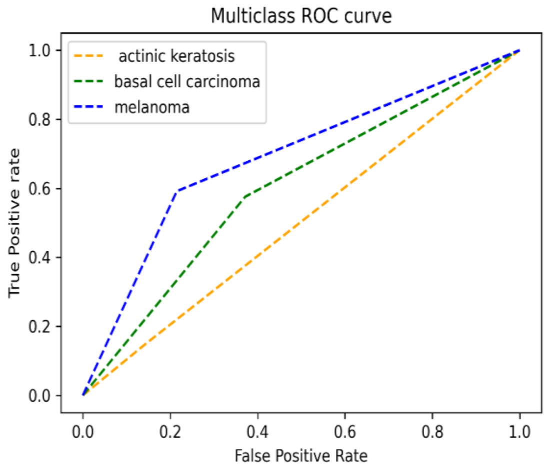

Figure 6: Multiclass ROC of decision Tree

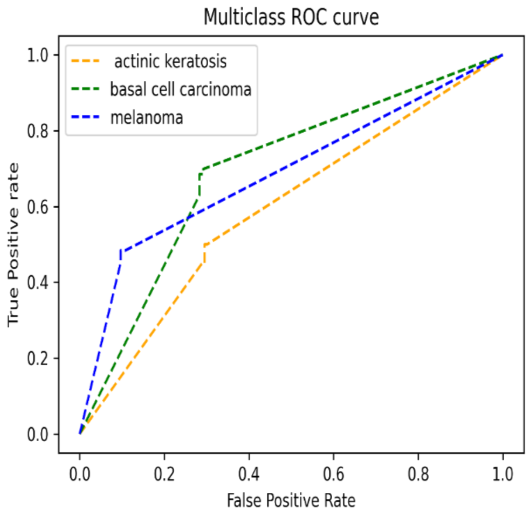

Figure 7: Multiclass ROC of Naïve Bayes

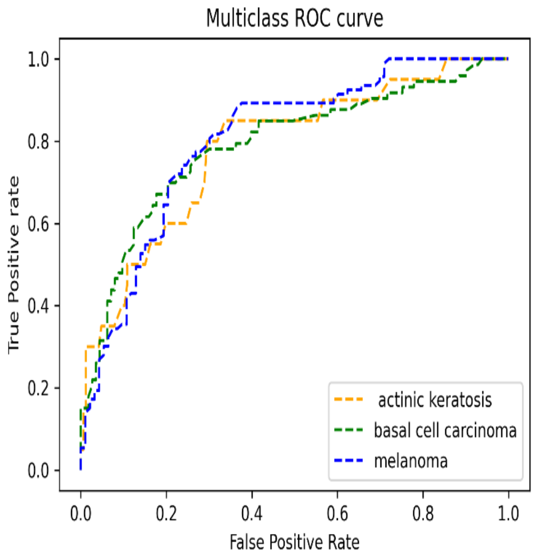

Figure 8: Multiclass ROC of Random Forest

CONCLUSION AND FUTURE SCOPE

In the past few decades, the incidence of malignant melanoma as a lethal form of skin cancer has risen considerably. Malignant melanoma is the deadliest type of skin cancer that, however, can be treated successfully, if detected early. Early intervention will lead to better survival rates. Since clinical observation of melanoma is subject to human error, early detection can be enhanced by utilizing an automated process. Although there are many developments in imaging technology like dermoscopy, they have limitations. A physician's diagnosis is looked upon as a primitive gateway for patients from the dermatology department. Since the diagnosis of melanoma is not an easy process in its early stages, the dermatologist should be trained as an expert. Moreover, since visual examination may not provide exact results, computer-based diagnosis systems are beneficial for both experts and physicians with less experience. It can be useful to take the information received by the computer into account for a final and precise decision. For this purpose, physicians need this automated system to be more reliable and accurate than what has been presented so far.
In this study, effective detection of skin cancer detection is proposed. Four features are chosen that are trained and tested by using various classification techniques like K-Nearest Neighbor, Decision Tree, Naive Bayes, Random Forest, XGBoost, and Multi-layer Perceptron have been done. The methodology actually has a good result for the various classifiers but still can be improved. The result discusses that XGBoost is a better classifier than K-Nearest Neighbor, Decision Tree, Naive Bayes, Random Forest has the highest accuracy of 68.75%. The results achieved are relatively good when compared. The future work will focus on improving the number of features selected and then classified to improve the accuracy.
With the implementation of such a system with individual features as well as combined features it has been shown that the proposed methodology can deliver an optimal solution for melanoma cancer detection. As future scope of study in this Existing computerized dermoscopy techniques lay marginal or no emphasis on depth for diagnosis. Authors particular work, the depth estimation technique proposed in this technique is naïve.
Future of the work presented here is to identify depth estimation error using clinical data and devise new techniques to minimize errors. Authors welcome dermatologists/ researchers to undertake collaborative research to develop the proposed system further considering clinical data. Refined and improvised classification and feature selection methods can be tried and tested. Also, since Machine Vision (MV) is a continuously evolving concept, evolutionary computing techniques can be used for performance enhancement.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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