• Intelligent Ophthalmology •

Enhanced diagnosis of diabetic retinopathy: integrating advanced algorithms for automated detection and classification

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Abstract

● **AIM:** To develop an automated diagnostic system for early detection of diabetic retinopathy (DR) using fundus images by identifying exudates, hemorrhages, and microaneurysms with advanced image processing and machine learning techniques.

● **METHODS:** Fundus images from the IDRiD dataset and additional Kaggle datasets were used. A wavelet-based band-pass filter was applied for edge enhancement of retinal features. Gaussian mixture model (GMM) clustering was used to segment and extract texture features. These extracted features were classified using machine learning algorithms, including a random forest classifier and a multilayer perceptron neural network. Performance metrics such as sensitivity, specificity, and accuracy were computed to evaluate the proposed model's diagnostic effectiveness.

● **RESULTS:** The random forest-based classification system achieved a sensitivity of 95.08%, specificity of 86.67%, and overall accuracy of 95.20% in detecting DR lesions. The combination of wavelet-based edge enhancement, GMM clustering, and neural network-based feature classification demonstrated high reliability in lesion identification.

● **CONCLUSION:** The proposed method effectively detects early signs of DR from fundus images, offering a high-accuracy, automated, and scalable solution for assisting ophthalmologists. Its application can support large-scale screening programs, particularly in regions with limited access to specialized eye care.

● **KEYWORDS:** diabetic retinopathy; random forest algorithm; Gaussian mixture modelclustering; multilayer perceptron; fundus image analysis

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INTRODUCTION

Diabetic retinopathy (DR) is a severe complication of diabetes mellitus that damages the retinal blood vessels, potentially leading to vision impairment or blindness if left untreated. With the global rise in diabetes prevalence, DR poses a significant public health concern[1-2]. Early and accurate diagnosis is crucial to prevent vision loss. Traditional DR diagnosis methods rely on manual assessment of fundus images. However, clinical grading of DR also depends on identifying various abnormalities, including exudates, hemorrhages, and microaneurysms, which can be time-consuming, subjective, and prone to inter-observer[3-4]. Deep learning-based approaches have recently gained prominence, and various studies have shown that they have considerable advantages in DR diagnosis.

This research proposes a novel automated diagnostic framework to address these limitations. Figure 1 illustrates the difference between a normal retina and a retina affected by DR, highlighting the pathological changes that need

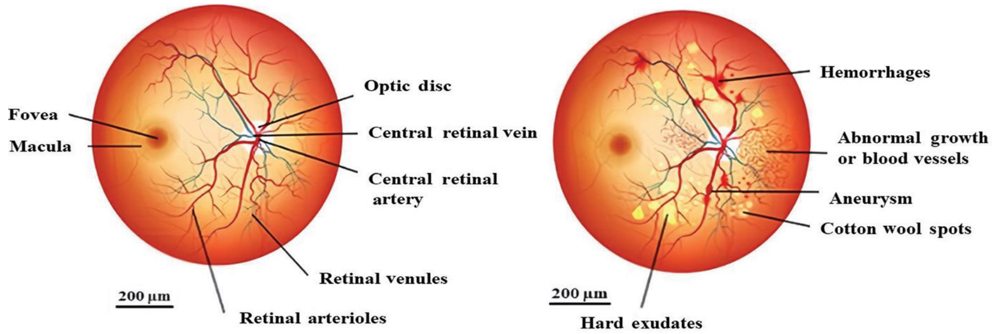

Figure 1 Difference between a normal retina and diabetic retinopathy.

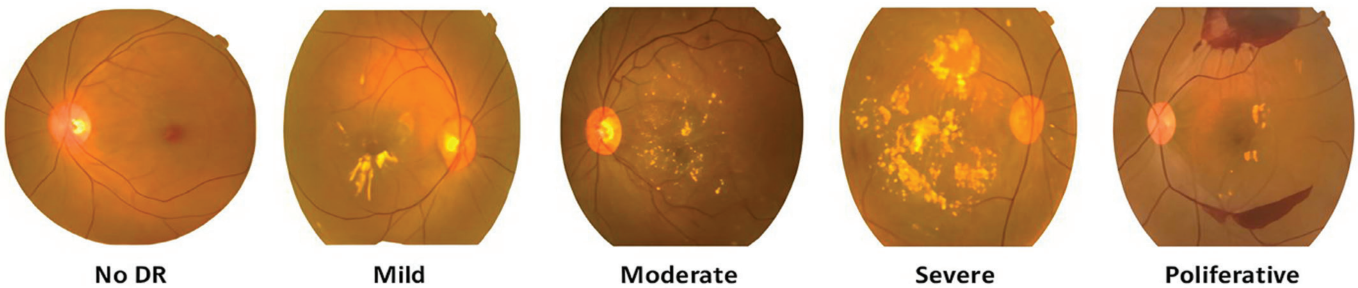

Figure 2 Categorization of diabetic retinopathy (DR) images according to severity level.

to be detected[5]. The proposed methodology begins with preprocessing fundus images using wavelet-based edge enhancement techniques and Wideband band-pass filters to improve image clarity and isolate features such as exudates, which are key indicators of DR.

Feature extraction is achieved using a combination of Gaussian mixture model (GMM) clustering and random forest (RF) algorithms. GMM clusters pixel intensities to capture the structural distribution of retinal features, while RF identifies discriminative statistical and texture features related to DR. These features are then fed into a multilayer perceptron (MLP) neural network for classification. The MLP effectively categorizes the images into normal and varying levels of DR severity, as depicted in Figure 2, which shows the categorization of DR images based on severity levels[6]. The framework is evaluated using 516 fundus images from the Kaggle database, and metrics such as specificity, sensitivity, and accuracy demonstrate its high diagnostic efficacy. These results underscore the potential of this approach to streamline DR diagnosis, enable early detection, and improve.

Ainapur and Virupakshappa[7] proposed a multi-step DR detection framework named Logistic Adaboost Light Gradient, which included Gray-Level Co-occurrence Matrix (GLCM) texture feature extraction and binary Archimedes optimization-based segmentation. While compared to current techniques for early DR identification on the APTOS-2019 dataset, the proposed model classified DR severity with an accuracy of 99.47%. Musluh *et al*[8] established a DR classification system for detecting retinal diseases and extracting visual and morphological data. Synthetic lesions and composite masks were created to improve segmentation and then used with latent features to improve classification. On the DDR, E-Ophtha, and IDRiD datasets, the algorithm achieved 88.04% accuracy and 93.71% Quadratic Weighted Kappa (QWK), compared to state-of-the-art convolutional neural network (CNN) approaches. Arora *et al*[9] proposed an EfficientNetB0-based deep learning system for classifying the severity of DR using retinal images. Using advanced CNN layering techniques, the model categorized five DR stages from 35 108 photos in Kaggle's "Diagnosis of Diabetic Retinopathy" dataset. The methodology achieved 86.53% accuracy with a loss of 0.5663, exhibiting great generalizability and efficacy when compared to other methods. Zhang *et al*[10] developed a multi-source-free domain adaptation (multi-SFDA) method for detecting DRs from unlabeled data that addresses labelling and privacy concerns. Multiple source models created synthetic pseudo-labels for the target domain, while softmax-consistence minimization improved class separability. On the APTOS2019, DDR, and Eye PACS datasets, the technique attained F1-scores of 0.8917 (referable DR) and 0.9795 (normal/abnormal), demonstrating its efficacy. Wang *et al*[11] proposed an automated algorithm for detecting DR lesions in ultra-widefield scanning laser ophthalmoscopy images using a FasterRCNN+ResNet50 architecture combined with Feature Pyramid Networks. Subimage segmentation with a deeper residual network enhanced feature extraction, while FPN-based feature fusion improved detection performance. Evaluation on 1076 ultra-widefield SLO images (2600 dpi×2048 dpi) achieved accuracy rates of 87.23% for hemorrhagic spots, 83.57% for cotton wool spots, 86.75% for exudates, and 54.94% for microaneurysms.

Ali *et al*[12] highlighted the transformative role of deep learning in medical imaging, particularly for improving diagnostic accuracy and treatment planning. Incremental Modular Networks provide a novel approach by incrementally adding modules to a single network, enabling models to focus on learning task-specific features rather than processing all data simultaneously. This flexibility makes Incremental Modular Networks particularly valuable for medical imaging applications, such as DR detection, where precise feature learning is critical. Menaouer *et al*[13] utilized VGG16 and VGG19 CNNs to classify DR into five severity levels: no DR, mild, moderate, severe, and proliferative DR. This mixed deep learning approach was tested using APTOS-2019, Messidor-2, and local public datasets. The model achieved an accuracy of 90.6%, a recall of 85%, and an F1 score of 94%, demonstrating the effectiveness of CNNs for feature extraction and classification. Similarly, Nguyen *et al*[14] developed an automated DR lesion detection algorithm based on Faster R-CNN with ResNet50 and Feature Pyramid Networks (FPN) for ultra-widefield scanning laser ophthalmoscopy images. The model detected hemorrhages, cotton wool spots, exudates, and microaneurysms using subimage segmentation and deep residual feature extraction. Tested on 1076 images (2600 dpi×2048 dpi), it achieved accuracy rates of 87.23%, 83.57%, 86.75%, and 54.94%, respectively, demonstrating improved performance over conventional color fundus–based methods. Khan *et al*[15] employed transfer learning with networks like VGG, ResNet, and InceptionV3, integrating Gaussian preprocessing to reduce noise and enhance image quality. Their study used a dataset categorizing DR into five classes and reported the highest performance with InceptionV3, achieving 81.2% training accuracy and 79.4% testing accuracy. Elloumi *et al*[16] addressed challenges in smartphone-based DR screening by using NasnetMobile, a lightweight neural network. Despite potential issues with image quality, their approach achieved remarkable results, including 95.91% accuracy, 94.44% sensitivity, 96.92% specificity, and 95.71% precision. These findings highlight the potential of portable devices for DR screening, particularly in resource-constrained settings. Comparative studies, such as those by Bajwa *et al*[17] evaluated various deep learning architectures like CNN, VGG16, ResNet50, and DenseNet for DR classification. Kommaraju and Anbarasi[18] proposed a CNN-based model to classify fundus images, trained on Kaggle datasets, and demonstrated significant improvements in DR detection accuracy. Das *et al*[19] introduced a framework using segmented fundus images, adaptive histogram equalization, and CNNs, achieving 98.7% accuracy on the DIARETDB1 dataset. Meanwhile, Vives-Boix and Ruiz-Fernández[20] integrated synaptic metaplasticity into InceptionV3, enhancing feature learning and achieving a 95.56% accuracy rate on public DR Datasets. These diverse methodologies underline the promise of deep learning in DR diagnosis. Techniques such as feature fusion, transfer learning, and portable device integration offer valuable insights. Together, they inform the development of advanced systems like RF-GMM feature fusion combined with MLP Neural Networks, potentially enhancing diagnostic accuracy and efficacy in DR detection.

Previous methods[8,10-11,15] are limited by either focusing only on binary classification without detailed lesion analysis or relying on computationally heavy deep detection networks that struggle with small lesion accuracy. In this study, the proposed model introduces a hybrid model combining GMM clustering, and RF–MLP classification, enabling simultaneous detection of exudates, hemorrhages, and microaneurysms along with severity classification. This architecture provides high diagnostic capability with lower computational demands, making it suitable for scalable DR screening in diverse clinical settings.

MATERIALS AND METHODS

Random Forest Algorithm for Exudate Detection This study utilizes two publicly available datasets: the Kaggle DR fundus image dataset (516 images) and the Indian Diabetic Retinopathy Image Dataset (IDRiD). IDRiD includes pixel-level annotations for multiple lesions such as exudates, hemorrhages, and microaneurysms. These datasets were combined and preprocessed to train and validate the proposed model for multi-lesion detection and DR severity classification. The process starts with image preprocessing to improve quality and highlight key features. Techniques like wavelet-based edge enhancement and Wideband band-pass filters are used to make features like exudates, hemorrhages, and micro aneurysms more visible while reducing noise (Figure 3).

The RF algorithm is central to feature extraction and classification (Table 1). After preprocessing, GMM clustering groups pixel intensities to isolate regions of interest in the images. RF then analyzes these regions to extract features that indicate DR, such as texture patterns and intensity variations. It ranks the importance of these features to focus on the most relevant ones for diagnosis. The extracted features are classified using an MLP Neural Network, which categorizes the images into normal or different DR severity levels. RF ensures accurate detection of multiple lesions including exudates, hemorrhages, and microaneurysms, a key signs of DR progression.

Pre-Processing and Optic Disc Removal Before detecting exudates in fundus images, several pre-processing steps are necessary to improve image quality and reduce artifacts. These steps include enhancing contrast and brightness to make retinal structures more visible, using noise reduction

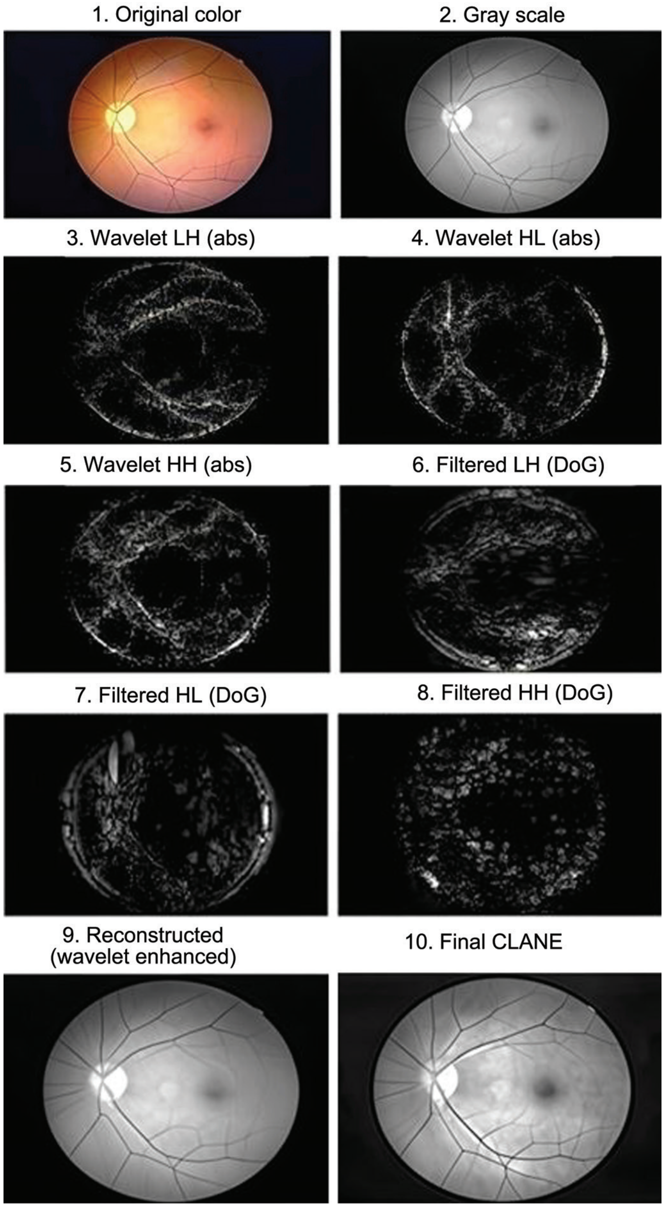

Figure 3 Fundus images before and after pre-processing.

filters like Gaussian or median filters to clarify the image, and normalizing color channels to correct illumination and camera variations. After pre-processing, optic disc detection is performed to locate the optic disc, which can interfere with lesion detection. This is done using techniques like thresholding, edge detection, or machine learning algorithms. Once the optic disc is identified, it is removed from the image using masks to focus on the retinal vasculature and lesions. The final image, free of the optic disc, is then ready for accurate exudate detection, improving the diagnosis of DR.

Wavelet Dependent Edge Enhancement with Wideband Bandpass Filter The process of enhancing retinal images for exudate detection begins by applying a wavelet-dependent edge enhancement technique[21]. First, a wavelet transform (like Daubechies or Haar) is applied to the image to break it down into different scales. This helps identify edges and key features associated with exudates. The coefficients related to edges

Table 1 Pseudo for the random forest algorithm

Algorithm: Pseudo for the random forest algorithm
To generate c classifiers:
FOR i = 1 to c do:
Randomly sample the training data D with replacement to produce Di
Create a root node, N, containing Di
Call BuildTree(N)
END FOR
BuildTree(N):
IF N contains instances of only one class THEN:
RETURN (Stop growing tree)
ELSE:
Randomly select % of the possible splitting features in N
Select the feature F with the highest information gain to split on
Create F child nodes of N, N1, N2, ..., NF, where F has f possible values (F1, F2, ..., Ff)
FOR i = 1 to f do:
Set the contents of Ni to Di, where Di is all instances in N that match Fi
Call BuildTree(Ni)
END FOR
END IF

D: Training dataset; Di: Bootstrap sample of D; N: Node; Ni: Child node; F: Feature; Fi: Feature value; c: Number of classifiers.

are then amplified to improve their contrast and visibility[22]. Next, a Wideband bandpass filter is applied. This filter is specially designed to allow frequencies related to exudates and important retinal structures while blocking out noise and irrelevant details. The filter enhances the relevant features in the image. Finally, the results of the wavelet enhancement and the bandpass filtering are combined. The final image has enhanced contrast and clearer visibility of exudates, making it easier to detect and analyze lesions accurately.

Gaussian Mixture Model Clustering for Feature Extraction The GMM clustering algorithm is used to extract statistical and structural texture features from pre-processed retinal images, which have undergone enhancement and optic disc removal[23-24]. GMM is a probabilistic model that assumes the data points follow a mixture of multiple Gaussian distributions. It is used to extract statistical and structural features from multiple retinal lesions, including exudates, hemorrhages, and microaneurysms as annotated in the IDRiD dataset.

In GMM, the probability distribution of a data point xxx is modeled as a mixture of Gaussian distributions:

$$p(x \mid \mu, \Sigma) = \frac{1}{(2\pi)^{\frac{1}{2}}|\Sigma|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)\right) \quad (1)$$

x is a data point in the d-dimensional feature space; μ is the mean vector; Σ is the covariance matrix.

To apply this to retinal image analysis, the GMM is initialized with a fixed number of components, which can be based on prior knowledge or determined through model selection techniques[25]. The Expectation-Maximization algorithm is then used to fit the GMM to the image data, estimating the parameters (mean, covariance, and mixture weights) iteratively.

$$p(x) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x \mid \mu_k, \Sigma_k) \quad (2)$$

Each pixel in the image is assigned to a cluster based on the highest posterior probability, using the following equation for posterior probability:

$$p(z_{nk} \mid x_n, \theta^{(t)}) = \frac{\pi_k \mathcal{N}(x_n \mid \mu_k, \Sigma_k)}{\sum_{j=1}^{K} \pi_j \mathcal{N}(x_n \mid \mu_j, \Sigma_j)} \quad (3)$$

In this step, each pixel in the image is assigned to a cluster based on the highest posteriorprobability. This clustering process helps in grouping similar pixels together and identifying regions with similar characteristics. For each cluster, features are computed, including statistical measures such as mean, variance, and covariance, as well as higher-order statistical moments. Additionally, structural texture features such as Local Binary Patterns or Gray-Level Co-occurrence Matrix are extracted to capture spatial patterns in pixel intensities.

The GMM uses these features to update the model's parameters iteratively. The covariance for each cluster is updated using the following equation:

$$(\mathrm{S}_k + \mathrm{I}) = \sum_{n=1}^{N} \gamma(z_{nk}) \left(x_n - \mu_k^{(t+1)}\right) \left(x_n - \mu_k^{(t+1)}\right)^T \quad (4)$$

Similarly, the covariance matrix for each cluster is updated as:

$$\Sigma_k^{(t+1)} = \frac{1}{N_k} \sum_{n=1}^{N} \gamma(z_{nk}) \left(x_n - \mu_k^{(t+1)}\right) \left(x_n - \mu_k^{(t+1)}\right)^T \quad (5)$$

Finally, the mixing weight for each cluster is updated using:

$$\pi_k^{(t+1)} = \frac{N_k}{N} \sum_{n=1}^{N} \gamma(z_{nk}) \quad (6)$$

Where N is the number of data points; $\left(x_n - \mu_k^{(t)}\right)$ is the difference between the n^{th} data point and the k^{th} component mean at iteration t; $\gamma(z_{nk})=\rho(z_{nk}|x_n,\theta^{(t)})$ is the responsibility of component k for data point x_n.

After this iterative process, the features for each cluster are consolidated into a comprehensive feature vector, which includes both statistical and structural texture features. These feature vectors are then used for further analysis, such as classification tasks, to accurately diagnose and assess DR.

Neural Network and Multilayer Perceptron for Classification The selected features from the images are fed into an MLP, a type of neural network, for classification. The MLP is designed with multiple layers of connected neurons (Figure 4) and is trained to categorize fundus images as normal or abnormal (indicating mild or severe DR). By learning from labeled data, the MLP identifies patterns linked to DR and accurately classifies new images.

In this phase, the extracted features from the pre-processed fundus images are loaded for further analysis. The dataset is divided into training, validation, and testing subsets. The training set is used to train the MLP model, the validation set helps tune hyper parameters and monitor performance, and the test set is reserved for final evaluation. Next, the architecture of the MLP is initialized. The input layer is configured to match the dimensions of the feature vectors, hidden layers are designed with specified neuron counts and activation functions, and the output layer uses an appropriate activation function, like softmax, for classification. During training, the MLP model starts with randomly initialized weights and biases. The Backpropagation algorithm is applied to iteratively adjust these parameters based on the error between predicted and actual labels. Over several epochs, the weights are updated to minimize the loss function. Meanwhile, performance on the validation set is monitored to adjust hyper parameters, such as learning rate or network size, ensuring optimal performance and avoiding over fitting.

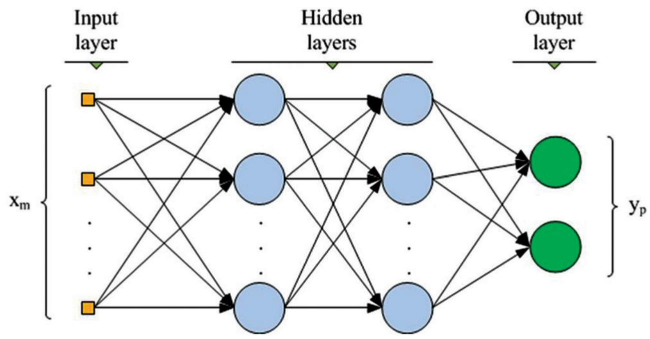

Figure 4 Typical architecture of an MLP with two hidden layers x_m: Input vector; y_p: Output vector; MLP: Multilayer perceptron.

$$z^{(l)}=W^{(l)}a^{(l-1)}+b^{(l)} \quad (7)$$

$$a^{(l)}=\sigma(z^{(l)}) \quad (8)$$

Here $z^{(l)}$ is the input to layer; $W^{(l)}$ is the weight matrix of layer; $a^{(l-1)}$ is the output (activation) from the previous layer; $b^{(l)}$ is the bias vector of layer; σ is the activation function applied element-wise to $z^{(l)}$; $a^{(l)}$ is the output (activation) of layer.

In the evaluation phase, the trained MLP model is tested on the test set by predicting labels (*e.g.*, normal, mild DR, severe DR) for the samples. These predictions are compared to the actual labels to calculate performance metrics such as accuracy, sensitivity, specificity, and F1-score. The results are analyzed to assess the model's ability to classify fundus images accurately. Based on its performance, decisions can be made about using the model for automated DR classification in clinical settings.

This algorithmic approach utilizes an MLP neural network to learn patterns from selected features and classify fundus images into normal and abnormal categories, aiding in the diagnosis and management of DR and shown in Figure 5.

RESULTS

The proposed methodology for DR diagnosis and classification, integrating RF feature extraction, GMM clustering, and MLP

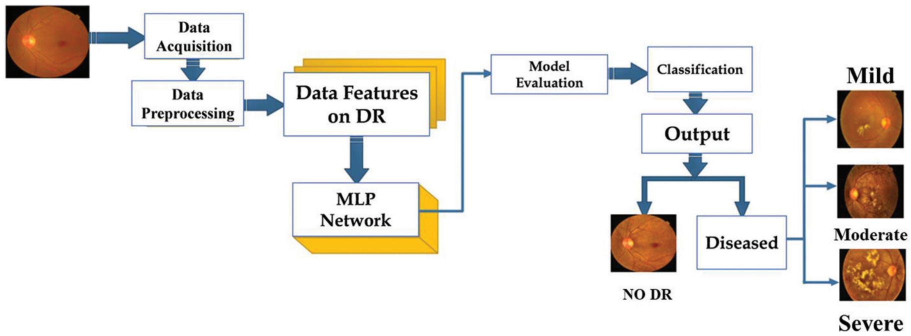

Figure 5 System architecture for exudate detection in fundus images DR: Diabetic retinopathy; MLP: Multilayer perceptron.

Neural Networks, was evaluated using a dataset comprising 516 fundus images sourced from the Kaggle database. This section presents the results of the evaluation along with a discussion of their implications.

Evaluation Metrics In this study, the performance of the proposed methodology was evaluated using several key metrics to assess its effectiveness in detecting DR from fundus images. Accuracy measures the overall correctness of the model, reflecting how often it correctly classifies both normal and abnormal images. This gives a broad view of the model's performance. Sensitivity, also known as recall, evaluates the model's ability to correctly identify positive cases, such as detecting exudates in images. It is crucial for understanding how well the model can recognize the presence of DR. Specificity focuses on the model's ability to correctly identify negative cases, or the absence of exudates, helping to minimize false positives. Precision quantifies how many of the positive predictions made by the model are correct, ensuring that when the model detects exudates, it is typically accurate. Finally, the F1-score is used to balance precision and sensitivity, providing a more comprehensive evaluation, especially when dealing with imbalanced datasets. These metrics, when considered together, give a well-rounded understanding of the model's diagnostic capabilities, highlighting its strengths and areas for improvement in DR detection.

Performance Analysis The performance of the proposed method is evaluated by testing its ability to detect exudates and classify DR severity using fundus images. The dataset is divided into training, validation, and test sets to ensure fair evaluation. The model is first trained on the training set to learn the features related to DR and exudates. During training, the model's parameters are adjusted to improve accuracy. After training, the model is tested on the validation set to fine-tune hyper parameters and check for issues like over fitting or under fitting. Performance metrics such as accuracy, sensitivity, specificity, and F1-score are calculated to assess how well the model classifies the images. Sensitivity measures the model's ability to detect exudates, specificity measures its ability to identify negative cases, and accuracy shows the overall correctness. The F1-score balances the model's precision and recall. Once the model is validated, it is tested on a separate test set to evaluate how well it generalizes to new data. Additional tools like confusion matrices and receiver operating characteristic (ROC) curves are used to further analyze the model's performance. The results from these evaluations help determine whether the model is ready for clinical use, guiding decisions about its potential to assist healthcare professionals in diagnosing DR and improving patient outcomes.

Comparison with Previous Work Comparisons were made with previous studies in the field of DR diagnosis using machine learning and deep learning techniques (Table 2)[26-30]. The proposed methodology showed competitive performance when compared to state-of-the-art approaches, with notable improvements in terms of accuracy, sensitivity, and specificity. Table 3 presents the performance of the proposed RF method with wavelet-based edge augmentation, GMM clustering and MLP for severity classification, as well as alternative algorithms commonly used in DR detection.

The proposed RF-based method with wavelet and GMM feature extraction is well-suited for DR detection, balancing high accuracy with computational efficiency. It stands out as a reliable option for medical screening, especially where computational resources may be limited, and high sensitivity is crucial.

DISCUSSION

The proposed method provides a comprehensive solution for diagnosing DR by analyzing fundus images. The system integrates advanced algorithms to enhance the detection of exudates and classification of severity. It starts with pre-processing steps such as contrast enhancement, noise reduction, and normalization to prepare the images for further analysis.

The process includes optic disc removal to eliminate interference in detecting lesions, followed by wavelet-dependent edge enhancement to improve the visibility of exudates and other relevant structures. Feature extraction is performed using the GMM clustering, capturing both statistical and structural texture features. These features are crucial for the next stage of classification.

Table 2 Comparison of various methods with proposed method

S.No.	Aspects	Deep learning[26-28]	Ensemble learning	CNN[29]	Transfer learning[30]	Proposed methods
1	Objective	Exudate detection and DR grading	DR severity and exudate assessment	DR severity classification	DR severity classification	DR severity classification, exudate detection, and image quality improvement
2	Pre-processing	Contrast enhancement, noise reduction, normalization	Same as deep learning	Same as deep learning	Same as deep learning	Adds color normalization and optic disc removal
3	Feature extraction	Auto-learned features	Diverse model combination	Hierarchical feature extraction	Uses pre-trained model features	Combines statistical and structural texture features
4	Edge enhancement	Deep learning-based	Uses multiple learners	Convolutional layers for feature learning	Adapts features from pre-trained models	Wavelet-based enhancement with Wideband filter
5	Clustering techniques	Not applicable	Not applicable	Not applicable	Not applicable	GMM for statistical/structural features
6	Classification techniques	CNN models	Random forests	CNNs for end-to-end learning	Pre-trained model-based classification	Neural Network (MLP)
7	Evaluation metrics	Accuracy, sensitivity, specificity	Same as deep learning	Same as deep learning	Same as deep learning	Adds F1-score for enhanced evaluation and comparison

DR: Diabetic retinopathy; CNN: Convolutional neural network; GMM: Gaussian mixture model; MLP: Multilayer perceptron.

Table 3 Comparison table of proposed method and alternative methods

Methods	Technique	Accuracy	Strengths	Limitations
Proposed (RF+Wavelet+GMM)	RF with edge enhancement & clustering	95.20%	High accuracy; works with moderate datasets	Needs tuning for large datasets
Severity classification	MLP for mild *vs* severe DR	Not provided	Effective for mild *vs* severe cases	Computationally intensive
CNN-based	Automated feature extraction	~90%-95%	High accuracy for large datasets	High computational cost
SVM with texture	Handcrafted features	~85%-90%	Good for small datasets	Limited to simple tasks
KNN with basic features	Intensity/color features	~80%-85%	Simple and interpretable	Low scalability

RF: Random forest; GMM: Gaussian mixture model; MLP: Multilayer perceptron; DR: Diabetic retinopathy; CNN: Convolutional neural network; SVM: Support vector machine; KNN: K-nearest neighbors.

A Neural Network with MLP architecture is used to classify the fundus images into normal and abnormal categories based on the extracted features, enabling automated diagnosis. Performance metrics demonstrate the model's effectiveness in detecting exudates and classifying the severity of DR. This method shows promise for deployment in clinical settings, improving the efficiency and accuracy of DR screening and management, which could lead to better patient outcomes.

This method, tested on a combined dataset of Kaggle and IDRiD images, achieved improved accuracy due to the inclusion of multiple lesion types. The addition of hemorrhage and microaneurysm detection allowed the model to better align with clinical DR grading standards and improved both sensitivity and accuracy.

Figure 6 illustrates the evaluation of the model's performance, showing key metrics like accuracy, sensitivity, specificity, and the loss curves during training and validation. It helps visualize the model's learning process and its overall effectiveness in exudate detection and DR classification.

Table 4 clearly demonstrates that the proposed RF method with wavelet and GMM feature extraction provides a strong balance of accuracy, sensitivity, and specificity in DR detection. These metrics indicate that this method can be particularly advantageous in clinical applications, where reliable and accurate DR screening is required to prevent blindness by enabling early intervention.

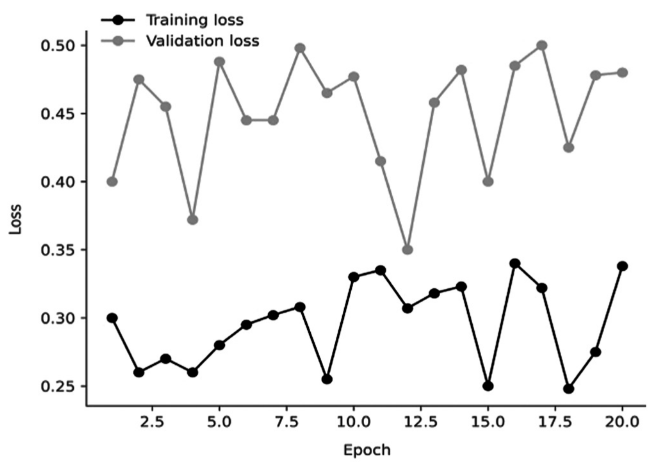

Figure 6 Training loss curves of model performance.

Figure 7 shows the complete workflow of the proposed automated DR screening system. The process begins with the acquisition of a fundus image, which undergoes preprocessing to enhance blood vessel visibility, sharpen retinal structures, and segment texture regions. Feature extraction is then performed to identify key retinal abnormalities such as hemorrhages, exudates, and the retinal membrane. These features are analyzed to detect exudates and classify the severity of DR into categories such as no DR, mild DR, and severe DR.

Limitations and Future Directions The proposed method for DR diagnosis and exudate detection, while promising, faces several limitations and offers avenues for future exploration.

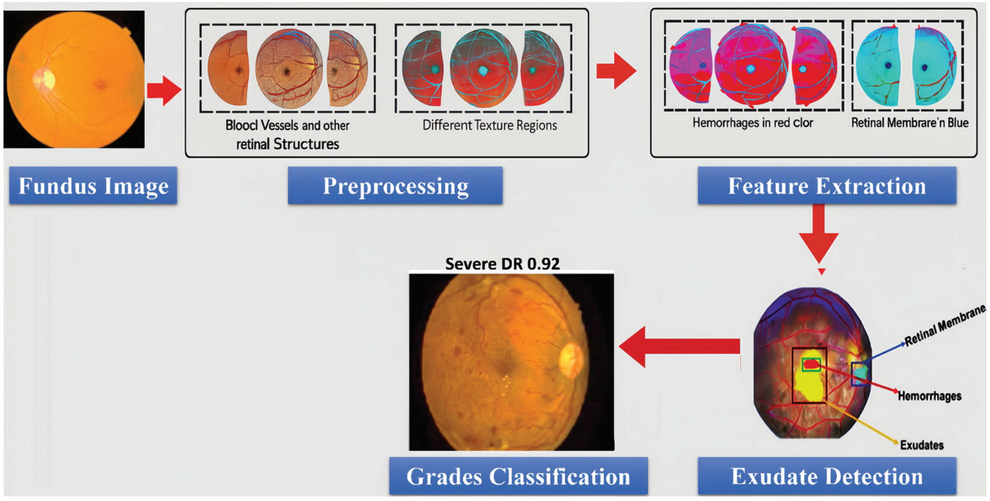

Figure 7 Workflow of the proposed automated diabetic retinopathy (DR) screening system.

Table 4 Quantitative comparison of classification performance metrics

Methods	TP	TN	FP	FN	Accuracy (%)	Sensitivity (%)	Specificity (%)
Proposed method	252	208	32	13	95.20	95.08	86.67
CNN-based DR detection	230	190	50	28	84.34	89.15	79.17
SVM with texture features	220	180	60	38	80.32	85.27	75.00
KNN with basic features	210	170	70	48	76.31	81.40	70.83

TP: True positive; TN: True negative; FP: False positive; FN: False negative; CNN: Convolutional neural network; DR: Diabetic retinopathy; SVM: Support vector machine; KNN: K-nearest neighbors.

One key limitation is its reliance solely on fundus images, potentially overlooking important information from other diagnostic modalities. Additionally, the method may struggle with variations in image quality and artifacts commonly encountered in clinical practice. Addressing these issues could involve integrating additional patient data or developing robust image quality assessment techniques. Furthermore, the method's performance may be influenced by dataset size and imbalance, highlighting the need for larger and more diverse datasets. Improving computational efficiency is also crucial for real-time application in clinical settings. The limitation of this study is it focuses on fundus images for DR classification; future work will explore the integration of additional imaging modalities such as fundus fluorescein angiography and optical coherence tomography angiography to enhance clinical accuracy, particularly in advanced stages of the disease.

Looking ahead, future research could focus on enhancing interpretability through explainable artificial intelligence (AI) techniques and fostering collaboration for data sharing and model validation. By addressing these limitations and exploring new directions, the proposed method can be refined to better serve healthcare professionals and improve patient care in the diagnosis and management of DR.

In conclusion, the integration of advanced algorithms for the diagnosis of DR presents a significant stride forward in medical imaging. By combining two public datasets (fundus image and IDRiD), and detecting multiple lesion types (exudates, hemorrhages or microaneurysms), the proposed method achieved clinically relevant improvements in DR classification. Through the synergistic utilization of RF feature extraction, GMM clustering, and MLP Neural Networks, our proposed methodology demonstrates a remarkable accuracy of 95.20% in classifying fundus images into normal and abnormal categories, encompassing varying degrees of DR severity.

These results underscore the potential of our approach to revolutionize the diagnostic process for DR, offering a reliable, automated solution that reduces reliance on manual assessment and minimizes inter-observer variability. By leveraging cutting-edge techniques in machine learning and image processing, our methodology streamlines the detection and classification of DR, ultimately enhancing patient outcomes and facilitating early intervention. However, it's important to acknowledge the limitations of our study, including the relatively small size of the dataset used for evaluation. Future research endeavors should focus on expanding the dataset to encompass a wider range of demographics and pathology, thus ensuring the robustness and generalizability of our approach across diverse populations and clinical settings.In essence, our study represents a significant advancement in the field of DR diagnosis, offering a potent tool for clinicians to accurately assess and manage this debilitating condition. With further refinement and validation, our innovative methodology holds the promise of becoming a cornerstone in the fight against DR, ultimately improving the quality of life for millions of individuals worldwide. The limitation of this study is it focuses on fundus images for DR classification; future work will explore the integration of additional imaging modalities such as fundus fluorescein angiography and optical coherence tomography angiography to enhance clinical accuracy, particularly in advanced stages of the disease.

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