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Research Article

Detection of Microaneurysm Model Using Kmean Clustering Method, Hough Transform Optimization and CNN

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ABSTRACT

Introduction: Diabetic retinopathy (DR) is a chronic disease that damages the retina due to damage to the small blood vessels caused by diabetes mellitus. This disease is one of the main causes of visual impairment in people with diabetes. Early detection of clinical signs of DR is essential to allow for effective intervention and treatment. Ophthalmologists are trained to recognize DR by examining small changes in the eye, such as microaneurysms, retinal hemorrhages, macular edema, and changes in the retinal blood vessels. Detection of microaneurysms (MA) plays a vital role in the early diagnosis of RD and has become a major focus of research in recent years.

Objectives: The objective of this paper is to propose an automated detection of microaneurysms (MA) in retinal fundus images. In this work, a private database consisting of 50 images from Hospital University Sains Malaysia (HUSM) is used to test the performance of the proposed model. The MA detection model is proposed through segmentation with the Kmean clustering method and Hough transform optimization with Particle Swarm Optimization (PSO) to ensure that the object is MA and is counted.

Methods: The methodology in this study is at the pre-processing stage, the image is filtered and the contrast is enhanced. Then in the detection stage the image is segmented using the H-maxima technique and kmean clustering, then the segmented microaneurysms are further identified based on the characteristics of the round shape of the microaneurysm using the Hough transform algorithm optimized with PSO. At the feature extraction stage, the PCA method is used and finally CNN is used to classify the detected MA candidates and calculate their number.

Results: The classifier performance was evaluated in terms of accuracy, sensitivity, and specificity as well as the number of microaneurysms before and after detection with Hough Transform optimized with PSO. The CNN classifier achieved good performance with an accuracy of 87.34%, a sensitivity of 93.33%, and a specificity of 88.06%. While PSO had a significant impact on the optimization of the Hough transform algorithm in the number of microaneurysm identifications, the number of Hough transform microaneurysms was better after optimization than before through the round shape feature.

Conclusions: This study presents a new model for automatic detection of MA using Kmean with Hough Transform optimized with PSO and CNN for classification. The proposed model successfully classifies MA well including its number quickly for real-time implementation.

Keywords: Microaneurysms, Detection Retinopathy Diabetic, Kmean, Hough Transform, PSO.

INTRODUCTION

Diabetic retinopathy (DR) is defined by damage to blood vessels in the retina due to long-term effects of diabetes, uncontrolled diabetes, and older age [1], [2], [3], [4], [5], [6]. The leading cause of blindness and visual impairment in working-age adults, is associated with poor quality of life, lower levels of psychosocial well-being, and increased risk of diabetes complications and death. In diabetic retinopathy, blood vessels in the human eye can swell, release fluid or blood, blood vessels can stop blood flow, sometimes abnormal vessels grow in the retina which is the main cause of vision and blindness [7], [8], [9]. It is estimated that the world's blind people will exceed 40 million in 2025 [10]. In 2019, Indonesia is the seventh country with the highest number of diabetics in the world [11]. The International Diabetes Federation (IDF) estimates that at least 463 million people aged 20-79 in the world suffer from diabetes in 2019, or the equivalent of an accuracy rate of 9.3% of the total population of the same age. This figure is expected to continue to increase to reach 578,000,000 in 2030 and 700 million in 2045 [2], [12].

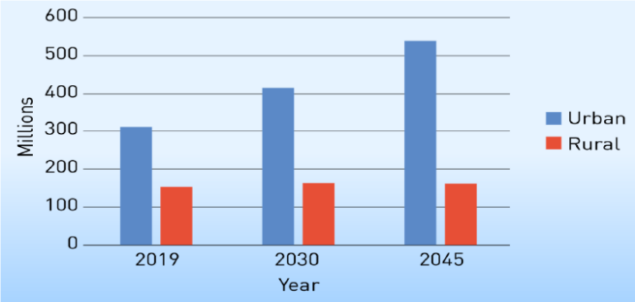


Figure 1. Number of people with diabetes 20–79 years [13]

Indonesia ranks 7th among the 10 countries with the highest number of sufferers, which is 10.7 million. Indonesia is the only country in Southeast Asia in the list, so it can be estimated that Indonesia's contribution to the prevalence of diabetes cases in Southeast Asia [11]. These findings indicate that there is a need to explore and pay attention to NPDR screening to help improve early detection, referral, and treatment to prevent its progression.

Early detection and treatment is most important which can reduce the chance of blindness by about 95% [14]. Early detection of diabetic retinopathy is important to guarantee the preservation of vision. The first signs of diabetic retinopathy can be seen using a fundus image obtained through a retinal fundus camera [10], see figure 2.8. There are various morphological characteristics of diabetic retinopathy that are the main components in human visual perception such as color, shape, size and texture [15]. Key criteria components will help to classify the severity of diabetic retinopathy based on normal and abnormal eye features on fundus images [16]. Normal eye features consist of the optic disc, macula, fovea, and blood vessels. Abnormal eye features consist of red lesions - microaneurysms (MA), hemorrhages (HE), Blood Vessel (BV); Hard Exudate (HE), Cotton Wool (CW) as shown in Figure 2 [8].

According to the Early Treatment of Diabetic Retinopathy Study (ETDRS) microaneurysm is the only clinical sign that indicates the onset of mild NPDR [17]. During the early stages of NPDR, retinal capillaries are damaged by hyperglycemia which weakens the capillary walls and results in microaneurysms [18]. So microaneurysms are the first signs of diabetic retinopathy [15], [19], [20] hat appear with a diameter range between 15 and 60 µm, rarely exceeding 125 µm [21], [22]. The small structure of microaneurysms makes them very difficult to observe [8]. Therefore, referring to an ophthalmologist is time-consuming due to the lack of specialists to check the initial examination task.

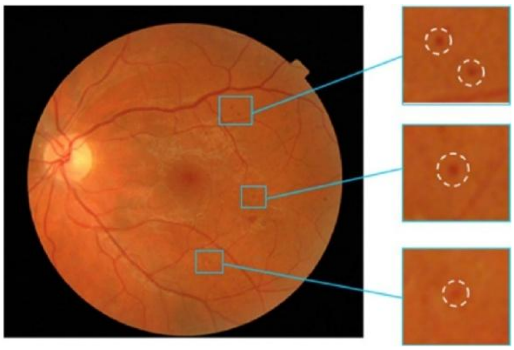


Figure. 2. A sample retinal image from local database with different size of MAs.

However, the original retinal fundus image always has low contrast [23], non-uniform illumination, noise and inhomogeneous intensity even though the camera uses the same optics and sensors [6], [24], [25], [26]. Perception of retinal images is a challenge; normal and abnormal retinal anatomical structures have low contrast with their background, including microaneurysms [9], [22], [27]. Many studies of microaneurysm detection using detection methods have been carried out before, such as multilevel thresholding method [27], mathematical morphology [9], graph cut [28], bi-linear top hat [22], Match Filter [29], Principal Componen Analysis [30], Statistical geometrical feature [31], maximum entropy thresholding [32], Shape-based Filter [33], Directional Local Contrast (DLC) [8] and many more.

Various methods have been proposed to overcome the intensity and noise in the fundus image so that the detection of microaneurysms can be done well through perceptual methods [34]. For microaneurysm dilation [35] introduced the level set extraction method, but this method could not correct the refractive field of the image properly. [21] use the threshold and curvelet method for feature extraction, but the preprocessing stage is not carried out for intensity and noise, there is a blood vessel effect that leads to the misclassification of microaneurysm. [36] used the hessian matrix method for segmentation, but there is still noise in the microaneurysm detection results and it is still difficult to distinguish between microaneurysms and image noise. Meanwhile [22] using the automatic hough spiral transformation method used for the detection and calculation of microaneurysms but has not worked well, it is still recommended to use other detection methods. [9] using mathematical morphology for microaneurysm detection, but the results are not good due to the influence of the low contrast of the fundus image, small size and faint color. [27] tried to detect microaneurysms with the h-maxim and multithresholding methods for segmentation in the hope of being able to segment accurately without noise and at the same time overcome the intensity problem and this overcomes the basic problems of fundus images, namely intensity and noise, but the results of this study have not been maximized because there are still several problems, namely when the location of the microaneurysm is too close to the blood vessels, the microaneurysm can be divided into several parts of the blood vessels and when the blood vessels are too thin, the segmented blood vessels can be divided into small and isolated areas. In this mazlan case, if the damaged blood vessels have characteristics similar to microaneurysms (for example, they appear round), then the damaged blood vessels can be said to be microaneurysms.

Based on the literature, it is known that the method used by Mazlan, namely thresholding, is not yet appropriate because the thresholding method is not only less effective in sensing and handling noise but also not automatic, therefore we offer a new microaneurysm detection model that is automatic and robust in segmentation while ensuring that the MA candidate is in accordance with the characteristics of the MA itself and the number of microaneurysms is calculated as an early detection of diabetic retinopathy so that a classification is obtained to determine patient care actions.

LITERATURE REVIEW

Diabetic retinopathy is one of the leading causes of vision loss and blindness in people with diabetes in the long term. Accurate detection is a major focus of researchers, as it can help ophthalmologists reduce manual work when dealing with increasing numbers of patients and medical data. In the machine learning approach, image preprocessing is a fundamental stage that has recently been widely used in the detection of diabetic retinopathy. [9] proposed a mathematical morphology algorithm that is performed in three main modules: first, image enhancement using morphological processing; second, extraction and removal of red structures, such as blood vessels, which begins with the detection and elimination of bright artifacts; and third, selection of true microaneurysm candidates from various structures based on a set of extracted features. Using e-Optha data, a sensitivity of 83% and a specificity of 82% were obtained. [37] conducted a unique approach to automatically detect microaneurysms in eye images from an early stage, using a unique ensemble classifier technique, where multiple classifiers are selected to build an ensemble model. After image preprocessing, common features such as shape and intensity are extracted from candidate microaneurysms. Next, the average absolute difference of each feature is calculated. The results of the various classifiers are then combined for each different characteristic, and the most frequently occurring category is used to determine the final decision. This approach has been thoroughly validated using the open dataset DIARETDB1, resulting in an accuracy of 87.3%, sensitivity of 85%, and specificity of 91%.

In the study proposed [38], the severity of mild, moderate, or severe diabetic retinopathy was assessed based on the presence of exudates and microaneurysms in fundus images. The automated approach applied involved image processing, feature extraction, and machine learning models to accurately detect exudates and microaneurysms as the basis for assessment. The study was divided into two segments: one for exudates and one for microaneurysms. Exudates were assessed based on their distance from the macula, while microaneurysms were assessed based on the number detected. Using the Threshold and KNN methods for microaneurysm assessment, an accuracy of 63%, sensitivity of 49.3%, and specificity of 56.9% were obtained, which is still relatively low in predicting disease severity. [39] investigated the use of morphological methods to automatically detect microaneurysms in digital color retinal images. In addition, characteristic elements of the retina such as blood vessels, optic discs, and exudate lesions that could potentially cause false detections were also identified. By utilizing the ground truth from the DIARETDB1 database, this method successfully detected microaneurysms with a sensitivity of 80.41% and a specificity of 92.79%. To detect microaneurysms, [40] proposed a sliding band filter for MA enhancement aimed at obtaining an initial set of MA candidates. The combination of filter responses with color, contrast, and shape information using an Ensemble classifier for the final classification candidates. A sensitivity of 81% was achieved for an average of 8 false positives per image (FPI) on MA was obtained for MA detection over the e-ophtha dataset.

METHODOLOGY

This study examined a raw retinal fundus image dataset provided by Ophthalmology, Hospital Universiti Sains Malaysia (HUSM), Kubang Kerian, Kelantan. This data set consists of 90 fundus images with a resolution of 3008 x 2000 and Joint Photographic Experts Group (*.jpg) format. In this experiment, 50 fundus images were selected consisting of Normal, Non Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). Images were taken by ophthalmology technologists from HUSM using a fundus camera.

1. *Green Channel:* The green channel will be used for MA detection as it shows the maximum contrast between the background and the red lesion. Red or blue channels are not used here because the red channel tends to be saturated, while the blue channel has low contrast and contains less information. Also, the red and blue channels tend to contain more noise than the green channel. The green channel is less complex than the original color image with three channels. Therefore, the green channel was selected for MA image analysis. The green channel image undergoes mean filtering to highlight dark areas of the image.
2. Contrast Enhancement: Contrast enhancement is used to highlight features of interest in an image. In this research, contrast enhancement with top-hat and bottom-hat combined morphological transformation (Top-hat) is used. This method will be used because it can improve the poor contrast in the image by improving the contrast between the lesions or blood vessels and the retinal background.
3. *Background Exclusions:* Background image removal is important in foreground image detection. By removing the background of the retinal image as it does not contain retinal information. With the help of this approach, the information in the foreground image can be retained and highlighted.
4. *Filtering:* A multi-filter is proposed in this research, it involves a combination of median and min filters. To the best of our knowledge, the implementation of hybrid filters has not been applied in MA detection. However, some researches use multi-filters to remove salt and pepper noise in the detection of other objects. The resulting information is sent to the median and min filters to complete the process. The desired multi-filter output can be obtained by arranging them in series. The minimum filter is defined as the minimum of all pixels within a local region of an image. The main function of the min filtering is to reduce or eliminate noise in the image. When the image has interference or noise, such as unwanted colored dots or small variations in color intensity, using a min filter can help smooth the image and remove the noise.
5. The min filter works by replacing the target pixel value with the minimum value of the neighboring pixels around it. The median filtering process is accomplished by sliding a window over the image. The filtered image is obtained by placing the median of the values in the input window, at the location of the center of that window, at the output image. For relatively uniform areas, the median filter estimates the gray-level value, with particular success in the presence of long-tailed noise. As an edge is crossed, one side or the other dominates the window, and the output switches sharply between the values. Thus, the edge is not blurred.
6. *Morphological Enhancement:* Morphological Enhancement is used to improve the structure or features in an image using morphological operations. This technique helps improve image quality by highlighting certain parts,

removing noise, or improving the shape of an object. In this study, White Top-Hat is used, this is a morphological operation used to extract certain features or components from an image based on differences in pixel intensity with the aim of highlighting brighter features from the background and increasing local contrast or clarifying smaller details compared to the surrounding structure.

7. *H-Maxima:* The H-maxima transformation is a part of mathematical morphology used to remove local maxima lower than a threshold. This method is introduced to obtain optimal segmentation results from the processed image. The 'imhmax' function is used to remove the area maxima and will only retain the significant part of the global maxima. This method reduces the number of intensity levels in the image which simplifies further processing.

$$Ht(k) = R_k^g(k - t) \quad (1)$$

8. *K-Mean Clustering:* In general, the steps of the K-Mean Method process Specify k (the value is independent) as the number of clusters to be formed.
   - Generate a random value for the initial cluster center (centroid) of k.
   - Calculate the distance of each input data to each centroid using the Euclidean distance formula (Euclidean Distance) to find the closest distance from each data to the centroid. Here is the Euclidian Distance equation:

$$d(xi,\mu j) = \sqrt{\Sigma}(xi - \mu j)2^2 \quad (2)$$

   - Classify each data based on its distance to the centroid (smallest distance).
   - Updating the value The new centroid value is obtained from the mean of the intended cluster using the formula:

$$\mu j(t+1) = \frac{1}{Nsj}\sum_{j\epsilon sj} xj \quad (3)$$

   - Repeat from steps 3 to 5, until the members of each cluster do not change.

K-means aims to minimize the distance between data (x_i) and cluster centers (c_k) for each k cluster, in general the algorithm is as follows:

$$J = \sum_{i=1}^{n}\sum_{k=1}^{K} r_{ik} \, \|x_i - c_k\|^2 \quad (4)$$

9. *Hough Transform :* Hough Transform is a technique in image processing and computer vision used to detect geometric shapes such as lines, circles, or other shapes in an image. This method is very useful for detecting imperfect or discontinuous shapes because of its robustness to noise and disturbances. Converting the representation of shapes from image space (spatial) to parameter space, where the shapes can be identified as peaks.

The Hough transform is a technique used to identify the parameters of a circle in an image. A circle with a given radius r and center coordinates (x0,y0) can be represented using parametric equations

$$(x - x0)^2 + (y - y0)^2 = r^2 \quad (5)$$

For every pixel in the image, a corresponding circle with the specified radius is drawn in the accumulator space. If multiple circles of the same radius overlap at a common point in the accumulator space, it indicates the presence of a circle with that radius at that specific location in the image

10. *Particle Swarm Optimization* (PSO) is a computational technique inspired by the collective movement of fish schools and bird flocks. It aims to optimize (either maximize or minimize) an objective function by searching within a defined space while maintaining multiple candidate solutions, referred to as particles. These particles navigate through a fitness landscape, each maintaining its position, velocity, and fitness value, which is determined using a fitness function in each iteration. The position of a particle represents a potential solution within the search space. In PSO, a particle's velocity is updated based on two key positions: the personal best position (pbest) and the global best position (gbest). The personal best represents the best solution an individual particle has encountered, while the global best is the top solution discovered by the entire swarm at any given point in time.

$$v_i(t+1) = \omega v_i(t) + c_1 r_1[pbest(t) - x_i(t)] + c_2 r_2[pbest(t) - x_i(t)] \quad (6)$$

$$x_i(t+1) = x_i(t) + v_1(t+1) \quad (7)$$

where $v_i(t)$ is the velocity, and $x_i(t)$ denote the position of the particle i at a time t, ω ($0 \leq \omega \leq 1.2$) is inertia weight, $c_1 (0 \leq c_1 \leq 2)$ is the cognitive coefficient, and $c_2 (0 \leq c_2 \leq 2)$ is the social coefficient. r_1 and r_2 are the random values in the range [0, 1]

11. *Feature Extraction :* After image segmentation, the feature extraction stage is applied with PCA. Here are potential microaneurysms, unwanted objects, and fragments of thin red blood vessels. Retinal specialists recognize microaneurysms by several key feature vectors such as intensity, size, shape, and color characteristics. PCA is a way to identify patterns in data and then express the data in another form to show differences and similarities between patterns. The goal of PCA is to reduce the dimensions of a large data space (observed variables) to smaller dimensions of a feature space (independent variables), which is necessary to describe the data more simply. The eigenfaces (important features) of the microaneurysm distribution are obtained from the eigenvectors. To obtain eigenfaces, PCA computes the covariance matrix of the training set of microaneurysm images. The eigenface will be the basis for calculating the microaneurysm distance which represents the individual weight values representing one or more microaneurysm images. This weight value is used to recognize the test microaneurysm image by finding the distance between the weight value of the test microaneurysm image and the weight value of the training microaneurysm image Calculation of the distance between weight values is carried out using Eucledian distance calculations
12. Classification : To classify microaneurysms after extraction with PCA, use a Convolutional Neural Network (CNN). CNN is a type of artificial neural network architecture that is very popular in the field of image processing. CNN has the ability to automatically extract features from image data through deep convolution layers. This technique is inspired by the way human visuals work, where convolution layers are responsible for detecting simple visual patterns such as edges and lines, while other deep layers function to recognize increasingly complex patterns.

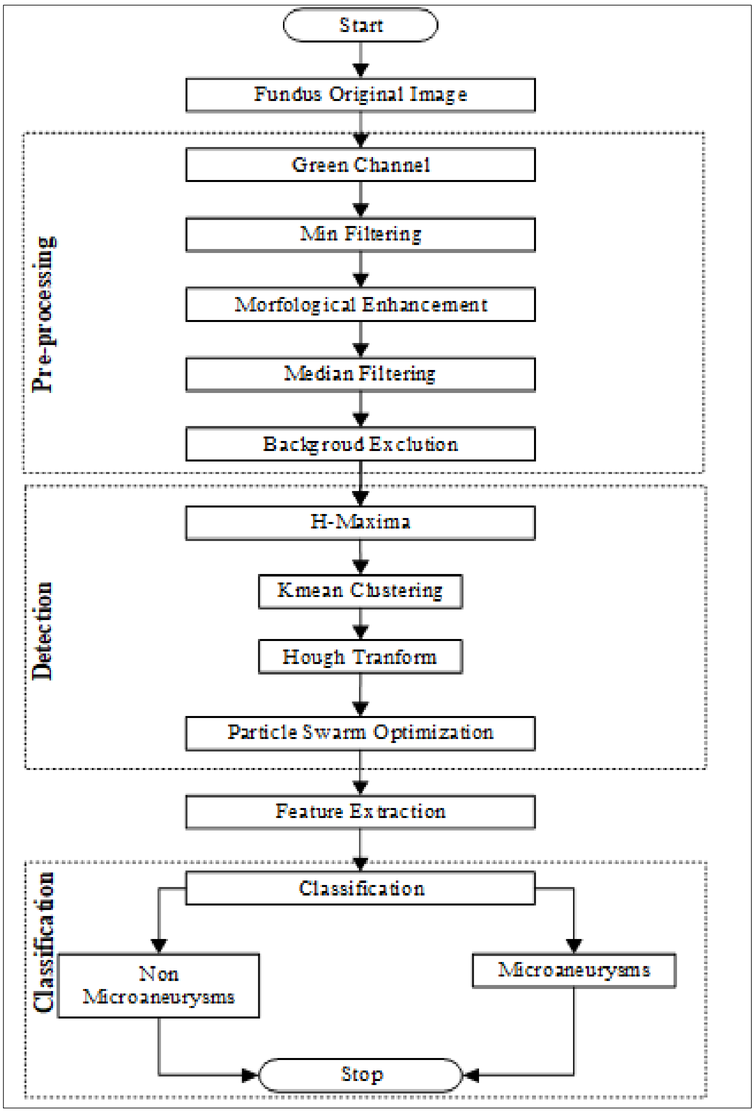


Figure. 3 Research flow of the proposed methodology

13. Performance Evaluation

This study uses Euclidean distance as a simple basis for comparison. The nearest neighbor classifier determines the class of the test sample based on its proximity to the nearest training data class. Evaluation parameters are assessed by comparing the detection results with the ground truth manually parsed by medical experts. Four types of metrics are used: True Positive (TP), which represents the number of correctly detected pixels; False Positive (FP), the number of non-microaneurysm pixels that are incorrectly classified as microaneurysm pixels; False Negative (FN), the number of undetected exudate pixels; and True Negative (TN), which refers to the number of correctly identified non-microaneurysm pixels consisting of accuracy, sensitivity and precision.

Accuracy represents the proportion of correct predictions made by the model out of the total number of predictions. It is one of the most commonly used metrics due to its simplicity and ease of interpretation. However, it can be deceptive when dealing with imbalanced data. The formula for accuracy is straightforward and can be expressed as follows:

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{5}$$

Sensitivity measures the proportion of actual positive cases correctly identified out of the total positive cases in the data. This metric is crucial in scenarios where minimizing false negatives is important, such as in disease detection, where it is critical to avoid misclassifying sick patients as healthy. In technical terms, sensitivity, also known as recall, is the ratio of true positive predictions to the total number of actual positive cases, as represented in a confusion matrix.

$$Sensitivity = \frac{TP}{TP+FN} \tag{6}$$

Precision is a more specialized metric than accuracy for evaluating a single label independently. It indicates the proportion of correct predictions for a specific label (in this case, the positive label) out of all predictions made for that label. In technical terms, precision is defined as the ratio of true positive predictions to the total number of positive predictions, including both correct and incorrect ones

$$Precision = \frac{TP}{TP+FP} \tag{7}$$

This section contains a complete and detailed description of the steps undertaken in conducting of research. In addition, the research step also needs to be shown in the form of flowchart of research or framework step in complete and detailed including reflected algorithm, rule, modeling, design and others related to system design aspect.

RESULTS AND DISCUSSION

This study presents an optimal combination of preprocessing, morphological detection processing, and feature-based candidate extraction for microaneurysm (MA) detection, demonstrating that the proposed system is effective as an automated tool for early diagnosis of diabetic retinopathy (DR). It introduces a novel area-based feature, called the MA factor, to characterize MA structure, proving to be a robust parameter for accurate MA identification. Furthermore, the approach confirms the feasibility of true MA detection through fundus imaging, addressing various DR-related pathologies and aiding in MA quantification to meet NPDR scoring criteria.

Utilizing the green channel, along with filtering and morphological enhancement during the pre-processing stage, improves the quality of fundus images by clarifying object features and reducing noise. Initially, microaneurysm detection is performed using the h-maxima method, which optimizes segmentation of the pre-processed images by filtering based on an intensity value, k. Here, Ht(k) refers to the h-maxima transformation that removes all maximum intensity values from the image. The subsequent step involves segmentation using the k-means clustering method, where the standard k-means algorithm is combined with calculations of sphericity and area—both of which are key indicators of microaneurysm characteristics. K-means clustering is initially employed to group image pixels based on their intensity and similar features, thereby isolating regions that might represent microaneurysms (MAs).

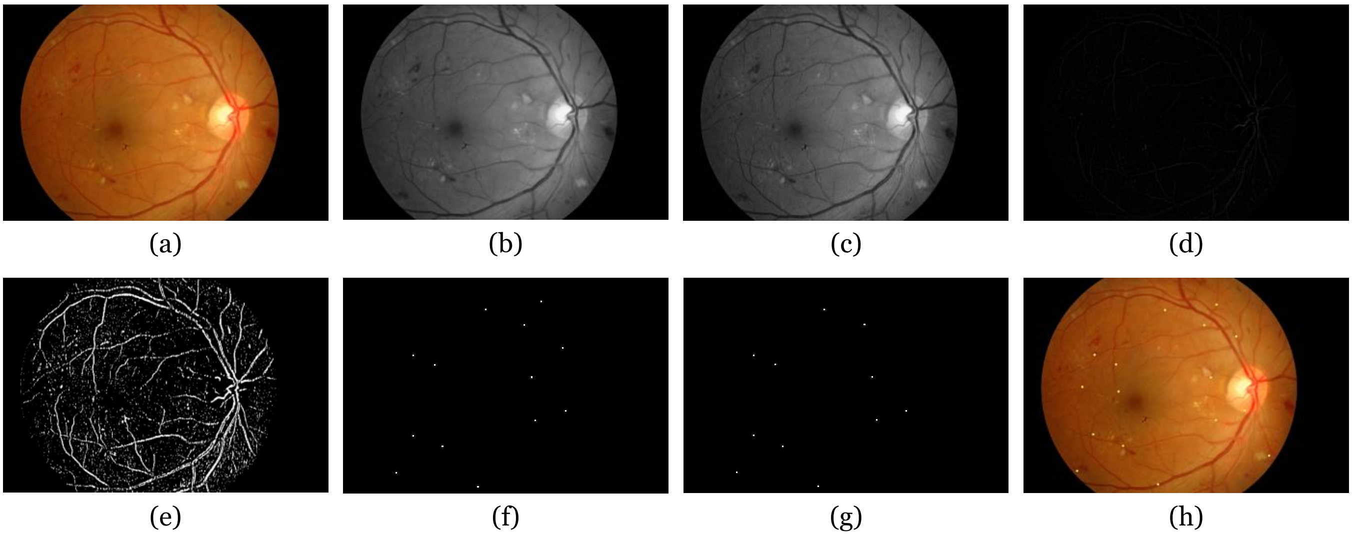
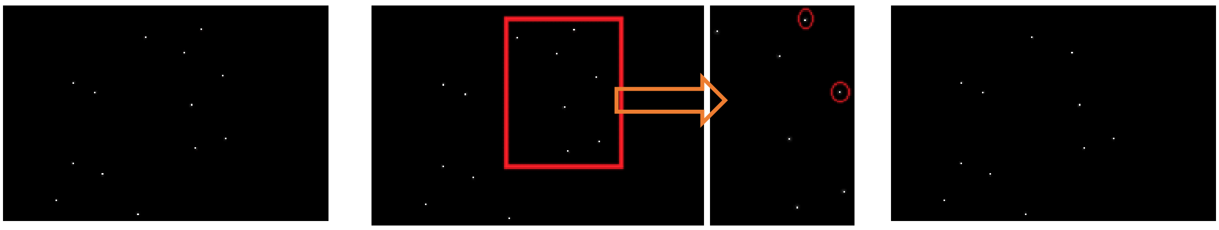


Figure. 4 (a) original image (b) green channel (c) morphological enhancement (d) h-maxina (e) clustering (f) Possible MA candidates image (g) MA candidates results Optimization Hough Transform (f) Ground Truth

Once these candidate regions are identified, a roundness metric is used to assess each region's shape. This metric measures how closely a region approximates a perfect circle, with values near 1 indicating a near perfect circle a key characteristic of MAs. By combining K-means clustering (e) with the roundness metric, the method can effectively separate potential MA candidates from other structures and prioritize those with the most circular shapes (f), thereby pinpointing the strongest MA characteristics

PSO optimizes the Hough transform by adaptively searching the parameter space for the best-fitting circles, specifically targeting the roundness characteristic of microaneurysms. It treats the circle parameters—such as center coordinates and radius—as particles in a swarm that iteratively adjust their positions based on both their own best performance and that of the group. This guided search helps quickly converge on the optimal circle parameters that match the round, microaneurysm features, reducing false detections and enhancing overall detection accuracy.

In the context of the Hough transform for circle detection, the primary parameters that are optimized include Center Coordinates (x, y): These determine the position of the circle within the image and Radius (r): This defines the size of the circle. These parameters are essential for accurately delineating the round shape of microaneurysms during detection.



(a) (b) (c)

Figure. 5 (a) MA segmentation results using kmean, (b) MA circle detection using Hough transform optimization, (c) final MA detection results from the proposed model.

This can be seen in Figure 4 (a) is the result of segmentation using kmeans which also detects circles, while Figure 4 (b) shows how the MA is re-detected for its circle using the Hough transform optimized with particle swarm optimization, the final result of this model is the actual MA obtained as can be seen in Figure 4 (c) and can be done to calculate the number of microaneurysms as one of the objectives of this study.

The same thing was done to 50 fundus image data obtained from the University of Science Malaysia Hospital (HUSM), the results can be seen in Table 1.

Table 1. Count of microaneurysm counts based on image number and method used

Image	Kmean	Kmean + HTPSO	Image	Kmean	Kmean + HTPSO	Image	Kmean	Kmean + HTPSO	Image	Kmean	Kmean + HTPSO
1.	15	15	14.	4	3	27.	12	8	40.	12	12
2.	18	17	15.	14	11	28.	8	8	41.	7	6
3.	21	19	16.	0	0	29.	8	6	42.	6	5
4.	15	11	17.	12	12	30.	6	4	43.	19	18
5.	8	6	18.	14	11	31.	8	6	44.	8	8
6.	19	17	19.	7	7	32.	6	4	45.	9	6
7.	17	15	20.	5	3	33.	4	3	46.	15	10
8.	14	12	21.	10	9	34.	10	9	47.	10	17
9.	6	5	22.	18	15	35.	12	10	48.	12	10
10.	16	13	23.	3	3	36.	20	18	49.	10	9
11.	13	11	24.	7	5	37.	5	3	50.	4	4
12.	15	10	25.	17	14	38.	3	3			
13.	10	7	26.	11	9	39.	3	1			

From a number of fundus images tested, it was found that the optimized Hough transform reading did not optimize the MA circle from the previous segmentation results, so how many MAs were detected by optimizing the MA circle reading, the number was the same, and this is a challenge for us, whether the segmentation results with standard kmean are very good or whether further improvements need to be made to the Hough transform algorithm

Table 2 summarizes comparisons between various methods using different datasets. Although these comparisons are not perfectly equivalent—due to differences in datasets and the proportions of images exhibiting DR symptoms—the performance metrics, such as sensitivity and accuracy, are still suitable for mutual evaluation. Additionally, since the e-optha dataset is relatively new, only a limited number of comparisons using e-optha are included in Table 2.

Table 2. Comparison With Previous Research

Author	Data set	Method	Accuracy	Sensitivity	Precision
Joshi [9]	Diaretdb I	Morphological	-	83%	82%
Pendekal [41]	Diaretdb I	Morphological, Ensamble classifier	87%	85%	91%
Malhi [38]	e-optha	Treshold, KNN	63,6	49,3%	56,9
Melo [40]	e-optha	Adapted Treshold, Ensamble	-	81%	-
Monohar [39]	Diaretdb I	Morphological	-	80,41%	92,79%
Proposed Aproach	HUSM	Kmean, HTPSO, CNN	87,34%	93,33%	88,06%

The proposed method achieves an MA detection accuracy of 87.34% and performs comparably to other MA detection techniques. Based on the results, [41] and [38] suggested that some MAs might be missed during the segmentation phase because their very small size and low contrast relative to normal regions can make detection challenging. The proposed method is implemented quickly and offers opportunities for improvement in preprocessing, feature selection, and database usage. It should be noted that some false positives and undetected MAs occur. Image ranking is determined by comparing the centroids of candidate regions with the ground truth centroids, with each candidate MA's centroid detected and marked as shown in Figure 12

CONCLUSION

This study successfully proves that this detection model consisting of a combination of kmean with hough transform optimized with PSO is better than using only the kmean algorithm. The improvements obtained are not only better microaneurysm detection accuracy, but also better and stronger microaneurysm identification. Futrure work of researchers can improve the performance of the kmean algorithm with the aim of emphasizing the noise removal function in the segmentation process, either by using a filtering algorithm or by using an optimization method, while detecting microaneurysm circles is better by improving the optimization algorithm so that the weakness of the hough transform algorithm to detect the circumference of the object becomes better and stronger.

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