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Article Title: Skin Cancer Detection Using Clustering and Deep Learning-Based Classification

Skin Cancer Detection Using Clustering and Deep Learning-Based Classification

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ABSTRACT

In this work, to develop an accurate segmentation and classification of skin lesions, have presented a fuzzy clustering and deep neural network (DNN) in segmentation and classification of skin lesions. The proposed effective segmentation and classification procedure is described as; initially input image is taken from the dermoscopy images database. In the pre-processing stage, the input dermoscopy image undergoes Gaussian filter and morphological operations. Then fuzzy clustering is applied to the pre-processed images for the segmentation of lesion regions. Subsequently, effective features such as texture features are extracted from the segmented output images. Finally, the proposed DNN classifier classifies the skin lesion images into normal or abnormal images based on the extracted features. The results were analyzed to demonstrate the performance of the proposed segmentation and classification technique with the existing techniques.

Keywords: Segmentation, Fuzzy Clustering, Deep Neural Network, Dermoscopy Images, Skin lesion

1 Introduction

Image processing is a method to perform some operations on an image, to get an enhanced image, or to extract some useful information from it. It is a type of signal processing in which the input is an image and the output may be an image or characteristics/features associated with that image [1]. Nowadays, image processing is among the rapidly growing technologies. It forms core research areas within engineering and computer science disciplines too [2].

There are two types of methods used for image processing namely, analog and digital image processing. Analog image processing can be used for hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. Digital image processing techniques help in manipulation of the digital images by using computers [3]. The three general phases that all types of data have to undergo while using digital techniques are pre-processing, enhancement, and display, information extraction.

The Convolution-based deep neural networks have been used for skin cancer detection using ISIC public dataset. Cancer detection is a sensitive issue, which is prone to errors if not timely and accurately detected. The performance of the individual machine learning models to detect cancer is limited [4]. The combined decision of individual learners is expected to be more accurate than that of individual learners. The ensemble learning technique exploits the diversity of learners to yield a better decision. Thus, the prediction accuracy can be enhanced by combing the decision of individual learners for sensitive issues such as cancer detection. In this paper, an ensemble of deep learners has been developed using learners of VGG, CapsNet, and ResNet for skin cancer detection [5].

2. Related Work

Adegun et.al [6] These ROI-based approach helps to identify discriminative features as the images containing only melanoma cells are used to train the system. Further, use a Convolutional Neural Network (CNN) based transfer learning model with data augmentation for ROI images of DermIS and DermQuest datasets. The proposed system gives 97.9% and 97.4% accuracy for DermIS and DermQuest respectively. Hasan et.al [7] paper proposed an artificial skin cancer detection system using image processing and machine learning method. The features of the affected skin cells are extracted after the segmentation of the dermoscopic images using the feature extraction technique. A deep learning-based method convolutional neural network classifier is used for the stratification of the extracted features. An accuracy of 89.5% and the training accuracy of 93.7% have been achieved after applying the publicly available data set. Bozkurt et.al [8] the goal of the DLCAL-SLDC model is to detect and classify the different types of skin cancer using dermoscopic images. During image pre-processing, dull razor approach-based hair removal and average median filtering-based noise removal processes take place. Finally, the classification is carried out by the Swallow Swarm Optimization (SSO) algorithm-based Convolutional Sparse Auto Encoder (CSAE) known as the SSO-CSAE model. The proposed framework has accomplished promising results with 98.50% accuracy, 94.5% sensitivity, and 99.1% specificity over the other methods in terms of different measures.

3 Proposed Methodology

In this paper's preprocessing stage, the input dermoscopy image undergoes the filter and morphological operations. Then fuzzy clustering is applied to the preprocessed images for the segmentation of lesion regions. Subsequently, the effective features texture feature is extracted from the segmented output images. Finally, the proposed DNN classifier CNN classifies the skin lesion images into normal or abnormal images based on the extracted features shown in Fig 1.

3.1 Pre-processing

Detection procedures require pre-processing of raw data as the data may contain noise. In skin lesion images, captured images typically carry noises encompassing uneven illumination, skin surface light reflection, and hair. One of the techniques to resolve noises in pre-processing is the usage of filters.

3.2 Segmentation

This section of the project's goal is to isolate the lesion from the surrounding skin. Use the Fuzzy C-means Clustering, was applied. Because the morphology of each lesion varies from

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image to image, segmenting the lesion is a difficult task. Some lesions have sharp edges, while others have fuzzier margins. Furthermore, some lesions can be broken down into small condensed blobs of pixels, and others include very small regions of healthy skin within the central lesion.

Stage 1: The fuzzy clustering is given in condition (2).

$$S(A,B) = 1\left(1 + e^{-s_i(t)}\right) \tag{1}$$

Stage 2: Afterward, the enlargement action is one of the bases of morphology handling utilized. $\overline{A}$ Is expanded by $\overline{B}$, composing as $\overline{A} \oplus \overline{B}$ characterized:

$$\overline{A} \oplus \overline{B} = \left\{z \middle| \left(\hat{B}\right)_z \cap \overline{A} \neq \phi\right\} \tag{2}$$

Amongst them, ϕ is the unoccupied set, $\overline{A}$ which is for the organization component, and $\hat{B}$ is for the imprint of assortment $\overline{B}$. To put it plainly, that $\overline{A}$ is distended by $\overline{B}$ the set shaped by the preliminary opinion seats of entirely essential fundamentals. Here, the pre-processed images are grouped into clusters. The clustering is to minimalize the cost function.

$$I_c = \sum_{k=1}^{n} \sum_{c=1}^{C} \frac{u_{kc}^{m} \left\| x_k - v_c \right\|^2}{S(A,B)} \tag{3}$$

With constraints of,

$$\sum_{c=1}^{C} u_{kc} = 1, \quad 0 \le u_{kc} \le 1, \tag{4}$$

By the side of this point, v_c is the centroid of c^{th} the cluster, u_{kc} which labels the fuzzy association of n^{th} text document in the direction of the c^{th} cluster, m depicts the fuzziness of calculating [m ≥ 1], anticipated for example, slighter m recommends crisper grouping as well as $\|.\|$ attitudes for some norm. Here, it is Euclidean distance. Cluster Centre is calculated as,

$$v_c = \frac{\sum_{k=1}^{n} u_{kc} x_k}{\sum_{k=1}^{n} u_{kc}} \tag{5}$$

Therefore, matrix U = [u_{kc}] as well as vector V = [v_c] necessity be efficient as declared by (6) in addition to (7) up until received the stopover criterion characteristically as

$$\left\| U(t) - U(t-1) \right\| \le \bar{\varepsilon} \tag{6}$$

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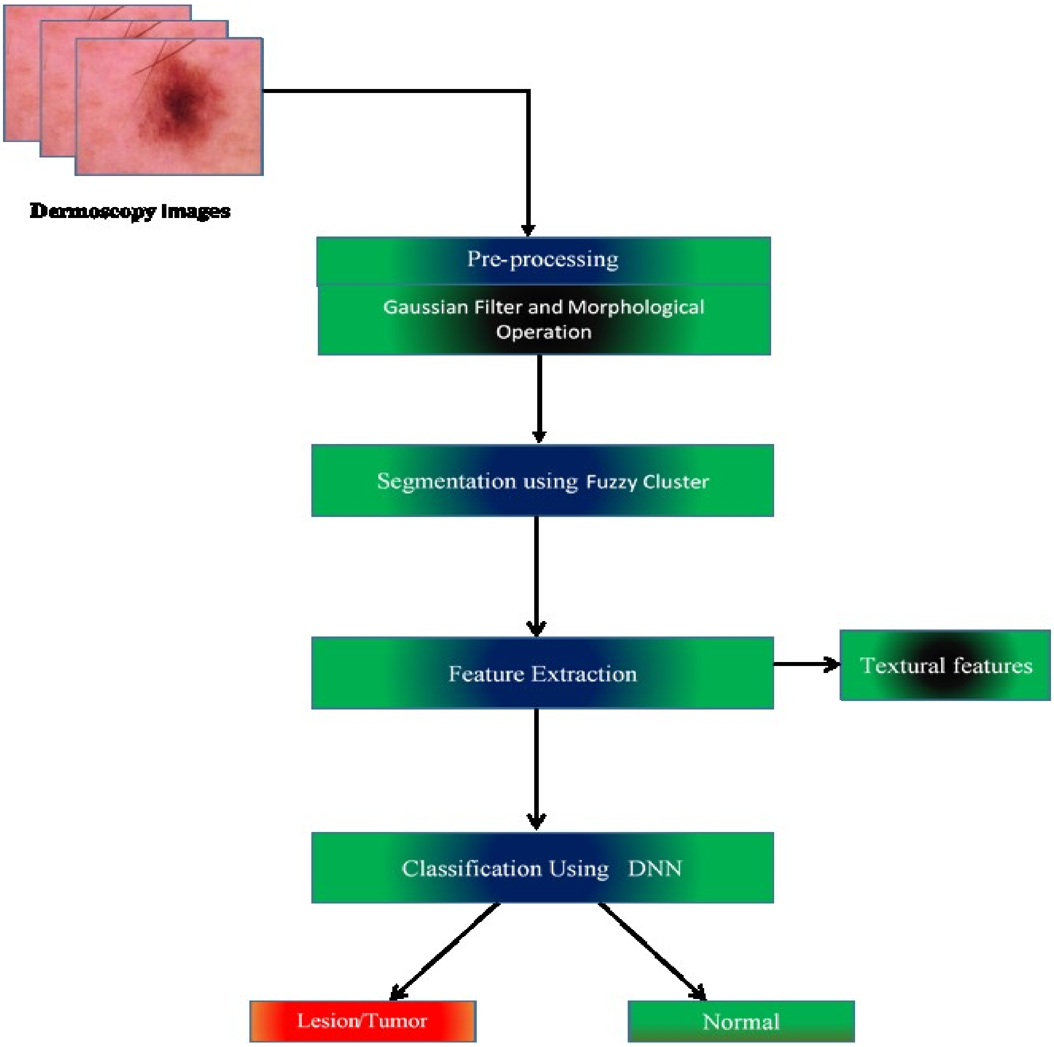

Figure 1: *Proposed System Architecture*

This point $\bar{\varepsilon}$ signifies the threshold limit. In this enthalpy-based fuzzy c-means clustering process; actual features are extracted on behalf of Cluster processing.

3.3 Feature Extraction

Texture Feature

LGXP (local Gabor XOR pattern) the fundamental idea of implementing the LGXP technique is to obtain texture value. This results in the texture features of the image which is easier to find the similarity with the texture features while imaging retrieval.

3.4 Classification

Deep Neural Network (DNN)

They are different DNNs are typically networks where data flow from the input level to the output layer. The proposed DNN solves the DNN problems. C-convolution, MP-max pooling, and FC-full connectivity are explained in the layer type. Table 1, containing three

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convolutionary layers, two max-pointing layers, a fully connected layer, and a softmax classification, gives a comprehensive illustration

Table 1: *Details of the proposed Deep Neural Network*

Patch Size		Layer1	Layer2	Layer3	Layer4	Layer5	Layer6	Layer7
16X16	Layer Type	C	MP	C	MP	C	FC	Softmax
	Filter Size	5 X 5	2X2	5 X 5	2X2	5X5	3X1	1X1

Layer 1: Convolution layer: This layer finishes the convolution of the input data with the kernel by using a condition (12).

$$C_k = \sum_{m=0}^{M-1} Z_n \hat{h}_{k-n} \tag{7}$$

Where Z_n represents reproduced segmented images, $\hat{h}$ represents the filter, and M represents the number of components in Z & the output vector C_k.

Layer 2: Normalization layer: The linear alteration of data to fit into a specific range is known as normalization. For data standardization, the Z-score normalization method is used, which transforms data linearly. By using equation (8) describes how to normalize Z-scores:

$$Z_{norm} = \frac{1-\mu}{\sigma} \tag{8}$$

Layer 3: Pooling layer: The max-pooling algorithm selects only the highest value in each feature map, resulting in fewer output neurons. Pooling layers are often used after convolution layers to simplify the data within the output of the convolution layer.

Layer 4: Fully connected layer: The output layer uses the softmax function to search out a preceding layer outcome that matches the foremost normal or malignant or benign.

$$p_i = \frac{e^{y_i}}{\sum_1^k e^{y_i}} \tag{9}$$

Where y, which represents the resultant image. Here, the DNN is adapted with the sigmoid function-based normalization to direct the over-fitting in layers and conclusions in the important classification of skin cancer into normal or lesion.

4 Result and Discussion

This work uses the ISIC dataset. The statistical measures of sensitivity, specificity, and accuracy can be represented in terms of TP, FP, FN, and TN value. The performance of our

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proposed work is investigated by using the statistical measures referenced in this section, The Performance Measures Formula is shown in Table 2.

Table 2: *Representation of Performance Measures Formula*

Performance Measures	Formula
Accuracy	$\frac{(TN + TP)}{(TN + TP + FN + FP)}$
F1-Score	$\frac{2TP}{2TP + FP + FN}$
Precision	$\frac{TP}{TP + FP}$
Recall	$\frac{TP}{TP + FN}$

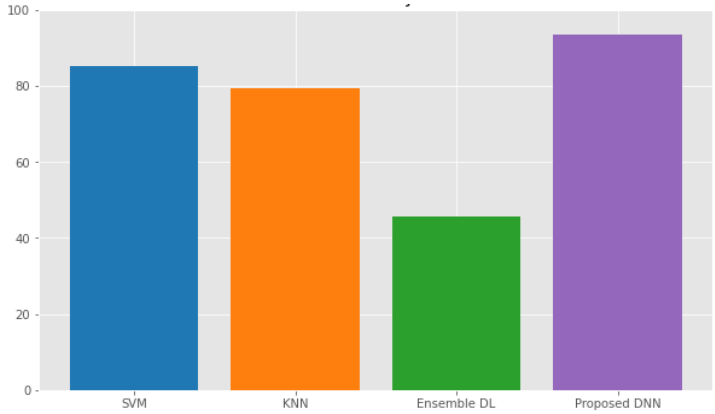

Figure 2: *Accuracy*

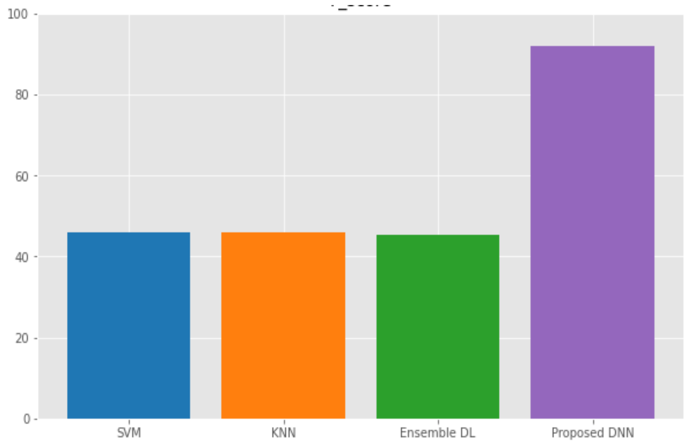

Figure 3: *F1-Score*

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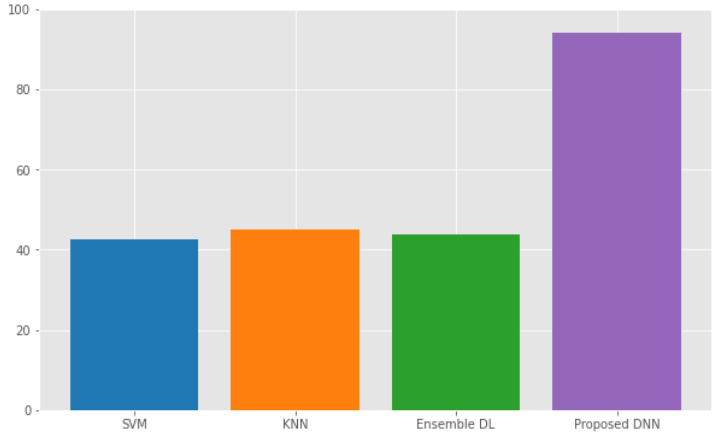

Figure 4: *Precision*

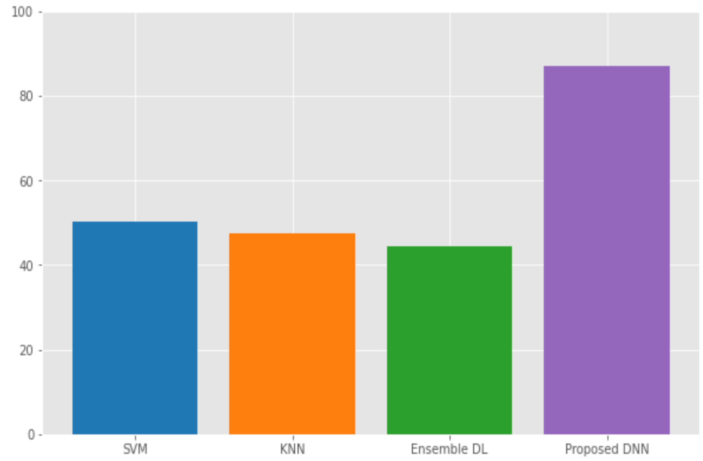

Figure 5: *Recall*

The analytical classification execution of the proposed method is illustrated in Figure 2, the analysis result shows that our proposed method beats the current SVM [9], KNN [10], and Ensemble DL classifiers. Determine that the most extreme accuracy of the proposed technique is up to 99%, while the least accuracy is KNN at 79% and Enable DL at 55%. The outcomes further confirm the adequacy and strength of the proposed technique. The analytical classification execution of the proposed method is illustrated in Figure 3. Determine that the most extreme F1 Score of the proposed technique is up to 90%, while the least F1 Score is KNN 58% and Enable DL 55%. The outcomes further confirm the adequacy and strength of the proposed technique. The analytical classification execution of the proposed method is illustrated in Figure 4. Determine that the most extreme precision of the proposed technique is up to 90%, while the least precision is KNN 58% and Enable DL 55%. The analytical classification execution of the proposed method is illustrated in Figure 5. Determine that the most extreme recall of the proposed technique is up to 90%, while the least recall is KNN at 58% and Enable DL at 55%.

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5 Conclusion

The lesion is the leading cause of death due to skin cancer. To overcome such issues, a method called fuzzy clustering and DNN in the segmentation and classification of skin lesions is used. The input images are taken at the initial stage. Those images are pre-processed using image acquisition and contrast enhancement followed by Segmentation using the Fuzzy clustering method and the texture features are extracted from the segmented output images. In the final step, a DNN classifier is used which classifies the skin lesion images into normal or abnormal images based on the extracted features. In this work, our proposed technique is compared with the other three existing methods called SVM, KNN, and Ensemble DL for the evaluation of performance metrics. Our proposed method attained results of about 94% Accuracy, 85% Sensitivity, and 86% Specificity. The results show that our method outperforms well in comparison to the other methods.

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