



# Comparative Study of Diabetic Retinopathy Detection Using Machine Learning Methods

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## Abstract

Untreated diabetic retinopathy, a consequence of poorly managed chronic diabetes, can lead to complete vision loss. Early diagnosis and treatment are crucial to prevent severe complications. Currently, ophthalmologists dedicate significant time to manually diagnose diabetic retinopathy, causing discomfort to patients. Automated technologies offer a promising solution by swiftly identifying diabetic retinopathy and facilitating timely treatment to mitigate further ocular damage. This study proposes leveraging machine learning to extract and classify key features such as exudates, hemorrhages, and microaneurysms using a hybrid classifier combining support vector machines, k-nearest neighbors, and random forests.

**Keywords:** Diabetic Retinopathy; Machine Learning; KNN; Random Forest; SVM.

## 1. Introduction

Diabetes, a chronic condition affecting millions worldwide, presents a spectrum of complications, among which diabetic retinopathy stands out for its potential to cause irreversible vision impairment, even leading to total blindness in severe cases. Early symptoms such as eye floaters, blurred vision, darkened areas, and color perception difficulties serve as critical indicators of diabetic retinopathy's onset. Timely and accurate diagnosis during these early stages is paramount in preventing irreversible vision loss. This research addresses the challenge of early detection through automated computer-aided methods, specifically focusing on extracting and analyzing key features—hemorrhages, microaneurysms, and exudates—from retinal images. Leveraging a hybrid machine learning approach, combining Support Vector Machines (SVM) and k-Nearest Neighbors (KNN), the proposed model aims to enhance diagnostic accuracy and efficiency in identifying diabetic retinopathy. By integrating these advanced technologies, the study endeavors to improve patient outcomes and mitigate the devastating impact of diabetic retinopathy on visual health.

## 2. Literature Review

Recent advancements in deep learning have revolutionized various fields, particularly in the realm of medical image classification and analysis. Among these innovations, convolutional neural networks (CNNs) have emerged as highly effective tools for processing medical images due to their robustness and efficiency. This literature review examines current methodologies in the classification and detection of diabetic retinopathy (DR) using deep learning algorithms, reflecting on their efficacy and application in analyzing color fundus images [1]. The availability and analysis of comprehensive color fundus retina datasets for DR have also been a focal point, underscoring the importance of robust datasets in training and validating deep learning models. Early detection of diseases like diabetic retinopathy is critical in medical practice as it significantly enhances the effectiveness of treatment interventions. Diabetes, a widespread chronic condition affecting 425 million adults globally, is characterized by insulin deficiency and elevated blood glucose levels. Its impact extends beyond metabolic disturbances, affecting vital organs such as the kidneys, heart, nerves, and notably, the retina. The retina, being highly sensitive to fluctuations in blood glucose



levels, is particularly susceptible to diabetic retinopathy, which, if left untreated, can lead to severe vision impairment and even blindness. As such, leveraging deep learning techniques for the early detection and classification of diabetic retinopathy holds promise in improving patient outcomes by enabling timely intervention and management strategies. This review synthesizes current research efforts aimed at harnessing deep learning's potential in advancing medical imaging diagnostics, with a specific focus on diabetic retinopathy detection and classification [2-4].

### **3. Methodologies**

Machine learning, a prominent subfield of artificial intelligence and computer science, focuses on developing algorithms that learn from data to improve accuracy over time, emulating human learning processes. This literature review explores the application of machine learning in a healthcare setting, specifically in managing and analyzing patient data within a comprehensive system comprising four modules: admin, doctor, patient, and lab. The admin module serves as the central authority, allowing administrators to manage healthcare professionals, facilities (such as labs and hospitals), and oversee patient details securely through authentication with a valid email address. This administrative oversight ensures organizational efficiency and regulatory compliance. Within the doctor module, healthcare providers access a tailored interface enabling them to add new patients, update their medical records, and manage their own professional profiles securely. This functionality enhances patient management and facilitates timely healthcare interventions. Patients, utilizing the patient module, log in securely with their credentials to access personalized health information and medical records. This patient-centric approach empowers individuals to actively engage in their healthcare journey, promoting transparency and informed decision-making. The lab module plays a crucial role in the diagnostic process by examining patient medical data, including retinal images, to predict diabetic retinopathy. Leveraging advanced image processing and machine learning techniques, labs contribute to early detection and intervention

strategies, thereby improving patient outcomes and reducing healthcare costs associated with advanced disease stages. This integrated system exemplifies how machine learning technologies enhance healthcare delivery by streamlining administrative processes, facilitating data-driven medical decisions, and advancing diagnostic capabilities. By harnessing these advancements, healthcare systems can achieve greater efficiency, accuracy, and patient satisfaction, ultimately fostering a more proactive approach to healthcare management and disease prevention.

#### **3.1. Machine Learning**

Artificial intelligence (AI), specifically through machine learning (ML), empowers computer programs to predict outcomes with heightened accuracy, leveraging historical data as input without explicit programming of every possible scenario. Machine learning algorithms achieve this by analyzing patterns and relationships within data to generate predictions for new output values. To elaborate on the methodology, machine learning operates through several key stages. Initially, data is collected and preprocessed to ensure quality and relevance. This involves cleaning the data, handling missing values, and transforming features to make them suitable for analysis. Subsequently, the data is divided into training and testing sets. The training set is used to train the machine learning model, where the algorithm learns from the input data to identify patterns and correlations. Once trained, the model is evaluated using the testing set to assess its predictive performance. Various metrics such as accuracy, precision, recall, and F1-score are employed to gauge the model's effectiveness in making predictions. Iterative refinement may occur by fine-tuning parameters, adjusting the model architecture, or employing feature selection techniques to optimize performance. In practical applications, AI and ML are deployed across diverse domains, from healthcare and finance to marketing and autonomous vehicles. Their ability to handle large volumes of data, identify complex patterns, and make data-driven decisions has revolutionized industries, leading to more efficient processes, improved decision-making, and enhanced outcomes.

### 3.2. K Nearest Neighbour (KNN) algorithm

**Step 1:** Choose the number KKK of neighbours.

**Step 2:** Calculate the Euclidean distance between the new data point and all points in the dataset.

**Step 3:** Select the top KKK closest neighbours based on the Euclidean distance.

**Step 4:** Determine the class labels of the KKK nearest neighbours.

**Step 5:** Assign the new data point to the class that is most common among its KKK nearest neighbours.

**Step 6:** End of the algorithm; the model is now ready for predictions.

This algorithm utilizes the Euclidean distance metric to find similarities between data points and assigns new points to the category most prevalent among their nearest neighbours.

### 3.3. Support Vector Machine (SVM) Algorithm

**Step 1:** Import the necessary libraries.

**Step 2:** Pre-process the dataset:

- Handle missing values.
- Encode categorical variables.
- Scale numerical features if necessary.

**Step 3:** Instantiate and train the Support Vector Machine model:

- Select the appropriate SVM variant based on the problem (e.g., linear SVM, kernel SVM).
- Fit the SVM model to the pre-processed training data.

This algorithm involves importing required libraries, preparing the dataset through preprocessing steps such as handling missing data and scaling features, and then training the SVM model to make predictions based on the input data.

### 3.4. Random Forest Algorithm

**Step 1:** Randomly select KKK data points from the training set.

**Step 2:** Construct decision trees using the selected data points:

- Each tree is built independently and uses a random subset of features for splitting nodes.

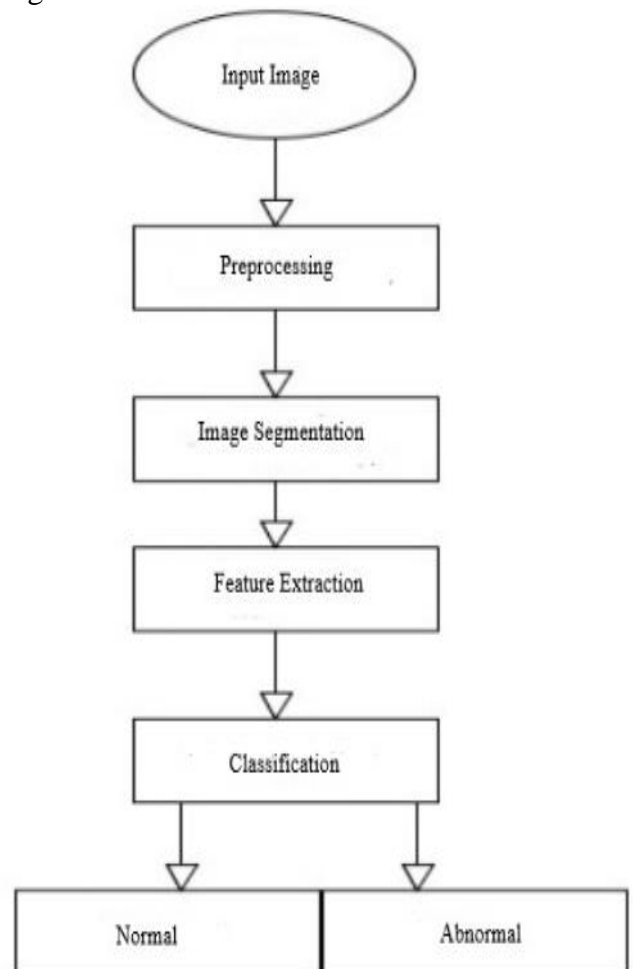
**Step 3:** Specify the number NNN of decision trees to build.

**Step 4:** Repeat Steps 1 and 2 to create NNN decision trees in the forest.

**Step 5:** For a new data point, classify it by aggregating predictions from all decision trees:

- Each tree gives a classification, and the final prediction is the majority class among all trees (for classification tasks).

This algorithm leverages the power of ensemble learning by constructing multiple decision trees and aggregating their predictions to achieve robust and accurate classifications for new data points are shown in Figure 1.



**Figure 1** Flow of Diabetic Retinopathy Detection Model

### 3.5. Datasets

Our dataset comprises a diverse collection of high-resolution retinal images acquired under various imaging conditions. Each subject is represented with images from both their left and right eyes, identified by a unique subject ID and the eye designation (e.g.,

"1 left.jpeg" denotes the left eye of patient 1). The dataset encompasses a substantial volume of high-quality retinal images captured using different camera models and types, leading to variations in how the left and right eye images appear. The dataset undergoes pre-processing to prepare input images according to the standard requirements of the proposed system. This process aims to enhance microscopic image quality by mitigating undesired distortions and accentuating crucial image attributes necessary for subsequent analyses. Typical pre-processing operations involve resizing images, removing noise, and eliminating artifacts that could mislead interpretations. This step is particularly beneficial for accurate identification and categorization of red blood cells. The RGB images are converted to grayscale, and further enhancement is achieved using a median filter to refine borders, identify relevant components, and reduce noise levels.

### 3.6. System Architecture

The system begins with inputting the image dataset, followed by a series of preprocessing steps. Initially, each image undergoes resizing to standardize dimensions across all inputs, addressing variations in sizes captured by different cameras. Subsequently, noise reduction techniques are applied to enhance image clarity. The next stage involves image segmentation and morphology operations. Here, the image is segmented to distinguish foreground objects from the background, with additional noise reduction techniques employed to refine segmentation quality. Following segmentation, features such as exudates, hemorrhages, and microaneurysms are extracted from the images. These features serve as crucial indicators for subsequent classification tasks. In the classification step, the extracted features are utilized to classify the image as normal or abnormal. This classification leverages machine learning algorithms to predict the health status of the retina based on the extracted features. Overall, this systematic approach—from preprocessing and segmentation to feature extraction and classification—facilitates accurate assessment of retinal images, aiding in medical diagnostics and treatment decisions are shown in Figure 2.

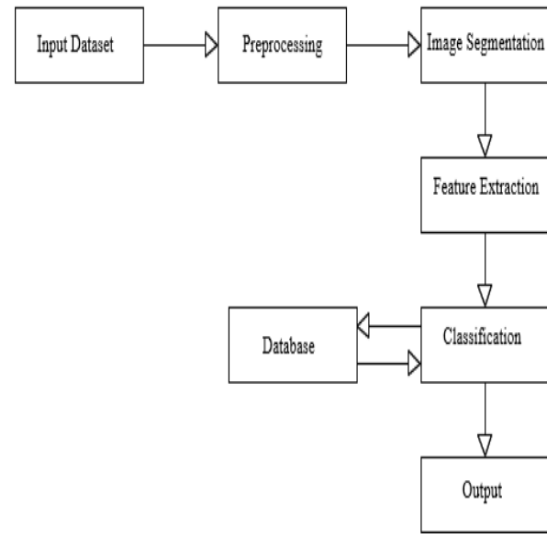


Figure 2 Architecture of Proposed Model

## 4. Results And Experimental Analysis

Below Figure 3 illustrates a comparison of accuracy between the SVM and KNN algorithms. The X-axis denotes the accuracy score, while the Y-axis represents each algorithm. According to the results, the SVM algorithm achieves an accuracy score of 0.8, whereas the KNN algorithm achieves 0.65. These findings highlight the superior performance of SVM over KNN in this evaluation. Such insights are crucial for selecting the most effective algorithm for specific machine learning tasks.

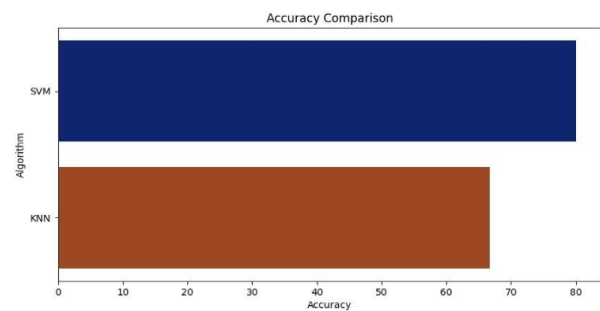


Figure 3 Accuracy Comparison Graph

Figure 4 displays the precision score, recall score, f1-score, support, confusion matrix, and accuracy score for the KNN classifier, achieving an accuracy of 0.65. In contrast, Figure 5 presents these metrics for the SVM classifier, which achieved an accuracy score of 0.8. The F1 score, combining accuracy and recall,

provides a comprehensive measure of the model's predictive performance. Accuracy assesses the ratio of correct predictions to all predictions made. Precision measures the proportion of correctly predicted positive outcomes among all predicted positives. Recall, on the other hand, evaluates the proportion of correctly predicted positive outcomes relative to all actual positive instances in the dataset.

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Classification report :
              precision    recall  f1-score   support

     0.0         0.60      0.90      0.72        10
     1.0         0.80      0.40      0.53        10

 accuracy          0.65      0.65      0.63        20
 macro avg         0.70      0.65      0.63        20
 weighted avg      0.70      0.65      0.63        20

Confusion matrix :
[[9 1]
 [6 4]]
Accuracy score : 0.65
    
```

**Figure 4 Evaluation of KNN**

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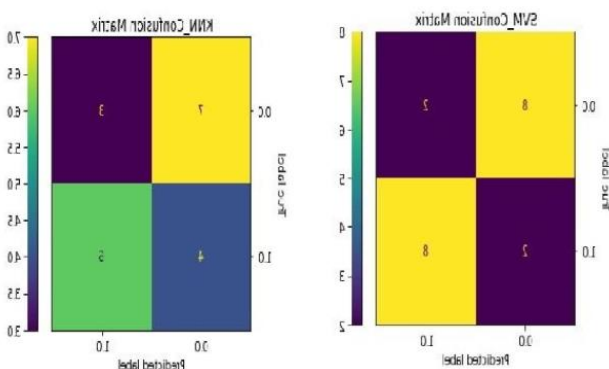
Classification report :
              precision    recall  f1-score   support

     0.0         0.80      0.80      0.80        10
     1.0         0.80      0.80      0.80        10

 accuracy          0.80      0.80      0.80        20
 macro avg         0.80      0.80      0.80        20
 weighted avg      0.80      0.80      0.80        20

Confusion matrix :
[[8 2]
 [2 8]]
Accuracy score : 0.8
    
```

**Figure 5 SVM Accuracy Evaluation**



**Figure 6 Confusion Matrix for SVM And KNN Classifiers**

Figure 6 presents the confusion matrices for both the SVM and KNN classifiers, detailing the true and predicted label values. A confusion matrix succinctly summarizes the expected outcomes of a classification task, counting accurate and inaccurate predictions per class. In terms of computational performance, the SVM algorithm consumes a total CPU time of 1.47 seconds, with user and system times noted as 897 ms and 576 ms, respectively. Comparatively, the KNN algorithm operates with a total CPU time of 988 ms, comprising user and system times of 932 ms and 56 ms, respectively. These timings provide insights into the computational efficiency of each algorithm in processing the dataset.

### Conclusion

The proposed method successfully identifies hemorrhages, exudates, and microaneurysms through a systematic approach. Specifically, exudates are effectively isolated using channel extraction, masking, smoothing, and bitwise green AND operations. Meanwhile, for hemorrhages and microaneurysms, morphological techniques like opening—employing erosion and dilation—are employed. By quantifying the occurrences of these features in retinal images, the severity of diabetic retinopathy can be determined. These extracted features are then utilized as inputs for SVM, KNN, and Random Forest classifiers. The final prediction is derived from the combined results of these classifiers, categorizing the disease grade as normal or abnormal. Early detection and diagnosis play a pivotal role in preventing blindness and mitigating the progression of diabetic retinopathy. By leveraging these advanced computational techniques, this approach enhances diagnostic accuracy and supports timely intervention, thereby improving patient outcomes. In conclusion, the methodology of AI and machine learning represents a paradigm shift in computational capabilities, enabling systems to forecast outcomes accurately and efficiently based on historical data patterns. As these technologies continue to evolve, their integration into everyday applications promises to drive further advancements and innovations across various sectors.



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