# AUTOMATED RETINAL ABNORMALITIES DETECTION WITH FUNDUS IMAGE USING IMAGE PROCESSING

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**ABSTRACT**

*Retinopathy is the most common cause of severe vision loss in elderly persons in developed countries and accounts for one-third of cases of untreatable vision loss. Retinopathy is a painless, irreversible, degenerative eye condition associated with the damage and ultimate death of photoreceptors. There are two types of Retinopathy, dry and wet; dry form is far more common, but wet form is usually a more advanced disease state and is associated with rapid distortion and sudden loss of central vision. Various agents are used for treatment, and lifestyle changes and dietary constituents are important for preventing Retinopathy and halting its progression. As new therapies become available, early identification of patients with risk factors for Retinopathy will be increasingly important.*

*This implemented pipeline consists of a number of sub-procedures ranging from Retinopathy infection segmentation to classification. The initial part of the pipeline implements the segmentation of the Retinopathy using Social-Group-Optimization and Kapur's Entropy thresholding and k-means clustering and morphology-based segmentation and the proposed technique helped to achieve a segmentation accuracy higher than 91%. The next part of the pipeline implements feature extraction from the grayscale and binary image, feature-selection,feature-fusion and classification. In this work, the classifiers, such as Random Forest, k-Nearest Neighbors, and Support Vector Machine with Radial Basis Function (SVM-RFB) are considered to classify the CTI. The proposed research implements PCA based serial fusion technique to fuse the features attained from the grayscale and binary image and Fused-Feature-Vector (FFV) is then employed to train, test and validate the classifier. The experimental results suggest that the proposed ML scheme with KNN offers detection accuracy higher than 87%.*

**Keyword: -** *Retinopathy, dry form, wet form, Social-Group-Optimization, Kapur's Entropy thresholding.*

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## 1. INTRODUCTION

Retinopathy is a progressive degenerative disease of the retina in which the macula is most affected. It is the commonest cause of blindness in the UK and it affects mainly older people.

Age-related macular degeneration goes through various stages, called early, intermediate and advanced. The first signs are yellowish deposits in the retina called drusen. Then abnormalities in the colour of the retina develop paler areas called hypopigmentation, and darker areas with hyperpigmentation. Advanced Retinopathy takes two forms, wet and dry, both of which lead to visual loss. Advanced dry form is characterised by atrophy of the retina it wastes away and patches of retina and vision are lost. Because the patches were thought to resemble countries on a map, it became called ‘geographic atrophy’ (GA). The central most detailed vision is lost, making it difficult to drive, read or recognise faces.

Wet form, also called exudative form, is characterised by the development of abnormal new vessel [choroidal neovascularisation (CNV) and retinal angiomatous proliferation (RAP)]. It is now treated with drugs that inhibit a compound called vascular endothelial growth factor (VEGF), so they are called ‘anti-VEGF drugs’. They include bevacizumab (Avastin, Roche), ranibizumab (Lucentis, Novartis, Basel, Switzerland) and aflibercept (Eylea, Bayer). The Retinopathy sections of this report are concerned with treatments for only dryform, at all stages, from prevention of early changes progressing to advanced form, both dry and wet, and treatment of advanced dry AMD. As part of the background, we also look at some epidemiological studies of risk factors for Retinopathy.

Most people with macular degeneration have the dry form, but the dry form can lead to the wet form. Only about 10% of people with macular degeneration get the wet form.

Asystem is going to be proposed to automatically detect age related macular degeneration in colour fundus images. The system first determines the optic disclocation. The drusen is detected by applying the threshold, choosen from the intensity characteristics and then the pixels of optic disc will be removed from the drusen detection due to similar pixels intensity property of the optic disc to obtain true The image assisted methods are also frequently implemented to sketch the disease in the macula, which can be additionally examined by a expert physician or a computerized arrangement to recognize the severity of the pneumonia. Compared to the chest X-ray, the CTI is frequently considered due to its advantage and the three-dimensional view. The research work published on Retinopathy also confirmed the benefit of the CT in detecting the disease in the respiratory tract and pneumonia. This work initially implements a series of procedures for an automated extraction of the Retinopathy infection from the benchmark macula CTI. This work executed a sequence of techniques, such as tri-level thresholding based on Social-Group-Optimization based Kapur’s Entropy (SGO-KE), k-means clustering based separation, morphology-based segmentation to extract Retinopathy infection. Later, the segmentation accuracy of the proposed method is confirmed by executing a comparative study among the extracted Retinopathy infection with the Ground Truth (GT) images. During this work, 78 numbers of images from benchmark dataset is considered and the proposed procedure is implemented using grayscale images of dimension 256×256×1 pixels and the mean segmentation accuracy achieved in this work is higher than 91%. Finally, the achieved classification accuracy has been found to be higher than 87%.

## 2. LITERATURE SURVEY

TITLE*:* **A contribution of image processing to the diagnosis of retinopathy detection of exudated in colour fundus image of the human retina**

AUTHOR: Walter,J.Kelvin,P.Massin,and A.Erginary

YEAR: 2017

Advantage: Time consumption is reduces as it use mathematical morphology technique. Disadvantage: The paper ignored some types of error on the border of the segmented exudates in their reported performance.

TITLE**: Automation Exudate Detection from Non-dilated Retinopathy-Retinal images using Fuzzy C-menas Clustering**

AUTHOR: Akara Sopharak,Bunyarit Uyyanonvara and Sarah Barman

YEAR:2018

Advantage: The low contrast retinal image-intensity increased and a number of edge pixels were extracted. Disadvantage: More time consuming.

## 3. PROPOSED SYSTEM METHODOLOGY

This work consists of the following two stages
Implementation of an image segmentation work to extract the Retinopathy infection from the chosen 2D macula; CTI and

Execution of a ML scheme to separate the considered macula CTI database into AMD/NON-AMD class.

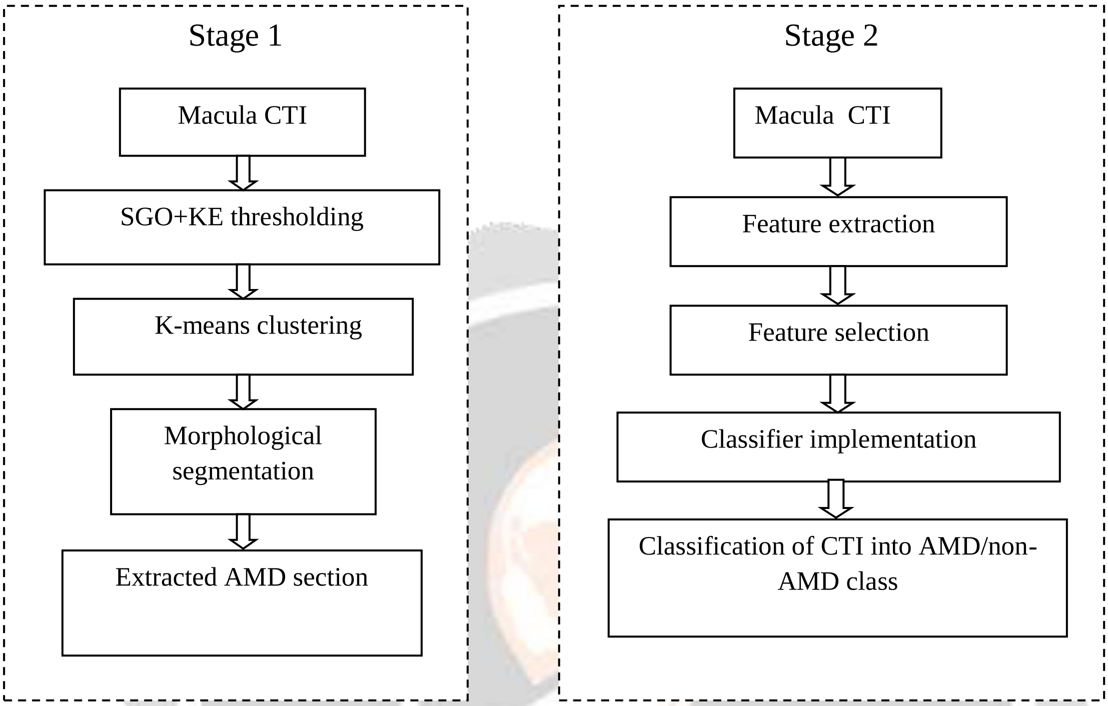


**Figure 1**: The image processing stages implemented in the proposed work

**STAGE 1:** The image processing system proposed to extract the pneumonia infection in the macula due to Retinopathy. Initially, the required 2D slices of the macula CTI are collected from the open source database . All the collected images are resized into 256×256×1 pixels and the normalized images are then considered for evaluation. In this work, Social-Group-Optimization (SGO) and Kapur's Entropy (SGO-KE) based tri-level threshold is initially executed to enhance the macula section. Later, K-means clustering is then employed to segregate

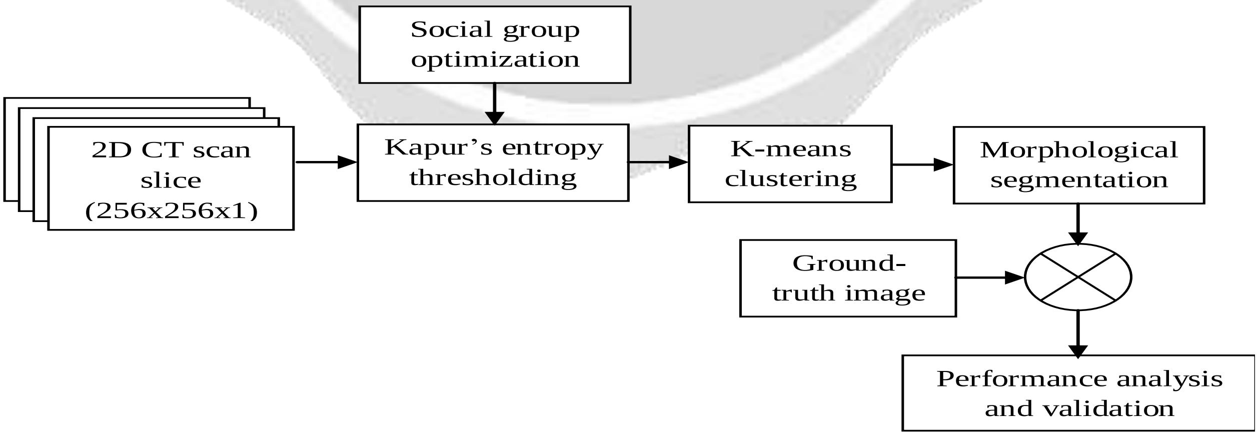


**Figure 2**: Image segmentation framework to extract AMD infection from 2D macula CT scan image

the thresholded image into background, artifact and the macula segment. The unwanted section coupled with macula is then removed using a morphological segmentation procedure and the extracted binary image of the macula is then compared with its related GT provided in the database. Finally, the essential performance measures are computed in this study and based on its value, the performance of the proposed Retinopathy system is validated.

**STAGE 2:** the proposed ML scheme to separate the considered macula CTI into AMD/NON-AMD class. This system is constructed using two different images, such as (i) the original test image (AMD/NON-AMD class) and (ii) The binary form of the Retinopathy section. The various procedures existing in the proposed ML scheme is depicted in above image.

This procedure is implemented only for the CTI associated with the Retinopathy infection. The complete details on various stages involved in this process are depicted in figure 1. The series of procedures implemented in this figure is used to extract the Retinopathy infection from the chosen test image with better accuracy.

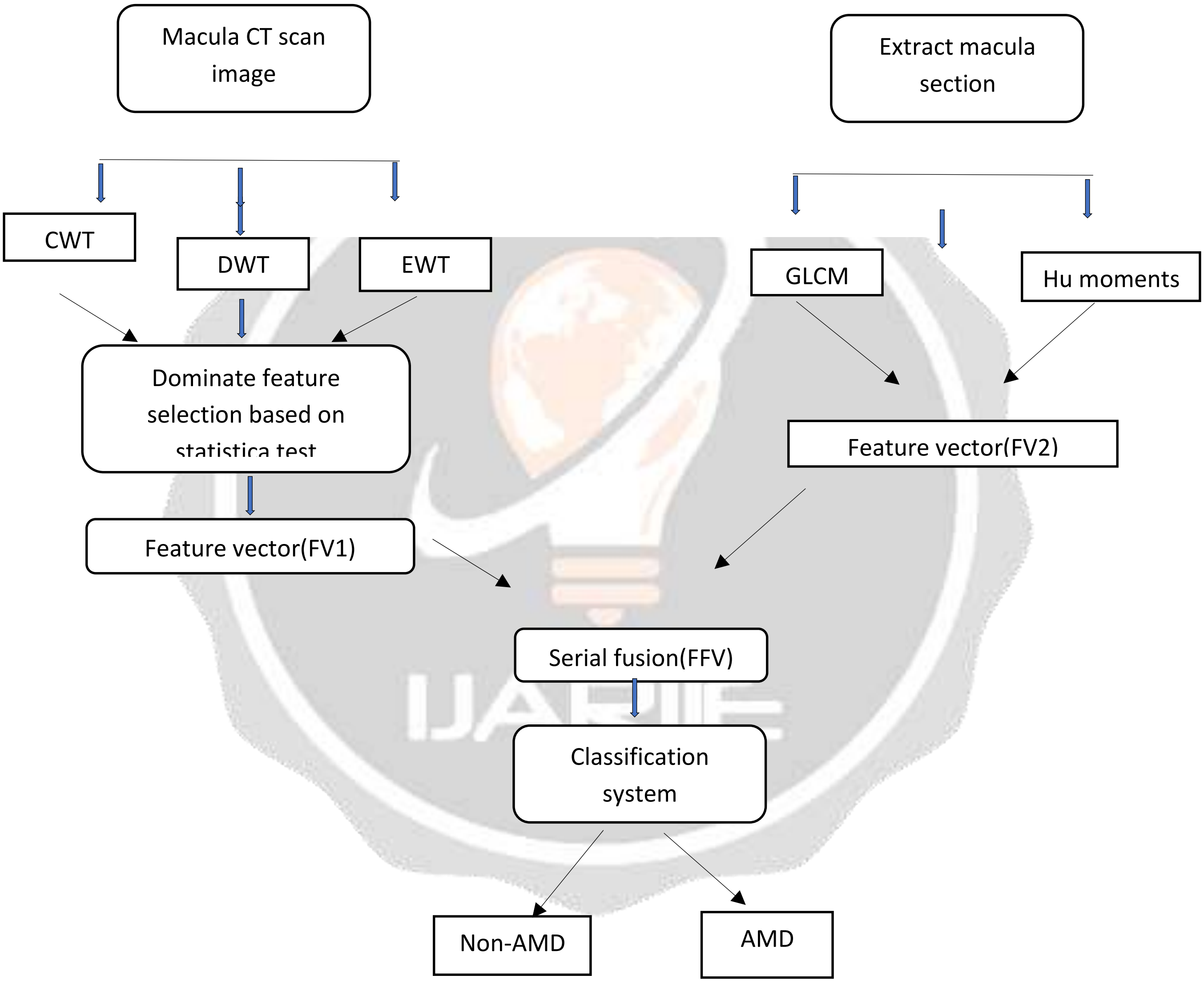


**Figure3**: Proposed machine-learning scheme to detect AMD infection

**Segmentation of Retinopathy infection** This procedure is implemented only for the CTI associated with the Retinopathy infection. The complete details on various stages involved in this process are depicted in above image The series of procedures implemented in this figure is used to extract the Retinopathy infection from the chosen test image with better accuracy.

***Image thresholding***

Initially, the enhancement of the infected section is achieved by implementing a tri-level threshold based on SGO and the KE. In this operation, the role of the SGO is to randomly adjust the threshold value of the chosen image till KE is maximized. The threshold which offered the maximized KE is considered as the finest threshold. The related information on the SGO-KE implemented in this work can be found . The SGO parameters discussed in Dey et al is considered in the proposed work to threshold the considered CTI.

***Segmentation based on K-means clustering and morphological segmentation***

The Retinopathy infection from the enhanced CTI is then separated using the K-means clustering technique and this approach helps to segregate the image into various regions. In this work, the enhanced image is separated into three sections, such as the background, normal image section and the Retinopathy infection. The essential information on K-means clustering and the morphology-based segmentation can be found. The extracted Retinopathy is associated with the artifacts and hence, a morphological enhancement and segmentation discussed is implemented to extract the infection, with better accuracy.

***Performance computation***

The outcome of the morphological segmentation is in the form of binary and this binary image is then compared against the binary form of the GT and then the essential performance measures, such as accuracy, precision, sensitivity, specificity, and F1Score are computed. A similar procedure is implemented on all the 78 images existing in the benchmark AMD database and the mean value of these measures are then considered to confirm the segmentation accuracy of the proposed technique. The essential information on these measures is clearly presented .

**Implementation of Machine Learning Scheme**

The ML procedure implemented in this research is briefed in this section. This scheme implements a series of procedures on the original CTI (non-AMD/AMD class) and the segmented binary form of the Retinopathy infection as depicted in figure 2. The main objective of this ML scheme is to segregate the considered CTI database into non-AMD/AMD class images.

***Initial processing***

This initial processing of the considered image dataset is individually executed for the test image and the segmented Retinopathy infection. The initial processing involves extracted the image features using a chosen methodology and formation of a one-dimensional feature vector using the chosen dominant features.

***Grayscale* image feature-vector**

The accuracy of disease detection using the ML technique depends mainly on the considered image information. In the literature, a number of image feature extraction procedures are discussed to examine a class of medical images. In this work, the well-known image feature extraction methods, such as Complex-Wavelet-Transform (CWT), Discrete-Wavelet-Transform (DWT) and Empirical-Wavelet-Transform (EWT) are considered to extract the features of the NON-AMD/AMD class gray scale images. The information on the CWT, DWT and EWT are clearly discussed in the earlier works [48]. After extracting the essential features using these methods, a statistical evaluation and student's t-test based validation is implemented to select the dominant features to create the essential feature vectors, such as $FV_{CWT}$ (34 features), $FV_{DWT}$ (32 features) and $FV_{EWT}$ (3 features) are considered to get the principle feature-vector set (FV1=69 features)by sorting arranging these features based on its p-value and t-value. The implementation of the feature selection process and FV1 creation is implemented as discussed .

***Feature*-vector2**

The essential information from the binary form of Retinopathy infection image is extracted using the feature extraction procedure discussed in Bhandary et al and this work helped to get the essential binary features using the Haralick and Hu technique. This method helps to get 27 numbers of features ($F_{Haralick}$=18 features and $F_{Hu}$ =9 features) and the combination of these features helped to get the 1D feature-vector (FV2=27 features).

***Serial feature fusion***

In this work, the original test image helped to get the FV1 and the binary form of the Retinopathy helps to get the FV2. To implement a classifier, it is essential to have a single feature vector with a pre-defined dimension. In this work, a SFF based on the PCA is implemented to attain a 1D FFV (69+27=96 features) by combining the FV1 and FV2 and this feature set is then considered to train, test and validate the classifier system implemented in this study.

***Classification***

In classification is one of the essential parts in a verity of ML and Deep Learning (DL) techniques implemented to examine a class of medical datasets. The role of the classifier is to segregate the considered medical database into two-class and multi-class information using the chosen classifier system. In the proposed work, the classifiers, such as Random-Forest (RF), k-Nearest Neighbors (KNN), SVM-RBF, and Decision Tree (DT) are considered. The essential information on the implemented classifier units can be found . A five-fold cross validation is implemented and the best result among the trial is chosen as the final classification result.

***Validation***

From the literature, it can be noted that the performance of the ML and DL based data analysis is normally confirmed by computing the essential performance measures. In this work, the common performance measures, such as accuracy, precision, sensitivity, specificity, Negative-Predictive-Value (NPV) and F1Score are computed.

The mathematical expression for these values is as follows:

$$Accuracy = \frac{T_P+T_N}{T_P+T_N+F_P+F_N} \quad (1)$$

$$Precision = \frac{T_P}{T_P+F_P} \quad (2)$$

$$Sensitivity = \frac{T_P}{T_P+F_N} \quad (3)$$

$$Specificity = \frac{T_N}{T_N+F_P} \quad (4)$$

$$F1-Score = \frac{2T_P}{2T_P+F_N+F_P} \quad (5)$$

$$NPV = \frac{T_N}{T_N+F_N} \quad (6)$$

where $T_P$= true positive, $T_N$= true negative, $F_P$= false positive and $F_N$=false negative.

## 4.RESULTS AND DISCUSSION

The experimental results obtained in the proposed work are presented and discussed in this section. This developed system is executed using a workstation with configuration-Intel i5 2.GHz processor with 8GB RAM and 2GB VRAM equipped with the MATLAB®. Experimental results of this study confirm that this scheme requires a mean time of 173±11sec to process the considered CTI dataset and the processing time can be improved by using a workstation with higher computational capability. The advantage of this scheme is, it is a fully automated practice and will not require the operator assistance during the execution.

The proposed research initially executes the Retinopathy infection segmentation task using the benchmark dataset . The results attained using a chosen trial image is depicted in depicts the sample image of dimension 256×256×1 and depicts the actual and the binary form of the GT image. The result attains with the SGO-KE-based tri-level threshold is depicted . Later, the k-means clustering is employed to segregate into three different sections and the separated images are shown. Finally, a morphological segmentation technique is implemented to segment the Retinopathy infection from and the attained result is presented

After extracting the Retinopathy infection from the test image, the performance of the proposed segmentation method is confirmed by implementing a comparative examination between the binary GT existing with and the essential performance values are then computed based on the pixel information of the background (0) and the Retinopathy section (1). For this image, the values attained are as follows; $T_P$=5865 pixels, $F_P$=306, $T_N$= 52572, and $F_N$=1949 and these values offered; accuracy=96.28%, precision=95.04%, sensitivity= 75.06%, specificity=99.42%, F1Score=83.88% and NPV=96.43%.

Similar procedure is implemented for other images of this dataset and mean performance measure attained for the whole benchmark database (78 images) is depicted Figure 3,1. From this figure, it is evident that, the segmentation accuracy attained for this dataset is higher than 91% and in future, the performance of the proposed segmentation method can be validated against other thresholding and segmentation procedures existing in the medical imaging literature.

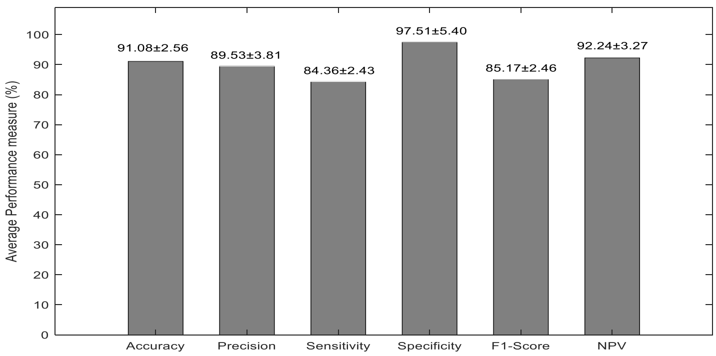


**Figure 4** Mean performance measure attained with the proposed Retinopathy segmentation procedure

The methodology depicted in Fig.3 is then implemented by considered the entire database of the CTI prepared in this research work. This dataset consists 400 grayscale images with dimension 256×256×1 pixels and the non-AMD/AMD 19 class images have similar dimension to confirm the performance of the proposed technique.

Initially, the proposed ML scheme is implemented by considering only the grayscale image features (FV1) with a dimension 1×69 and the performance of the considered classifier units, such as RF, KNN, SVM-RBF and DT are computed. During this procedure, 70% of the database (140+140=280 images) is considered for training and 30% (60+60=120 images) are considered for testing. After checking its function, each classifier is separately validated by using the entire database and the attained results are recorded. Here, a five-fold cross validation is implemented for each classifier and the best result attained is considered as the final result. The obtained results are depicted in Table 1 (first three rows). The results reveal that, the classification accuracy attained with SVM-RBF is superior (85%) compared to the RF, KNN and DT. Also, the RF technique helped to get the better values of the sensitivity and NPV compared to other classifiers.

**Table 5** Disease detection performance attained with the proposed ML scheme

| **Features** | **Classifier** | $T_P$ | $F_N$ | $T_N$ | $F_P$ | **Accuracy (%)** | **Precision (%)** | **Sensitivity (%)** | **Specificity (%)** | **F1-Score (%)** | **NPV (%)** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| FV1 (1x69) | RF | 163 | 37 | 172 | 28 | 83.75 | 85.34 | ***81.50*** | 86.00 | 83.37 | ***82.30*** |
| | KNN | 159 | 41 | 177 | 23 | 84.00 | 87.36 | 79.50 | 88.50 | 83.24 | 81.19 |
| | SVM-RBF | 161 | 39 | 179 | 21 | ***85.00*** | ***88.46*** | 80.50 | ***89.50*** | ***84.29*** | 82.11 |
| | DT | 160 | 40 | 168 | 32 | 82.00 | 83.33 | 80.00 | 84.00 | 81.63 | 80.77 |
| FFV (1x96) | RF | 169 | 31 | 178 | 22 | 86.75 | ***88.48*** | 84.50 | ***89.00*** | 86.45 | 85.17 |
| | KNN | 178 | 22 | 173 | 27 | ***87.75*** | 86.83 | ***89.00*** | 86.50 | ***87.90*** | ***88.72*** |
| | SVM-RBF | 172 | 28 | 177 | 23 | 87.25 | 88.20 | 86.00 | 88.50 | 87.09 | 86.34 |
| | DT | 174 | 26 | 172 | 28 | 86.50 | 86.14 | 87.00 | 86.00 | 86.57 | 86.89 |

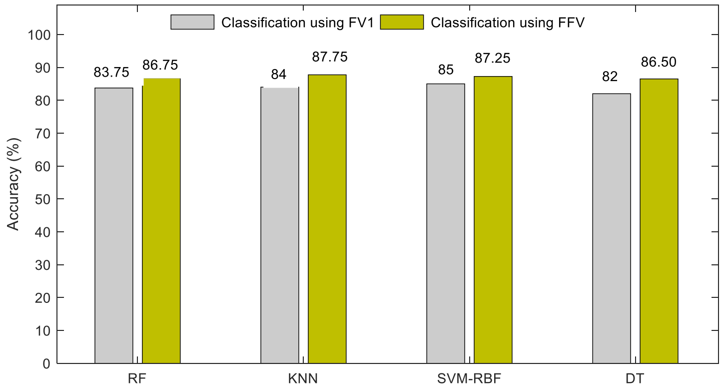


**Figure 6** Detection accuracy attained in the proposed system with various classifiers

To improve the detection accuracy, the feature vector size is increased by considering the FFV (1×96 features) and similar procedure is repeated. The obtained results (as in Table 1, bottom three rows) with the FFV confirm that the increment of features improves the detection accuracy considerably and the KNN classifier offers an improved accuracy (higher than 87%) compared to the RF, SVM-RBF and DT. The precision and the F1-Score offered by the RF is superior compared to the alternatives. The experimental results attained with the proposed ML scheme revealed that, this methodology helps to achieve better classification accuracy on the considered lung CTI dataset. The accuracy attained with the chosen classifiers for FV1 and FFV is depicted in Fig.8.

The future scope of the proposed method includes - (i) Implementing the proposed ML scheme to test the clinically obtained CTI of Retinopathy patients, (ii) Enhancing the performance of implemented ML technique by considering the other feature extraction and classification procedures existing in the literature, and (iii) Implementing and validating the performance of the proposed ML with other ML techniques existing in the literature, and (iv) Implementing an appropriate DL architecture to attain better detection accuracy on the benchmark as well as the clinical grade Retinopathy infected macula CTI.

## 4.CONCLUSION

The aim of this work has been to develop an automated detection pipeline to recognize the Retinopathy infection from macula CTI. This work proposes an ML-based system to achieve this task. The proposed system executed a sequence of procedures ranging from image pre-processing to the classification to develop a better *Retinopathy detection* tool. The initial part of the work implements an image segmentation procedure with; SGO-KE thresholding, k-means clustering based separation, morphology based Retinopathy infection extraction and a relative study between the extracted Retinopathy sections. This segmentation helped to achieve an overall accuracy higher than 91% on a benchmark CTI dataset. Later, an ML scheme with essential procedures such as feature extraction, feature selection, feature fusion, classification is implemented on the considered data and the proposed scheme with the KNN classifier achieved an accuracy higher than 87%.

Retinopathy causes blindness worldwide, often seenin aged people. Retinopathy cause central vision deteriorates resulting dark spots. The retinal disease needs to be detected in early stage to avoid further losses. However, current methods of assessment are still handed manually. In this paper, proposed system is to detect the presence of drusen in retinal imageautomatically, which has a strong association with Retinopathy. This system detects both the optic disc anddrusen. Then removal of optic disc pixels is done to obtain true detection of drusen in retinal fundus images by applying the digital image processing. In future, main focus will be on improving the performance of the method to pick out individual regions of drusen by applying image segmentation technique and to execute that method on a large data set. Successful implementation of the method will be used as a clinical tool for Retinopathy screening.

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