An Efficient Image Processing and Machine Learning based Technique for Skin Lesion Segmentation and Classification

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***Abstract*—Skin cancer is one of the most lethal types of cancer that has grown extensively over the last decade and can lead to death if not treated on time. However, if skin cancer is diagnosed and treated at an early stage, it can be curable. Several image processing and machine learning methods have been considered to detect and classify skin cancer lesions (melanoma) accurately. However, a lower contrast of images also affects the segmentation efficiency and further increments classification error. Thus, in this work, a simple yet effective image processing and machine learning based technique has been proposed for skin lesion segmentation and classification to overcome this problem. The proposed technique increases the segmentation accuracy in its pre-processing stage, removing noise and hair and enhance image contrast by adjusting intensity values of RGB channels. Otsu thresholding and image subtraction methods are applied to extract the region of interest and segmented lesion area. Morphological operations are performed to remove noisy pixels and reshape the segmented image at the post-processing stage. For extraction of image features, color and ABCD features are applied. The PH2 dataset is used in this work, consisting of imbalanced classes; therefore, Synthetic Minority Over-sampling Technique (SMOTE) is used to balance the distribution of the dataset. A supervised machine learning classifier further uses the extracted image features to classify skin lesions. The proposed technique accurately segments the lesion with an accuracy of 90.25% and classifies them into melanoma and non-melanoma with an average accuracy of 98.13% using the Adaboost classifier.**

I. Introduction

Skin cancer or malignancy is recognized as one of the major global health problems due to the growing prevalence of damaging ultraviolet rays and radiation in the earth's atmosphere. Researchers revealed that further depletion of the ozone layer would raise the problem and diseases of skin cancer [1]. Every year, millions of melanomas and non-melanoma cases are reported globally. Recent research on the prevention of skin cancer reported that 86% of melanoma and 90% of non-melanoma cases are caused because of unnecessary exposure to ultraviolet rays [1]. These ultraviolet rays and radiation damage the DNA present at the inner skin layers, triggering skin cells and cause the independent increase of skin cells that might be developed as a cancer. The most significant and efficient way to manage skin cancer and the fatality rate because of these dangerous diseases is the timely diagnosis. According to the reports [1], the survival rate of skin cancer patients (melanoma) increases when diagnosed and screened early. However, dermatologists usually use visual examination methods (image-based) to identify skin cancer; it is challenging due to the obvious similarity between different skin cancers. Nevertheless, dermoscopy has become widely adopted for diagnosing skin cancer. This is because it can visualize skin lesions that are not accurately observable with the naked eye. Although, the investigations on dermoscopy require to produce an automated and effective system for diagnosing skin cancer because the fledgling may decrease skin lesions' diagnostic accuracy.

Researchers utilized and proposed various computer vision, and machine learning-based methods to process dermoscopy images and classify various types of skin cancer. However, the performance of these methods is affected due to different factors such as different skin types, shapes, different lesion sizes, colors, hair on the skin, skin marks, low contrast, and illumination. Hence, a simple yet effective image processing technique has been introduced in this work for skin lesion segmentation and classification. The proposed method increases the segmentation accuracy by removing noise and hair and enhancing image contrast at the pre-processing stage. For segmentation of skin lesions, Otsu thresholding and image subtraction techniques are used. To remove noisy pixels and reshape the segmented image, morphological operations are performed at the post-processing stage. For extraction of image features, color and ABCD features are used. Finally, a supervised machine learning classifier uses to classify skin lesions.

The paper is structured as follows: Section II provides an overview of the related work. Section III provides the complete methodology for the classification of skin cancer. Experimental results are given in Section IV. Finally, Section V concludes

[1] https://www.cancer.org/cancer/melanoma-skin-cancer

the entire paper.

II. Related Work

Recently, various techniques have been proposed for the automatic detection and classification of skin lesions. These methods may assist medical experts in the effective diagnosis of various skin cancer diseases. Abbas et al. [2] used edge detection operation on grayscale images for segmentation, Grey Level Co-occurrence Matrix (GLCM) for texture features extraction, and support vector machine classifier for classification of skin lesion.

Authors in [3] presented a method for the classification of three skin diseases, i.e., Warts, Hemangiomas, and Vitiligo, by extracting first and second order statistical features of a grayscale image. In another work [4], authors performed region segmentation using k-mean clustering and hybrid features, i.e., a combination of Grey Level Co-occurrence Matrix (GLCM), Local Binary Pattern (LBP), and color for features extraction. Aalmaraz et al., [5] proposed segmentation technique by applying the flood fill method to grayscale images and then subtracting the grayscale image from the resultant image. Their work utilized median filter and then Otsu thresholding, canny edge detection, and morphological closing for skin lesion segmentation.

An optimized edge detection method has been proposed in [6], authors used edge detection algorithms canny, Sobel and Prewitt with Ant Colony Optimization. [7] used a decision tree classifier that performs classification on extracted features called Grey Level Co-occurrence Matrix (GLCM) and Image Quality Assessment (IQA) for skin disease detection. Wei et al., [8] classified images using an SVM classifier with a radical base function. The aim of the presented method in [9] is segmentation using a Sobel edge detection operator and evaluating the quality of the segmented image by computing its Entropy value. [10] classified three different skin diseases on a manually created dataset. Grochowski et al., [11] used Wavelet transform, GLCM, and Tamura Texture features and performed image segmentation using the Otsu thresholding method. Nasir et al., [12], introduced efficient image segmentation using uniform segmentation and active contour method.

Authors in [13] presented Dermoscopic Skin Network (DSNet) for skin lesion segmentation. [14] presented methods for diagnosing skin cancer by carrying out segmentation using four different segmentation techniques, namely Otsu thresholding, active contour, k-means clustering, and maximum entropy base method. For feature extraction, color, texture, and shape features are extracted. [15], presented an image processing based skin lesion segmentation method using harris corner detection and region growing method.

From the above discussion, it can be concluded that a lot of work has been done for the accurate classification and segmentation of skin lesions. Researchers utilized image processing (noise removal, image filtering) and image segmentation-based methods for lesion segmentation with improved performance. For the classification of skin cancer images, color and texture features are mostly employed, later used by various machine learning-based classifiers. This work presented an efficient image processing and machine learning-based method for skin lesion segmentation and classification of skin cancer images.

III. Methodology

A simple yet effective image processing and machine learning-based technique has been presented. The overall flow of the proposed method is provided in Fig.1. The developed technique comprises five major steps:

1) Image pre-processing
2) Segmentation
3) Features Extraction
4) Data pre-processing
5) Classification

The dermoscopy images go through the pre-processing stage, where hair, noise removal, and image enhancement are performed. Then, we used Otsu thresholding and flood fill operation, and finally, for post-processing, morphological operations are implemented on the segmented image. We then extracted features of skin lesions using color and ABCD features. We also performed data pre-processing, transformed the data and removed inconsistencies. Finally, for the classification of skin cancer, types of supervised machine learning algorithms are applied. The details of each step are provided in the following subsections.

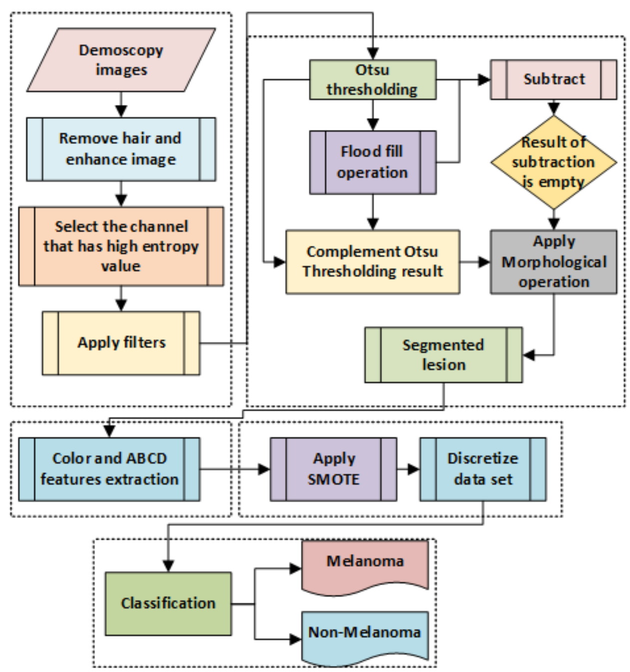

Fig. 1: Flow chart of the proposed methodology.

A. Image Pre-Processing

For accurate skin lesion detection, the dermoscopy images are pre-processed, unwanted noise (hair and air bubble) is removed. For removing unwanted noise and image enhancement, firstly, hair removal is performed. Then the image is enhanced by adjusting the intensity values of three channels (RGB) individually. After that entropy of channels red, green, and blue is calculated. The color channel that has the highest entropy is selected for further segmentation process. After that, the non-linear filter (Median filter) with 5×5 neighborhood is applied on the selected channel as it removes unwanted noise and preserves the edges of the image, and then the Gaussian filter is used with the standard deviation of 8. In

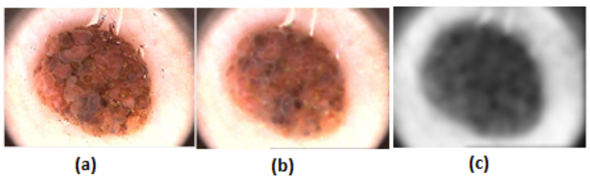

Fig. 2: (a) original Image (b) Hair removal and contrast enhancement (c) applying filter.

Fig.2, (a) represents the original image, (b) shows the image after removing unwanted hairs. After that, the entropy of the three channels of the RGB image is calculated, and the channel with high entropy is selected onto which Median and Gaussian filters are applied to remove noise removal. While Fig.2(c) shows the pre-processed image, which is used for segmentation.

B. Segmentation of Skin lesions

To extract the region of interest and skin lesions in dermoscopy images, segmentation techniques are applied to the image after pre-processing. The segmentation technique that is used in the proposed work consists of Otsu thresholding and image subtraction.

Otsu thresholding and image subtraction: In thresholding, the initial threshold value T is selected that divides the pixel intensities of the image into $P1$ and $P2$.

- The mean $\mu1$ and $\mu2$ of every individual partition $P1$ and $P2$ are computed.
- From that new threshold value is computed using the following equation:

$$T = \frac{(\mu1 + \mu2)}{2} \tag{1}$$

- Repeat the steps until a clear change in the value of $\mu1$ and $\mu2$ is achieved after iterations.

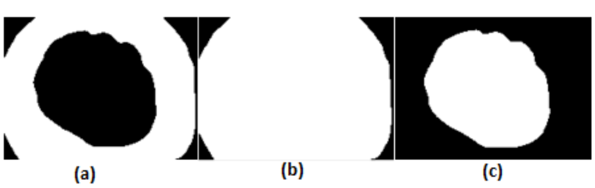

Fig. 3: (a) Otsu Thresholding (b)Flood Fill operation (c)Subtraction.

In Fig.4(a), the lesion segmented using Otsu thresholding and image subtraction is shown. However, the dermoscopy images in the data set consist of dark corners hence the corners from the image are removed using flood fill operation as shown in Fig.4(b). In addition, it will perform holes filling operation on the image achieved using Otsu thresholding. To remove the dark corner, the image obtained using Otsu thresholding and hole filling operation is subtracted as depicted in Fig.4(c), which will be the required for segmentation of the region of interest. Nevertheless, if there is no foreground object, i.e., skin lesion is segmented using image subtraction, then the complement of the region of interest obtained using Otsu thresholding will be the resultant segmented image.

C. Post-processing

To remove noisy pixels and to reshape the segmented image, post-processing is performed that consists of morphological operations. Disk shape structuring element is a small matrix consisting of zeros and ones used in this work with the value of 15x15 for opening and dilation. The opening operation performs the erosion of the image, followed by the dilation operation. For example, Eq2 shows the opening operation of the image where AS represents the binary image and BS is the structuring element.

$$AS \odot BS = (AS \ominus BS) \oplus BS \tag{2}$$

In Eq2, $\ominus$ is the erosion and $\oplus$ represents dilation operation. Finally, in the end, a morphological operation called dilation

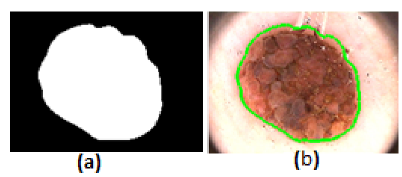

Fig. 4: (a) Region filling and dilation (b)Resultant ROI.

is performed on the resultant segmented image. The dilation of the binary image using structuring elements is represented in Eq3, where Img is the binary image, and SE represents the structuring element. The overall segmentation procedure is shown in Fig.4, where (b) shown the resultant region of interest.

$$Img \oplus SE = \{z|(\hat{s})z \cap A \neq \theta\} \tag{3}$$

D. Feature Extraction

To perform classification, skin lesions features are extracted using ABCD and color features method.

ABCD Features: ABCD is the clinical approved criteria by dermatologists for diagnosing skin cancer. It stands for Asymmetry, Border irregularity, Color and Diameter.

- Asymmetry is measured by dividing the extracted ROI from the middle, and the upper half is flipped on the lower half of the ROI to determine whether the skin lesion is asymmetric or symmetric. If the skin lesion is not symmetric, in that case, it is considered malignant.
- Border irregularity: The lesion tends to be malignant if it has an irregular border. It used a compact index to

compute the border irregularity of the lesion. To measure the border irregularity, Eq4 is used.

$$Compact_{index} = \frac{Perimeter^2}{4\pi area} \quad (4)$$

- Color: An important factor that helps determine the lesion as malignant or benign is color. The color of benign is brown; however, the color of malignant lesion varies. It contains shades of brown, tan or black, red, white, or blue color. In the proposed work mean color of the lesion is extracted.
- Diameter: Diameter is another important factor that helps in determining the lesion is malignant or non-malignant. The diameter is malignant, usually greater than 6mm, and it expands with time.

Color features: We also used chromatic features are used extracted from four-color models, namely RGB, Grayscale, HSV, and YCbCr color space. In this work, 30 color features are extracted by computing the mean, standard deviation, and skewness of each color channel.

E. Data Preprocessing:

The data set used in this work consists of unequal distribution of the class labels with 160 non- melanomas and 40 melanomas images. To transform the data by removing inconsistencies, data pre-processing is performed using SMOTE method. The imbalanced distribution of class labels highly affects the performance of the classification algorithms as this leads to the high favor of the majority class, thus resulting in the performance.

SMOTE: It stands for Synthetic Minority Over-sampling Technique. It balances the data set by creating synthetic data for the minority class. The algorithm for SMOTE is given below:

- Select a minority class
- Locate its k nearest neighbor.
- Select one of the neighbors of the selected minority class and put a synthetic point at any place on the line connecting the points of the class that is under attention and its chosen neighbor
- Repeat the steps until the data is balanced.

Secondly, the range of attribute values varies from one another, and they do not have the same scale it may lead to inaccurate prediction; hence, discretization is performed for that feature. Finally, it transforms the continuous attribute values into a finite set of intervals.

F. Classification

After the data pre-processing for prediction classification is performed. In the proposed work, supervised learning-based classifiers called Bayes Net, Naïve Byes, Ensemble of Naïve Bayes built using Adaboost and Random Forest are used. These are used with the 10-fold cross-validation method. It shuffles the data randomly by splitting the data set.

Bayes learning: Two types of Bayes learning classifiers are used called Bayes Net and Naïve Bayes. These are statistical classifiers that are based on Bayes's Theorem. Using posterior and a prior probability, it computes the class.

Random Forest: It creates many decision trees and joins them to get an exact, stable and accurate prediction. It also controls the overfitting of the training set. Random samples are chosen from the data set. For every sample decision tree is constructed. Then it will get prediction results from all of these decision trees. Voting is done for the results predicted by the decision trees. The most voted prediction result is decided as the final prediction result.

Adaboost using Naïve Bayes: AdaBoost or Adaptive boosting is an ensemble algorithm that combines the weak learner algorithm and turns them into strong leaner. It provides the sequence of weak learners by assigning various weighted training data. Firstly it predicts the original data set and provides equal weight to each observation. If the first learner's prediction is wrong, it assigns a higher weight to the incorrectly predicted observation. It repeats the process by adding learner(s) until accuracy, or a limit is reached in the number of models. In this study ensemble of Naïve Bayes is built using the AdaBoost classifier.

IV. EXPERIMENTAL RESULTS

In the present research, the PH2 data set is used from an online source [2]. The data set consists of 200 dermoscopy images. The images are in RGB format with a resolution of 768×560 pixels. The data set consists of 160 non- melanomas and 40 melanomas images. The output results of the above discussed segmentation method are shown in Fig.R1. The first column consists of the original image; the second column shows pre-processed image after removing of noise. The result of Otus thresholding is represented in the third column, and the resultant image after applying flood fill operation is depicted in the fourth column. The fifth column represents the final segmented image which is achieved by subtracting the third and fourth columns and applying morphological operations. Finally, the last column represents the highlighted region of interest on the original image.

To assess the performance of the above-presented method, different evaluation parameters have been used. To evaluate the outcome of segmentation overlap-based method called the Dice ratio is used, widely used in literature to evaluate the segmentation results. It is computed using ground truth and segmented images. In the proposed technique achieves 90.25% of segmentation accuracy with a Dice ratio of 80.1%. The proposed segmentation technique efficiently and robustly extracts the region of interest, skin lesion, from the healthy skin. In the proposed work, the performance of the classification method is measured by average computing precision, recall/sensitivity, specificity, and F1-score. TableIrepresents the performance of the classifier on the data set, which is not pre-processed. Without pre-processing the data set, the performance of the classifiers is badly affected. In an imbalanced data set, the classifier can produce bias results by targeting the majority

[2]https://www.fc.up.pt/addi/ph2%20database.html

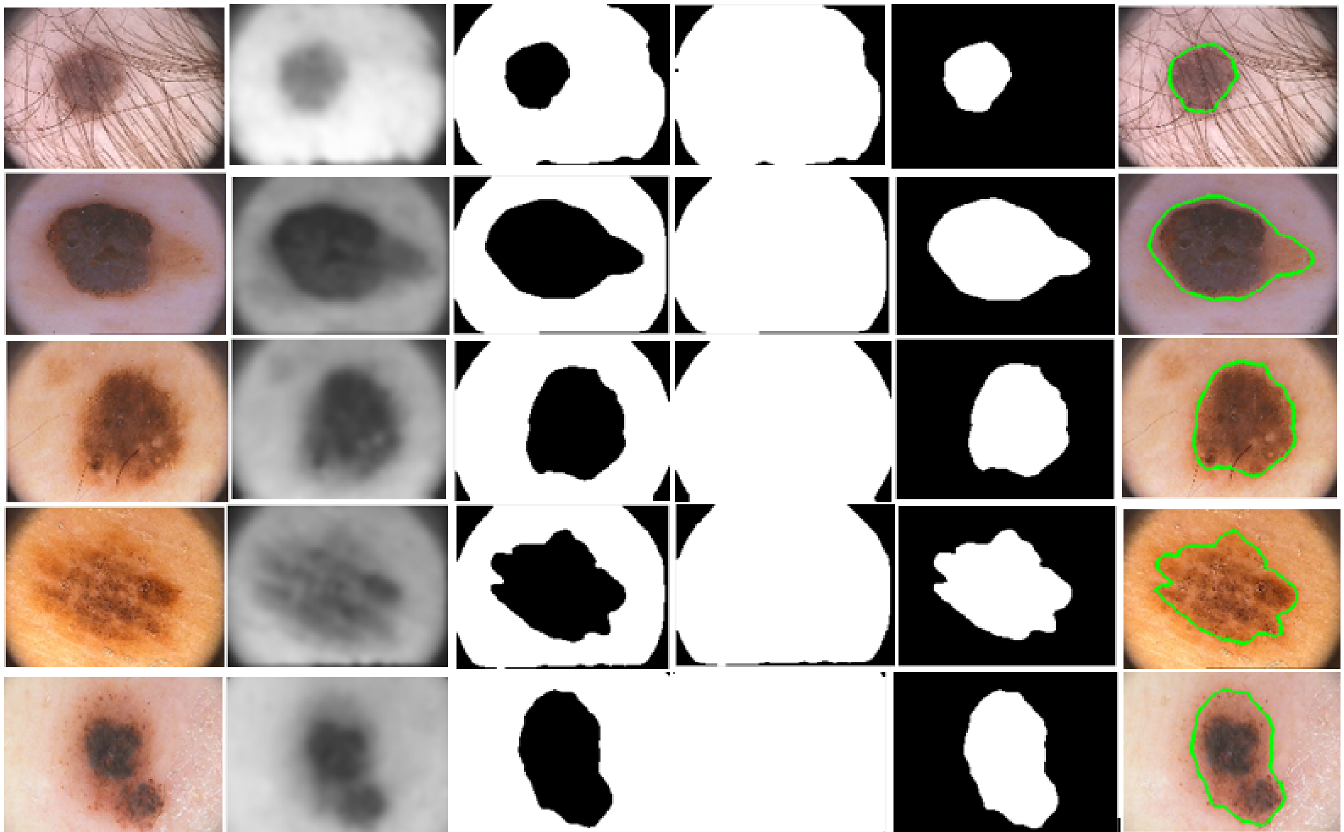

Fig. 5: (a)Original image (b)Pre-processed image (c)Otsu Thresholding (c) Flood fill operation (d) Subtraction and morphological operation (e) Highlighted skin lesion.

classes. Hence, in that case, the Precision and F-score of the model have to be considered. In TableI 95.51% is specificity, 74.42% is sensitivity, 82.05% and 78.05% precision and recall for Naïve Bayes classifier. The random forest results are also not good, with 91.76% as the value of specificity, the value of sensitivity is 86.21%, 64.1%, and 73.53% as the value of precision and recall.

TABLE I: Performance results before data pre-processing.

Classifier	Specificity	Sensitivity /Recall	Precision	F-score
Bayes Net	73.17 %	94.3 %	76.92 %	75 %
Naïve Bayes	95.51 %	74.42 %	82.05 %	78.05 %
Random Forest	91.76 %	86.21 %	64.1 %	73.53 %
AdaBoost With Naïve Bayes	93.79 %	76.32 %	74.36 %	75.32 %

The classifiers' performance in the proposed study has increased after the data set is pre-processed by removing the class imbalance problem and discretizing the data set. Table II shows the result of classifiers applied on the pre-processed data set using different evaluation measures. It can be viewed that the Ensemble of Naïve Bayes build using Adaboost classifier produces better results the value of specificity, the value of sensitivity is 96.95%, 99.38%, and 98.15% is the value of precision and recall.

TABLE II: Performance results after data pre-processing.

Classifier	Specificity	Sensitivity /Recall	Precision	F-score
Bayes Net	95.54%	93.87 %	95.63 %	94.74 %
Naïve Bayes	95.51 %	93.29 %	95.63 %	94.44 %
Random Forest	98.06 %	95.15 %	98.13 %	96.62 %
AdaBoost With Naïve Bayes	99.36 %	96.95 %	99.38 %	98.15 %

The impact of data pre-processing can be observed from Fig6 and Fig7 by comparing the value of precision and F-score. F-score is the efficient matrix to measure the performance of the imbalanced data set. It can be seen clearly in both Fig6 and Fig7 that the value of precision and F-score varies for the same classifier. Hence, the classifiers applied on the non-pre-processed data set misclassify class labels by targeting only the majority class, while in the case of the pre-processed data set, viewing the value of precision and F-score can be observed the classifier does not produce bias prediction.

Fig 8 depicts the accuracies of the classifier that is achieved

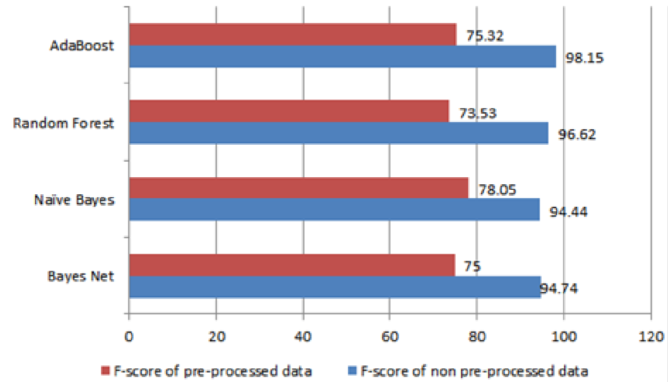

Fig. 6: F1-score values before data pre-processing (imbalanced) and after pre-processing (balanced).

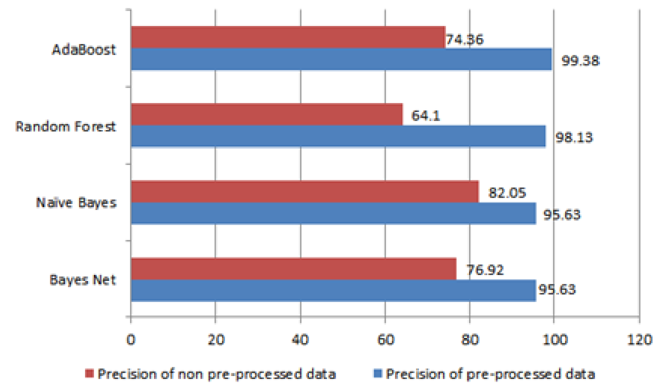

Fig. 7: Precision values before data pre-processing (imbalanced) and after pre-processing (balanced).

from the dataset before data pre-processing (imbalanced) and after pre-processing (balanced). It can be observed that despite the high average accuracy, the classifiers cannot predict the class labels accurately. Naive Bayes and Random forest produce high accuracy, i.e., 90.95%. However, the value of accuracy is not enough to analyze the performance of the method. The value of accuracy alone can be deceiving to identifying the performance of the method. It can be viewed that the Ensemble of Naïve Bayes build using Adaboost classifier produces better results with an accuracy of 98.13%. Fig. 8 shows the accuracies of the classifier that is applied to the pre-processed dataset. From Fig.8 it can be observed that AdaBoost predicts the class labels more accurately as compare to Bayes Net, Naïve Bayes, and Random Forest.

V. Conclusions

This work presented image processing and machine learning-based, a simple yet effective technique for segmentation and classification of skin lesion and skin cancer dermoscopy images, respectively. The proposed work consists of five major steps for the detection of skin cancer as non-melanoma and melanoma. It consists of pre-processing, segmentation of the region of interest, feature extraction, data pre-processing, and classification. First, it accurately segments the skin lesion with an accuracy of 90.25% and a dice ratio of 80.1%. After extracting color and ABCD features, data pre-processing has been performed. The dataset used in this work consists of 160 non- melanomas and 40 melanomas images which is an unequal distribution of class labels that leads to class imbalance issues. Imbalance class can affect the performance of the classifiers, thus leading to inaccurate prediction of the class label. Hence this issue is tackled by introducing the synthetic data for minority classes using SMOTE. Secondly, the range of attribute values varies from one another as they do not have the same scale, which can also affect the classifier's performance; hence the data was discretized. Four classification methods are used in this study, from which the Adaboost classifier provides better results with an average accuracy of 98.13% among all of the classifiers. The proposed method robustly classifies the images into non-melanoma and melanoma with high accuracy.

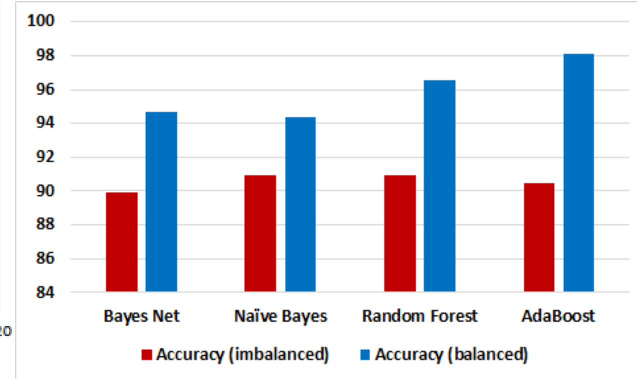

Fig. 8: Accuracy results of supervised machine learning classifiers before data pre-processing (imbalanced) and after pre-processing (balanced).

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