Recognizing Pigmented Skin Lesion based on LightGBM Classifier and Deep Saliency Segmentation using Convolutional Neural Network

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ABSTRACT
Malignant melanoma is the most detrimental type of skin cancer which has affected many people worldwide. Melanoma could be cured if diagnosed and treated early. However, it is a difficult to identify melanoma conditions at earlier stages due to data imbalance, large inter-class similarity, and high intra-class variations etc. On the other hand, manual diagnosis of melanoma is more prone to human error. Therefore, a novel strategy to identify and classify pigmented skin lesions using a deep learning approach is presented in this paper. The proposed approach uses a LightGBM classifier and convolutional neural network (CNN) for timely recognition and classification of skin lesions. The classification model is designed based on the saliency evaluation and selection of discriminant features where CNN is employed for performing saliency segmentation. The performance of the proposed classifier is measured using different evaluation metrics and results have validated the efficacy of the classifier for accurate classification of pigmented skin lesions.

Keywords
Skin Lesion, Image Segmentation, Feature Extraction, Image Classification, Convolutional Neural Network, LightGBM Classifier

1. INTRODUCTION
Skin is one of the most important organs of the human body which covers the exterior portion of the body. Due to the direct exposure, the skin layers are often affected by various types of skin diseases. While some of these diseases can be cured easily, few diseases can last for longer duration. One of the most dreadful diseases related to skin is melanoma which is a type of skin cancer. Recent studies reveal that most of the melanoma cases are due to the exposure of skin to ultraviolet radiations [1]. Melanoma is characterized by the brown or black pigmented lesions which are abnormal and uneven in nature. Pigmented skin lesions must be recognized in the preliminary stage for preventing the spread of carcinogenic cells. In general, skin lesions are classified as malignant or benign wherein the malignant lesions are due to the growth of abnormal cells that spreads widely across the body and the benign lesions are growth of more cells but not cancerous [2]. Inaccurate diagnosis of these lesions can cause severe damages and can spread to other parts of the body so it will be more complicated to cure the disease. Therefore, it is important to develop efficient techniques to recognize the skin lesions [3]. Various researchers have proposed different techniques for classifying skin lesions using computer vision methods, machine learning (ML), and deep learning (DL). Among different techniques, ML and DL models are being extensively used in skin lesion detection because of its ability to achieve better classification performance and detection accuracy [4]. The standard process in automated skin lesion detection is preprocessing, segmentation, feature extraction, and classification [5]. In the preprocessing stage, the uncertainties such as external noise, outliers, and missing data values associated with the images are filtered out. During segmentation, skin lesions are distinguished from the normal skin region. Conventional segmentation techniques are characterized by lack of focus, smooth texture, and monotone coloring. These factors restrict the performance of the segmentation techniques since they fail to segment specific regions from the rest of the image. To overcome this problem, this research employs a deep saliency segmentation approach which segregates image regions which have similar properties. The segmented images are subjected for classification wherein the features are classified as malignant or benign. Numerous ML algorithms are widely used in skin lesion detection which allow automatic classification of pigmented skin lesions. However, automatic classification involves a lot of complexities such as presence of artifacts, computational time cost during model training but DL algorithms can offer better solutions to these concerns. This paper presents a LightGBM boost classifier and Deep Saliency Segmentation using CNN for recognizing skin lesions.

The rest of the paper is organized as follows: Section II outlines existing frameworks on the recognition of pigmented skin lesions. Section III discusses the framework of the proposed technique and details about the recognition model. Section IV discusses the simulation results and performance evaluation of the proposed methodology. Section V concludes the paper and discusses the future work.

2. RELATED WORKS
ML and neural network algorithms are employed for recognizing skin lesions based on the image features [6-8]. In [9], developed an automated skin cancer diagnosis framework using deep learning which combines various dermoscopic features with texture features. Feature extraction was performed using Local Binary Pattern (LBP), Gray level run length matrix (GLRLM), and Histogram of oriented gradients (HOG) techniques, for identifying skin lesions. A CNN based skin cancer detection model is developed which employs a classification approach wherein the CNN model is trained using ISIC dataset to detect skin cancer during early stages

[10]. The SkinCan AI for the prediction of skin cancer by using a generative model is developed, which is limited data distribution for image classification and then implements the soft attention model through pipelining for image segmentation. This technique is an early diagnostic tool for skin care detection, and it improves the accuracy compared to the other existing approaches [11]. In [12], suggested the semi-supervised image segmentation method for high accuracy results for skin lesion images. It provides high accuracy using fuzzy c means clustering algorithm and compared with the five different public datasets. In [13], applied the discrete wavelet transform method for skin lesion image segmentation which helps to identify the backgrounds in color images and provides better results. The significance of image segmentation on the classification accuracy for skin lesion detection is discussed and investigated the efficacy of the segmentation techniques based on the clustering scheme [14].

Existing works reveal that a huge amount of research work is dedicated to the analysis and recognition of skin lesions. Despite the availability of different techniques, there is a great scope of research in the field of skin cancer detection. There is a lack of an effective technique which can overcome the limitations of existing cancer detection methods such as poor detection accuracy, inefficient performance, and high computational complexity.

3. MATERIALS AND METHODS

The preliminary aim of the proposed framework is to achieve high accuracy in recognition of pigmented skin lesions. A LightGBM classifier and Deep Saliency Segmentation based on CNN is employed to achieve faster and accurate results for skin lesion prediction as malignant or benign.This research included five-stage process for detecting and classifying the skin lesions. The first step is to collect different dermoscopic images as a input from the skin disease dataset. The second step is the preprocessing stage wherein the input images are processed and are subjected for segmentation in the third step. The fourth step is extraction of essential features from skin lesion image. Finally, the images are classified using the proposed LightGBM classifier model. The workflow and the system architecture of the proposed approach are illustrated in figure1 and 2.

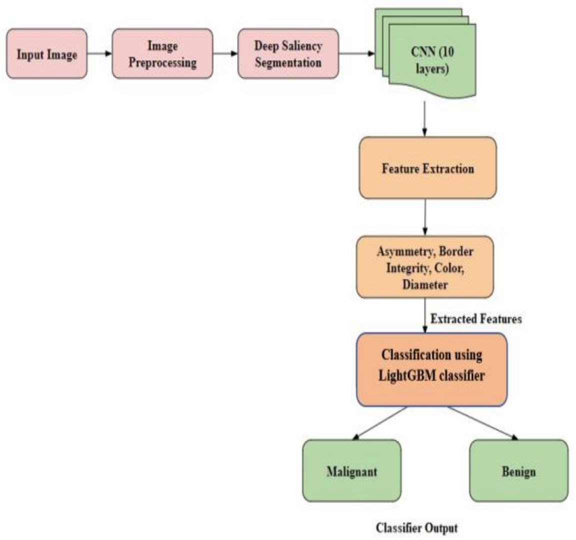

Fig 1: Workflow of the proposed approach

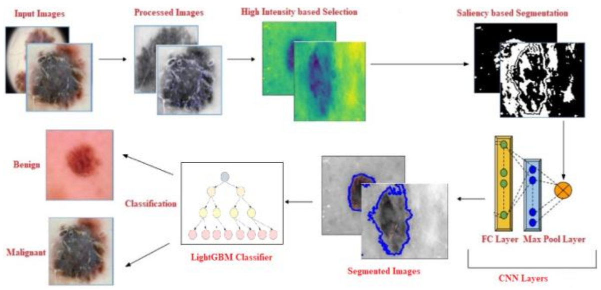

Fig 2: System architecture for skin lesion segmentation and classification

3.1 Data Collection

The image samples for experimental process are collected from Kaggle dataset [15]. The dataset consists of a balanced set of skin lesion images containing both malignant and benign images. The sample of the benign and malignant images collected from the dataset is illustrated in figure 3.

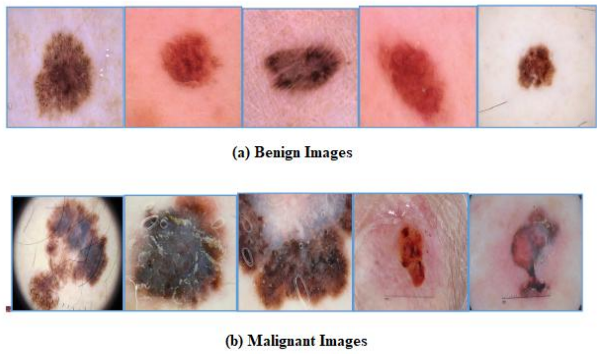

Fig 3: Sample dermoscopic images

3.2 Data Preprocessing

Preprocessing is one of the prerequisites for the segmentation and classification tasks for better performance. During preprocessing, the uncertainties from the image samples such as unwanted noise, redundant data, missing values, and null values are filtered, and all images are resized to a fixed size. In addition to these uncertainties, there are challenges in the skin lesion images such as presence of hair, illumination, and poor contrast [16,17]. These issues affect the segmentation performance, especially while detecting the lesion borders. Firstly, the RGB color skin cancer image is converted into the grayscale image. A global maxima function is applied on grayscale images, which creates a grayscale image with the maxima function based on the height ‘h’. Further, the maxima gray scale image is converted into a high contrast image using a median filter. In general, a median filter in preprocessing is used for reducing the noise [18,19]. In this research, the median filter reduces the magnitude of intensity variation between the pixels. The operation of median filters can be explained by considering a square shaped window with variable size for filtering. The size of the window for median filtering is selected according to the visual quality and processing time [20]. In the filtering process, the value of the image pixels is reinstated by the median value, which is computed by organizing the pixel values in ascending order. The pixel which is located at the center of the window is considered for denoising operation. By doing so, the amount of intensity variation is reduced thereby reducing the noise in images. A dilation morphological operation is performed next to increase the vision of the high-contrast images by maximizing the image size. This helps in detecting the pigmented skin lesion. In the dilation process, additional pixels are added to the image boundaries and the number of pixels to be added depends on the size and shape of the structuring element which is used for processing the image. Dilation improves the image brightness by connecting the regions that are separated by small spaces and helps in improving the image contrast.

3.3 Image Segmentation

Image segmentation is regarded as pixel-level prediction as it classifies every individual pixel into its identical category [21]. Saliency explores the image features and thereby helps in capturing the maximum details about the image. It improves the segmentation performance and allows multi-object segmentation by exploiting the data generated by the saliency map. Saliency segmentation techniques are more robust since they can extract more stable regions from images and helps in achieving better segmentation performance. One of the prominent advantages of employing CNN for deep saliency segmentation is the best use of the shared weight of the conventional layers and their efficiency in image recognition and in the sorting process [22]. The segmentation is said to be reliable when it satisfies two conditions: (i) When the pixels belonging to the same category possess similar greyscale of multivariate values and form a connected segment. (ii) When the neighboring pixels belonging to different or dissimilar categories possess dissimilar values.

A. Deep saliency segmentation using CNN: Segmentation helps in identifying the affected areas from skin images. In this research, the initial stage in the segmentation process is to calculate the region of interest (ROI). The ROI is the portion that helps in detecting the skin lesion. Here the size of image is same wherein the values for the continuous pixels are considered as 1 and the remaining will be considered as 0. A deep saliency segmentation is performed in this research using a saliency map with a 10 layered CNN model. In CNN, the surface layers contain low-level and skin lesion related features. The layers of the CNN are fine tuned to enhance the efficiency of the CNN in segmentation process. The process of CNN is categorized into 4 main stages [23]. Initially, pixel values of the images are stored in input layer. Next convolutional layer determines the output of the neurons associated with the input local regions by computing scalar product among the regions which are associated with the volume of input and weights of the neurons. At third stage, the lesion images are subjected for down sampling using CNN pooling layer where number of parameters got reduced. Lastly, fully connected layer generates a scores for the classes will be utilized for classification process.Deep saliency segmentation outperforms by obtaining the concatenated super pixel images. The image threshold is set to identify the required segmentation of the images. Later, the boundaries of the segmented image are computed with an active contour model. This deep saliency segmentation with the CNN model finds the exact location of the pigmented skin lesion. Mathematically, the convolution layer is expressed as follows with convolution and bias matrix.

$$C^n = \sum \omega_{x,y}\, X\, We^n + Ba^n \;\ldots\ldots (1)$$

Where, C^n is the convolution layer. n denotes the number oflayers. $\omega_{x,y}$is the extracted image with x and y dimensions. We^n is the weight of the n^{th} layer and Ba^n is the bias of the n^{th} layer. The salient image is identified by using the threshold function and it is expressed in equation 2.

$$\tau_d = \aleph\left(\omega_{sal}(x, y)\right) \;\ldots\ldots (2)$$

$$\omega_{seg}(x, y) = \begin{cases} 1, & for\ \omega_{sal}(x,y) > \tau_d \\ 0, & for\ \omega_{sal}(x,y) < \tau_d \end{cases} \;\ldots. (3)$$

Where, τd represents the threshold value and it identifies the possible salient imageω_{sal}(x,y). The segmented image is obtained by using the equation 3 and it denotes theω_{seg}(x,y). The binary value 1 will be considered if the salient image is greater than the threshold. The binary value 0 will be considered if the salient image is lesser than the threshold. Figure 4 shows the region of interest (ROI) of the segmented images which are obtained based on the high intensities ranges in the pre-processing image. In the figure shown below, A represents the selected channel, B represents the mapped image, C represents the ground truth image, and D represents detected lesions.

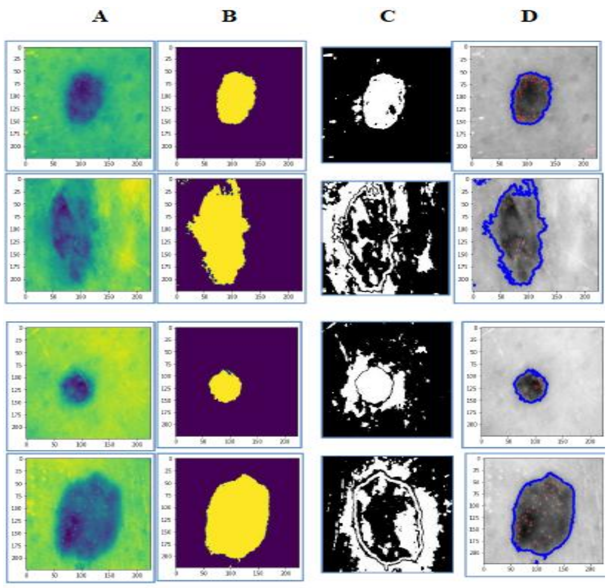

Fig 4: ROI of the segmented images

3.4 Feature Extraction

Feature extraction is performed to extract the relevant features from the segmented images to classify the images. The image features such as asymmetry, border irregularity, color, and diameter (A, B, C, D) are extracted in this work and discussed in below points:

A. Asymmetry: Asymmetry of the skin lesion region is identified using asymmetric index (AI) and eccentricity. AI is calculated by taking differences among the pixels of the skin lesion image with its both horizontal and vertical flip. Then ratio between differences and image area is computed, lastly their average is taken as shown in equation 4.

$$\text{Asymmetry\_Index} = 0.5 * \frac{imagearea\ - image\ hfliparea}{imagearea} + \frac{imagearea\ - imagevfliparea}{imagearea} \;\ldots\ldots (4)$$

B. Border Irregularity: The border irregularity is computed using equation 5, Where P is the perimeter of the lesion boundary and T is the lesion area.

$$B = \frac{P^2}{4\pi T} \ldots\ldots (5)$$

C. Color: Color of the pigmented skin lesions are extracted here. If the colored images occur in red, blue, green, and gray the value will be considered as 1. For other colors, the value will be considered as 0. Equations 6 is used to define the color components for RGB. Where, σ_r ,σ_g and $\sigma_b$are defined as standard deviations of the RGB components of lesion area and M_r, M_g and $M_b$are maximum values of the RGB components respectively.

$$Cr = \frac{\sigma_r}{Mr}, \qquad Cg = \frac{\sigma_g}{Mg},$$
$$Cb = \frac{\sigma_b}{Mb} \dots\dots\dots (6)$$

D. Diameter: Each image has a different diameter, usually, the mole will be less than 6mm but if the affected region is greater than 6mm diameter, there is a possibility of skin cancer occurs.

3.5 Classification

Classification of the skin lesions is the last phase for the recognition and categorization of skin cancer is performed using the light GBM classifier. It operates from based on the principle of gradient boosted decision tree (GBDT) technique [24-26]. Basically, it provides different hyper-parameters for attaining finest performance and outperforms most of the state-of-art machine learning algorithms as well. This classifier performs based on the gradient-based on side sampling (GOSS), which particularly eliminates the unwanted portions and considers only required region for the sampling process which improves the accuracy. This classifier categorizes efficiently and provide 96.6% of accuracy on Kaggle dataset. Out of 1000 image samples, 80% of data was used for training and 20% data was used for testing. The detail classification results are tabulated in Table 1 and also discussed in next section.

4. EXPERIMENTAL RESULTS

Experimental evaluation of proposed method is conducted using the training and testing data of Kaggle dataset. In the training phase, the model is trained to map the input of fused features to corresponding skin lesion category. In the testing process, the model is tested in terms of making accurate classifications. The proposed approach is evaluated using different performance metrics such as accuracy, sensitivity, and specificity. These metrics are the elements of the confusion matrix which provides the summarization of the classification results.

The confusion matrix compares the actual values and the predicted values. The performance of the classifier in terms of the performance metrics is calculated as shown in equation 7,8,9 and 10. Accuracy is the percentage of correctly detected skin lesions. Precision is defined as the accuracy of positive predictions. Recall is defined as the ratio of the skin lesions images that are accurately classified. Similarly, F1 score is determined as the weighted harmonic mean of its precision and recall.

$$Accuracy = \frac{TP+TN+}{TP+TN+FP+FN} \dots . (7)$$

$$Precision = \frac{TP}{TP+FP} \dots . (8)$$

$$Recall = \frac{TP}{TP+FN} \dots\dots (9)$$

$$F1\ score = \frac{2\ Precision * Recall}{Precision\ \ +Recall} \dots . (10)$$

The Total Dermoscopic Value (TDV) is calculated using equation 11. Where A denotes asymmetry, B denotes Border integrity, C denotes the color, and D denotes the diameter. Based on the TDV , the level of skin lesion can be estimated. If the TDV ranges from 1 to 4.76, the image sample is considered as a benign skin lesion. If the TDV ranges from 4.76 to 5.45, the image sample is considered as a suspicious disease. If the TDV is greater than 5.46, the image sample is defined as melanoma.

$$T_{DV} = (A * 1.3) + (B * 0.1) + (C * 1.5) + (D * 0.5) \dots . (11)$$

The performance of the proposed approach compared with the existing classifiers such as SVM and KNN. Table 1 shows the obtained results for the proposed and existing models.

Table 1. Comparison of experimental results

METHODS	**Precision (%)**	**F-score (%)**	**Recall (%)**	**Accuracy (%)**
KNN	75.5	72.8	70.4	75.8
SVM	50.7	61.8	79.2	53.2
Proposed LGB	**94.4**	**96.5**	**98.7**	**96.6**

In comparison to the other existing models such as SVM and KNN model, the proposed classifier provides more accurate results with the help of the ABCD feature extraction process. The Total Dermoscopic value (TDV) helps to calculate the skin lesion obtained from the images and the light gradient boosting model provides high accuracy in the results compared to the other existing models. It can be observed from the comparative analysis shown in figure 5 and Table 1, the proposed LightGBM classifier with CNN archives superior accuracy compared to existing SVM and KNN. The accuracy of 96.6% is obtained by using the proposed approach and with KNN is 75.8% and SVM is 53.2%. A precision of 94.4% is obtained for the proposed approach and the existing precision values are 75.5% and 50.7% for KNN and SVM techniques respectively. The recall for the proposed approach is 98.7% and the existing values are 70.4% and 79.2% for KNN and SVM techniques respectively. The F1 score of the proposed technique is 96.5% and the existing values of KNN and SVM have 72.8% and 61.8% respectively.

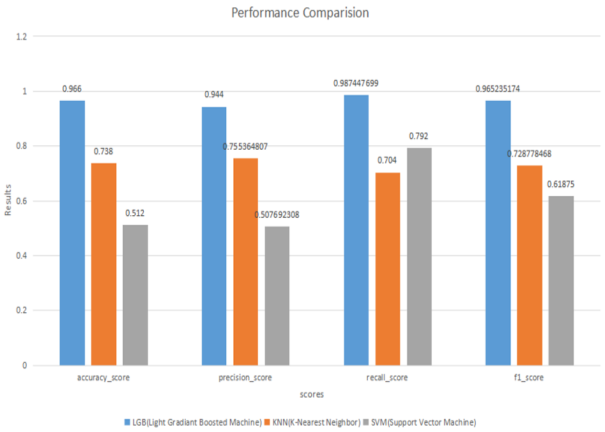

Fig 5: Comparative graph

Along with accuracy, the performance of the proposed classifier is also tested in terms of computational time and the resultant comparison is shown in figure 6. The computational time taken by the proposed classifier is 0.309 second which is lesser than the KNN and SVM classifiers whose computational time is 0.364 seconds and 0.996 seconds respectively. The time comparison results validate the fast computation performance of the LightGBM classifier.

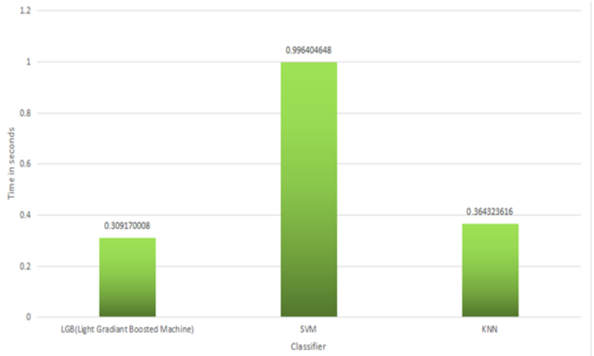

Fig 6: Time comparison graph of the classifiers

5. CONCLUSION

This research implemented an automated DL approach for skin lesion detection and classification. In this proposed method, the CNN model with deep saliency segmentation provides a high-quality salient image in the local and global view. The affected image is pre-processed before being segmented using deep saliency segmentation with ten different convolutional layers based on the threshold level. Asymmetry, boundary irregularity, Color, and diameter were used to extract image features and were further classified using the LightGBM classifier. Results of the experimental evaluation shows that the proposed approach achieves a phenomenal accuracy of 96.6% compared to existing SVM and KNN classifiers. It was observed from the analysis that the LightGBM classifier works faster compared to the other boosting based classification algorithm. Additionally, this technique provides accurate results even in the larger dataset by using a decision tree algorithm. This approach is best identified for image segmentation and image classification to predict accurate results in faster and large datasets. The proposed model can be extended in the future to reduce design complexity by analyzing automated image classification without the segmentation process.

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