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**Article Title**: **Skin Cancer Detection Using Deep Convolutional Neural Network with Advanced Segmentation Approach**

# Skin Cancer Detection Using Deep Convolutional Neural Network with Advanced Segmentation Approach

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## ABSTRACT

Skin cancer is a deadly disease, which require early detection to prevent and treat it successfully in its early stage. This paper address the detection of skin cancer using Deep Convolutional Neural Network (DCNNs) classification approach.The classification stage follows by implementing wiener filter to remove the impacts of noise and inverts the blurring in the input image .Further, Segmentation is done using k-means clustering which separates the interest area from the background to isolate the region of interest. The proposed method uses, Scale Invariant Feature Transform (SIFT) for feature extraction to identify unique and reliable characteristics in an image to increase the deep learning model's effectiveness and precision. For the accurate classification of skin cancer, a DCNNs model is analysed where the architecture combine Convolutional and Recurrent Neural Network (CNN-RNN) to enhance skin cancer classification. The proposed method is developed in python software with high accuracy of 93% makes the proposed methodology to be efficient and wellbeing.

**Keywords:** DCNNs, SIFT, Wiener Filter, K-means clustering, skin cancer.

## 1 Introduction

The skin cancer is extremely deadly type of cancer, which is dangerous and possibly fatal in the absence of treatment. It highlights the significance of frequent screening and raising awareness of cancer-related deaths among people globally [1]. There are numerous way to identify skin cancer like Biopsy and visual inspection. Many non-invasive methods have been developed to assess the skin cancer and detect it in its early stage.

The detection approach known as Biopsy is uncomfortable, time-consuming. However it is costly and it also injure the patient with scar, infections and discomfort [2-3].Technologies for image processing improve diagnostic precision by lowering false positive outcomes and improving abnormality. Image pre-processing includes multiple essential categories, comprising feature extraction, classification, segmentation and preprocessing. Preprocessing of an image is essential, however the presence of noise and poor image quality it is difficult to detect cancer cells. Implement wiener filter to lessen the impacts of noise and inverts the blurring simultaneously in image processing.

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Image pre-processing is used to smooth out images using a filtering process, remove noise, and enhance image quality. However mean filter is simple and efficient in lowering noise make it perfect for real time applications and quick processing but it affects the possibility of small details lost or blurred [4]. To overcome this challenge, Image preprocessing filtering investigates the Wiener filter as a solution to this problem, which reduces the effects of noise while preserving a number of characteristics. [5]. Segmentation is the process of separating an input sample into discrete areas to remove background and isolate the Region of Interest (ROI). Hence this approach show resilience and enhanced optimization performance, producing better segmentation results. Nevertheless, it is difficult to obtain reliable result since the segmentation are extremely sensitive to threshold selection [6]. To Overcome this limitations, k-means clustering has a high clinical usefulness and also helping medical specialists in diagnosis by using area filtering and template creation.

After segmenting and image processing, the feature extraction makes use of texture features. Techniques such as Discrete Wavelet Transform (DWT) uses low pass and high pass filters to decompose the image. However, during the decomposition process DWT cause information to lose which affect the relevancy of the extracted characteristics [7]. Gray Level Co-Occurrence Matrix (GLCM), a sequence of images is compared to each other to find the point of diminishing returns. However it faces high dimensionality of the matrix and the high correlation. To overcome this the feature extraction implement Scale Invariant Feature Transform (SIFT) to function key points by their local intensity extreme. Therefore it effectively detects and describes image extraction at different scales it also improves data motion and eliminates white space [8].

Finally classification methods in skin cancer processing involves classifying images based on features thus here the classification types such as Support Vector Machine (SVM) and K-Nearest Neighbour (KNN). SVMs for skin cancer classification analyse complex datasets related to skin cancer because of their capacity to handle high dimensional data effectively. Even with a small quantity of training data, it produces consistently strong classification results. Nevertheless, SVM is sensitive to the hyper parameter and kernel selection, which necessitates fine tuning and also it performs low when recognizing unusual cases due to imbalanced datasets [9]. KNN for skin cancer classification is simple and convenience of use enable clear interpretation of results and various dataset adaptation without a lot of parameter. However using this for skin cancer classification is sensitivity and the number of features rises leads to less accurate and larger costs.

Deep Convolutional Neural Network (DCNNs) is one type of neural network used for multidimensional sample processing and also used commonly to identify patterns in images. It is used for automatic feature extraction and outperforms high accuracy, sensitivity and precision [10]. However to tackle the dual difficulties of temporal and spatial complexities, provide a unique hybrid Convolutional and Recurrent Neural Network (CNN-RNN) model. To

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increase the thoroughness and precision of skin cancer classification, the benefits of both temporal sequence learning and spatial feature extraction are combined.

This paper enhances skin cancer through image processing technique particularly wiener filter that reduces the noise and gives excellent output for further process. By using k-means clustering for segmentation and SIFT for feature extraction, this indicate the damaged part and the result is more accurate for diagnosis. Hence DCNNs significantly results in classification accuracy and detect earlier to improve outcomes in skin cancer.

## 2 Related Work

**Tryan Aditya Putra *et al* (2020*),*** have analysed skin cancer prediction through machine learning using dynamic training and testing augmentation. The main objective of the proposed methodology is to increase the performance and deliver a superior result by having multiple probabilistic and dynamic augmentation. However to achieve high accuracy more steps are needed to train the model.

**H.L.**Gururaj ***et al*** **(2023),** have analysed the detection of skin cancer by using deep learning methodology. In this deep learning method, convolutional neural networks (CNN) has excelled in both object detection and classification tests. Thus it is excellent in image classification with high accuracy and process high dimensional data. However it suffer from information loss and time consuming is high.

**Adekanmi A.Adegunet *al (*2020*),*** have analysed the detection and classification of skin cancer using deep learning based computer-aided diagnosis (CAD) method. By using this technique the time complexity is reduced and increase the efficiency without decreasing the quality of the image. However the performance of this method is decreased when presented with large or complex datasets.

**Muhammad Attique Khan *et al (2021),*** have analysed the segmentation of skin lesion using 16-layered CNN architecture and a High Dimensional Contrast Transform (HDCT) approach. This process improved the accuracy of segmentation compare to advanced approach with less computational time. By using the transfer learning, classification module is performed which lead to more accurate results .Nevertheless the performance of hybrid strategy time consuming is high and harder to enforce.

**Azhar Imran *et al (*2022*),*** have analysed the detection of skin cancer using machine learning with convolutional based deep neural network. By using machine learning approach CNN provide an efficient prediction and identification from the input image and the time consuming is low. However, CNN requires huge amount of labelled training data to achieve high accuracy.

## 3 Proposed System Description and Modeling

### 3.1 Block Diagram

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The processing of skin cancer images plays a crucial role in early findings and diagnosis. Figure 1 represent the block diagram showing well image processing works in skin cancer. First, Wiener Filter is applied to the input skin images that technique effectively reduces noise and produce an output of excellent quality for subsequent analysis. The K-means clustering algorithm is used in segmentation after preprocessing. K-means allows for the detection of segmenting the image, such as tissues or possible abnormalities, by clustering pixels based on their intensity levels. This step is vital for isolating areas of interest that indicate skin cancer. Once segmentation is complete features are extracted using the SIFT method. To detect similar patterns in other images, a feature extraction method SIFT is used to reduce the image content to a set of points

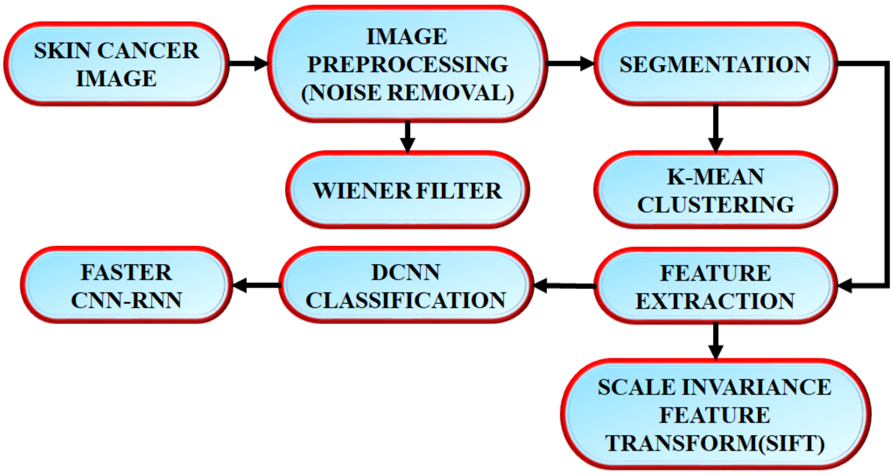


**Figure 1:** *Block Diagram of Proposed System*

By using SIFT, it support in predicting the spread of the disease and its severity by performing transformations such as rotation, scale scaling, brightness adjustments, view angle modifications and affine translation SIFT features stay stable. The collected characteristics are identified using DCNNs, a classification technique that ultimately increases diagnosis accuracy. This method contributes to prompt and efficient diagnosis which is necessary for improved patient outcomes by improving image quality and precisely detecting aberrant regions.

### 3.2 Preprocessing Based Wiener Filter

Preprocessing is essential for accurately analysing input images in skin cancer diagnosis. The Linear Minimal Mean Square Error (LMMSE) estimator of the Wiener filter, effectively reduce noise. By imposing a minimum mean square error restriction between the estimate and the original image the Wiener filter attempts to create an ideal approximation of the original image. The aim of wiener filter is to reduce noise from the input image to provide an estimation of the underlying sample of images. According to the degradation model, $E(M, N) = F(M, N) -$

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$F(m,n)$ is the error between the input image $f(M,N)$ and the estimated image is $f(m,n)$.The formula for the square error is

$$[F(M,N) - F(m,n)] \tag{1}$$

The formula for the mean square error is

$$E\{[F(M,N) - F(m,n)] \tag{2}$$

This method allows the filter to eliminate noise efficiently while maintaining texture and edge details. For later segmentation and classification tasks this preprocessing step is crucial which ultimately leads to more dependable diagnostic result. To identify and categorize the various features, segment the images after preprocessing them.

### 3.3 Segmentation Based K-Means Algorithm

K-mean clustering is the most popular and extensively used one for its simplicity and with low computational time. K-means segmentation is used in the analysis of images related to skin cancer, offering vital assistance in the processes of diagnosis and treatment planning. This method efficiently classifies pixel information from images used in medicine, including histology slides or skin images, enabling the identification of aberrant cells and tissues by grouping them into discrete clusters according to colour and texture characteristics.

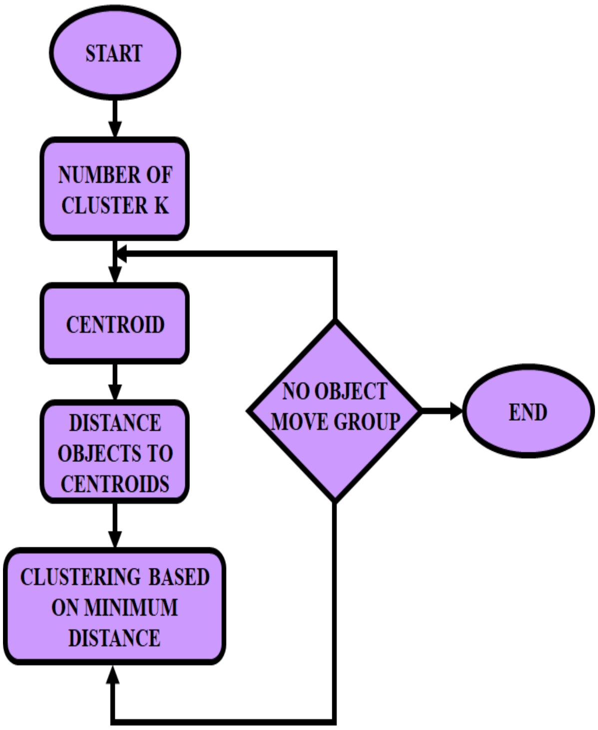


**Figure 2:** *Flow chart based on k-means algorithm*

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K-means segmentation is especially in the analysis of images related to skin cancer research since it distinguish between malignant, dysplastic, and normal cells. The data partitioning procedure called k-means clustering interactively allocates n observations to one of the $k$ clusters defined by centroid where the value of $k$ is predetermined. Let $X = \{x_1, x_{2,} x_3, \dots\dots x_n\}$ be the set of data points and is represented by $n$ and $C = \{c_1, c_2, c_3, \dots . c_{n\}}$ be the set of clusters represented by $m$. Clustering the $n$ data points into $c$ cluster centres is the goal. The objective function of the k-means clustering algorithm is defined by equation

$$J = \sum_{i=1}^{m} \sum_{j=1}^{n} \left\| x_{i-c_I} \right\|^2 \tag{3}$$

Here k = number of clusters and n = total number of data .Thus by minimizing this objective function the optimal centre is obtained. The flowchart of the k-means clustering technique, shown in Figure 2, shows how to divide a dataset into discrete groups step-by-step. Here the feature extraction is to determine the essential attributes that characterize each cluster and improve analysis after effectively implementing the K-means method for segmentation, which divided the data into discrete clusters based on similarity.

### 3.4 Feature Extraction Based Scale Invariant Feature Transform

Feature extraction is an essential step especially when it comes to texture analysis following image segmentation. Regardless of the scale, rotation or image modification applied to the input image SIFT retrieves key points from it. The image similarities are then calculated using the SIFT key points. SIFT keys are the feature vectors that are produced and object models are identified using a nearest-neighbour indexing technique using the SIFT keys extracted from an image. The two parameters that define the extraction of SIFT are the edge threshold and the peak threshold.

In the peak of Small-curvature there is a Difference of Gaussians (DOG) scale space that eliminated the edge of threshold. Low absolute values are displayed which removes the peak value of DOG space scale. A collection of SIFT key point identify the potential of suspicious areas is the result of the SIFT-based approach. The incorporation of SIFT traits has been shown in figure 3 to improve diagnostic outcomes by increasing the overall accuracy of skin cancer diagnosis. After features are extracted, the image is subjected to a classification system in order to classify the cells as either benign or malignant for the purpose of diagnosing skin cancer.

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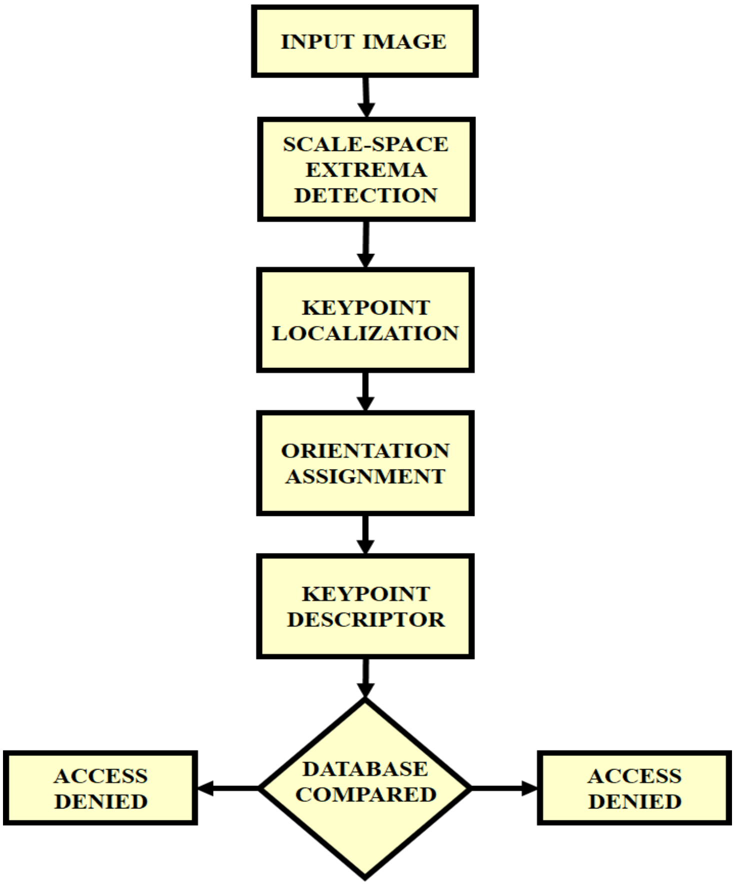


**Figure 3:** *Flow Chart Based On SIFT For Feature Extraction*

### 3.5 Classification Based Deep Convolutional Neural Network

The DCNNs is one type of neural network, which performs in image processing. Tens to hundreds of processing layers make up the architectures of DCNNs, which are capable of extracting several levels of characteristics from image-based data that would otherwise be extremely challenging and time-consuming for professionals to recognize and extract for classification. The Convolution layer, which is the initial layer that are able to extract various features from input images ranging from low level local features to high level global features. Complex features are transformed into the probabilities of specific labels by the fully connected layer at the end of the convolutional neural layers. Various layer types include dropout layer and batch normalization layer that normalizes the input of a layer. A pooling layer comes after the convolutional layer which preserves only the most crucial information while progressively shrinking the images size. Then it is applied last to the fully connected layer outputs it identifies the class which the image belongs to analyse whether there is abnormal tissues. It is used in image identification tasks and therefore yields extremely high accuracy and automatically identifies the key characteristics without the need of human oversight. The flat and progressive

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models were both recently developed, and the dataset was used to finely tune their insights into the categorization challenges of skin disorders.

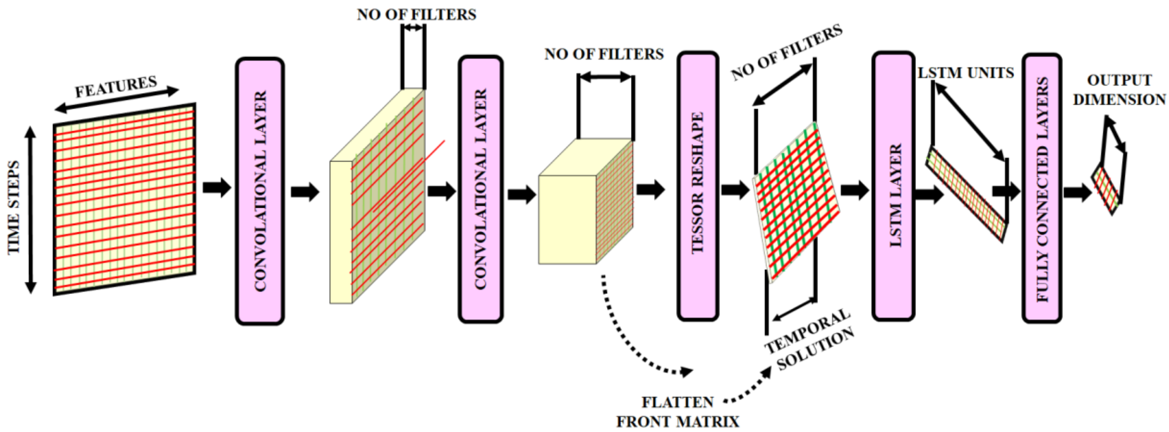


**Figure 4:** *Combined hybrid CNN and RNN*

DCNNs is used to quickly optimize classification and detect to prevent skin cancer in its early stages. The hybrid architecture in the proposed skin cancer classification model combines CNNs with Recurrent Neural Networks (RNNs). Suppose that X is the input image data set, which is a collection of distinct image $\{x_1 x_2 x_3 \ldots . x_{n\}}$. Here n stands for the collection of total number of images.

$fCNN$ Uses the ResNet-50 architecture to extract features from the input images, while I stands for the input images. This can be expressed as shown below equation (4) and (5)

$$fCNN = ResNet - 50(I) \tag{4}$$

$$ZCNN = fCNN(X) \tag{5}$$

The RNN model component the output that captures temporal relationships is represented by FRNN, and the CNN component extracted features are denoted by $fCNN$ . This can be formulated below equation (6) and (7)

$$fRNN = RNN(fCNN) \tag{6}$$

$$ZRNN = fRNN(ZCNN) \tag{7}$$

ZRNN capturing temporal dependencies is represented by the output of the RNN component, which is transmitted through a classification layer to get the final predicted probabilities for each class. This can be represented as

$$\hat{Y} = g(ZRNN) \tag{8}$$

The hybrid design that combines CNNs and recurrent neural networks (RNNs) allows the model to take advantage of the temporal associations recorded by the RNN and the spatial

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properties learned by the CNN. Both of these elements work together enable the model to efficiently extract features and represent the sequential information inherent in skin cancer images.

## 4 Result and Discussion

Skin cancer is detected using DCNNs classifier for more accuracy and the final result is more efficient using hybrid CNN-FNN based on the training and validation of the image analyses. Here the performance of the model is on python software to make the process valuable and efficient one by first initially inputting the image. The input image is then pre-processed with filter technique to make the performance reliable and accurate.

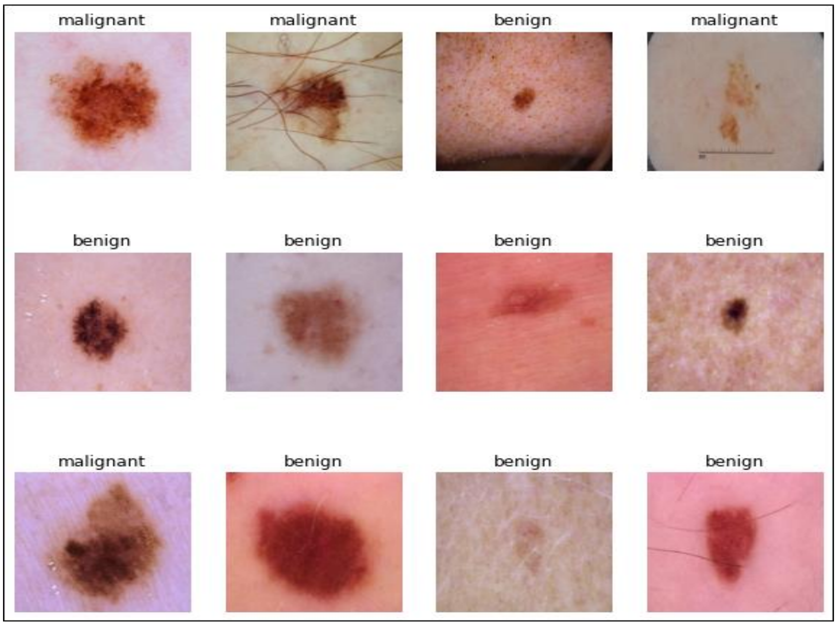


**Figure 5:** *Input of skin cancer*

Figure 5 represents the stages of skin cancer images that explaining the benign and malignant stages of skin cancer. The input images are selected for further process to analyse the skin cancer with preprocessing, segmentation, feature extraction and then classification.

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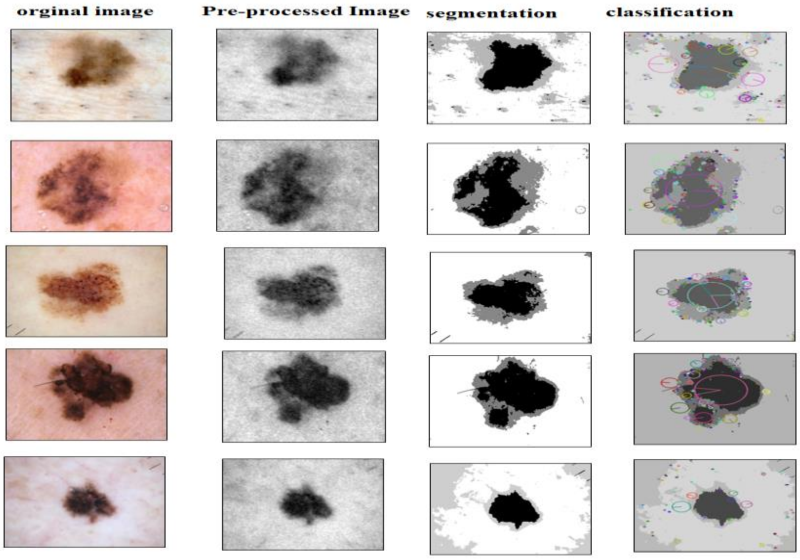


**Figure 6:** *Skin cancer detection using DCNNs*

Here the input images are identified with benign and malignant stage and then the image is pre-processed with wiener filter to remove the noise to make the image more processed for segmentation stage. Here the k-mean clustering is used to divide the dataset by making the process simple and more computing. Segmented images are allowed for feature extraction that indicate the damaged area makes it accurate for diagnosis and then DCNNs is used for classification to make the image to classify according to the stages of the training and validated one.

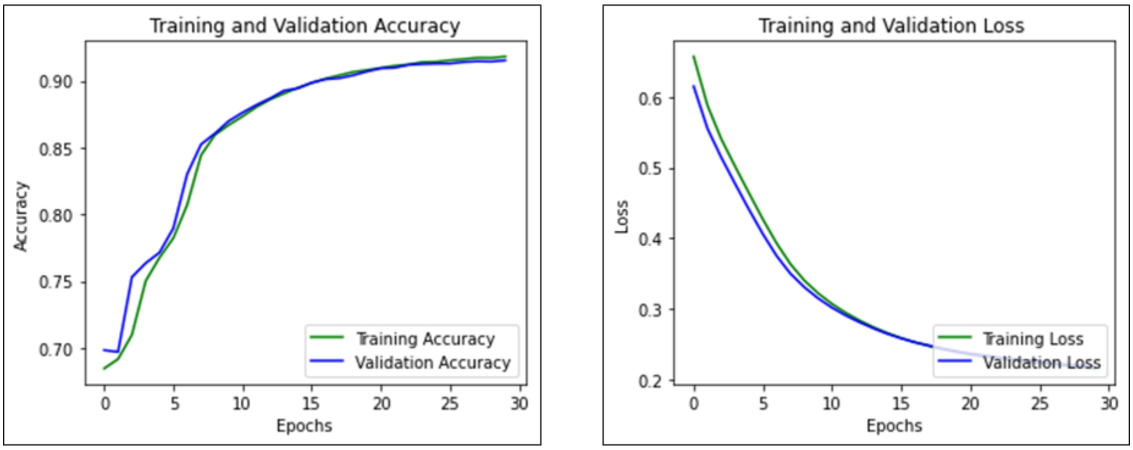


**Figure 7:** *model of training and validation accuracy and loss*

Figure 7 illustrates the training and validation of deep learning classification using models of accuracy and loss applied to the diagnosis of skin cancer. Here the accuracy of the model is high and the training and validation loss is predicted by comparing with other datasets.

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**Table1:** *Comparison classification of accuracy in skin cancer detection*

| METHOD | ACCURACY |
|---|---|
| DCNN | 93% |
| OPTIMIZED CNN[8] | 86% |
| KNN[11] | 89% |

Table 1 represents a comparison of various classification methods for skin cancer detection highlighting that the DCNNs model achieves the highest accuracy at 93% and then KNN model at 89% and optimized CNN at 86%.

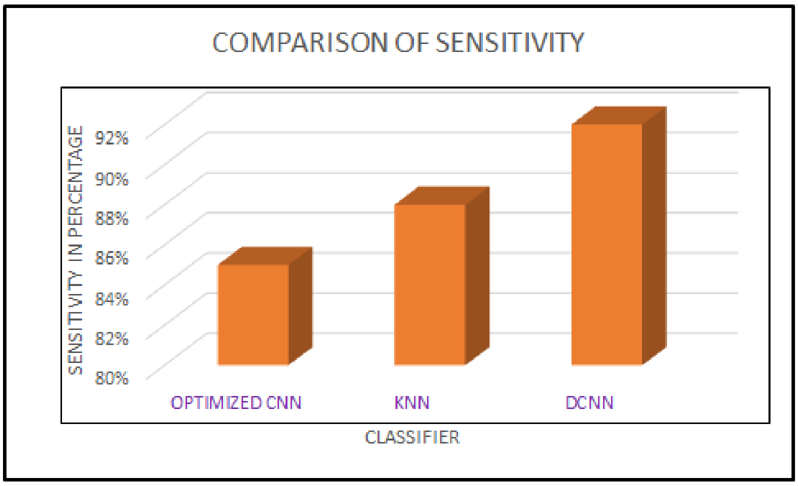


**Figure 8:** *Sensitivity Graph for Skin Cancer Classifier*

Figure 8 denotes the analysis of sensitivity in skin cancer by presenting a detailed comparison of diagnosis performance across different classification techniques. The results of graph indicate that the DCNNs classifier demonstrates a superior sensitivity at 92%, outperforming both the classifiers optimized CNN [8] at 85% and KNN [11] at 88 %.

## 5 Conclusion

This study proposes a technique for classification of skin cancer using a DL based hybrid CNN-FNN to make efficient and accurate outcome of the processed image. The performance of preprocessing to make the quality of the image high and helps to increase efficiency without degrading the image quality. The image that as input is segmented using the K-means clustering technique, which successfully isolated the ROI and made it possible to identify skin cancer with accuracy. Textural information, which is utilized to extract useful features from images for the detection of skin cancer, using the incorporation of SIFT for feature extraction producing highly promising outcomes. For further classification DCNNs is used, the classifier is proved to learn the features and finally classify the image for better relevance. The proposed methodology is that it do the detection in very quick time and hence help the techniques to perfect the diagnostic skills .The DCNNs has high sensitivity with 92% and classification

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accuracy with 93% and suggest that are dependable method for detecting skin cancer. In order to improve patient outcomes in the care of skin cancer, the suggested workflow greatly increases diagnostic sensitivity and accuracy.

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