International Journal of Applied Mathematics

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

DETECTION OF HEMMOREGES OF DIABETIC RETINOPATHY USING MACHINE LEARNING ALGORITHMS

Mr. Kale Sunil Manmath, Purushottam R Patil

[1]Research Scholar, School of Computer Sciences and Engineering,Sandip Univesity, Nashik,Maharashtra,India
[2]Professor, School of Computer Sciences and Engineering,Sandip University,Nashik,Maharashtra,India
Email: smkale14jan@gmail.com, purupatil7@gmail.com

Abstract

Diabetic retinopathy (DR) is one of the most common and dangerous capillary consequences of diabetes. It is marked by lesions like microaneurysms, haemorrhages, exudates, and new blood vessels growing in the retina. Haemorrhages are one of the most important signs of how bad the disease is and how fast it is spreading. They are often the first sign of severe DR stages that can cause permanent blindness if they are not found early. So, it's important to find haemorrhages quickly and correctly so that they can be treated quickly and prevent vision loss. Traditional ways of diagnosing depend on ophthalmologists looking at retinal fundus pictures by hand, which takes a long time and can be subjective. These problems have led to a lot of interest in automatic methods based on picture processing and machine learning over the past few years. The main goal of this study is to use machine learning methods to find haemorrhages in diabetes retinopathy. A set of retinal fundus images that was open to the public was used, and expert comments were used as the basis for confirmation. The method includes several steps: preprocessing to improve the image and get rid of noise; extraction of distinguishing features such as colour, texture, and shape descriptors; and classification using both deep learning models and traditional machine learning algorithms (Support Vector Machine, Random Forest, k-Nearest Neighbour). To find out how accurate, sensitive, and detailed the different methods were, a comparative performance review was done. These results show that machine learning-based classifiers are much more accurate at finding haemorrhages than traditional handcrafted methods. Additionally, deep learning approaches perform better because they can automatically capture complex feature representations.

Keywords: Diabetic retinopathy, hemorrhage detection, retinal fundus images, machine learning, deep learning, computer-aided diagnosis

I. Introduction

A. Background on diabetic retinopathy and its complications

One of the most common capillary consequences of diabetes mellitus is diabetic retinopathy (DR). It is also the main cause of vision loss and blindness around the world. It happens

Received: July 15, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

because of long-term high blood sugar, which hurts the tiny blood vessels in the retina. This harms the blood vessels more, blocks the capillaries, and causes new blood vessels to grow in a strange way. There are two main steps that DR goes through: non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). Small changes in the retina, like microaneurysms, haemorrhages, and hard exudates, show up in the early stages of NPDR. As the disease gets worse to PDR, abnormal neovascularisation happens. This can lead to serious problems like vitreous haemorrhage and tractional retinal detachment, which can eventually leave a person permanently blind if it is not fixed [1]. Not only does diabetic retinopathy cause eye loss, but it can also cause other problems. Patients often have their vision get worse over time, making it hard for them to read, see colours clearly, and recognise faces or items. Also, later stages of DR have a big impact on quality of life, raising the risk of sadness and making it harder to do daily tasks on your own. Figure 1.1 shows human eye cross-section highlighting cornea, lens, retina. As the number of people with diabetes rises, so does the number of people with DR. This is especially true in low- and middle-income countries where regular eye care is hard to come by.

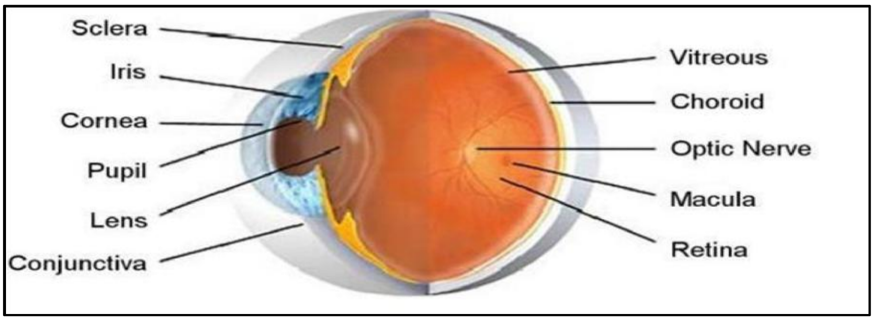

Figure 1.1: cross-section of human eye and points out its major components.

So, early evaluation and quick action are very important for stopping damage that can't be fixed. When creating automated detection systems, it is very important to know how DR can show up in an abnormal way, especially when there are bleeding problems. Figure 1.2 shows retinal image highlighting vasculature, optic disk, macula, fovea.

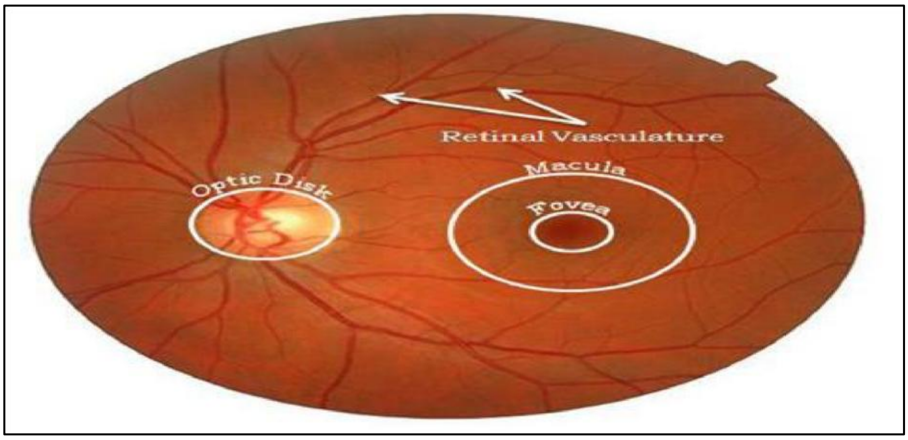

Figure 1.2: A Typical Retinal Image from the Left Eye Showing Retinal Vasculature, Optic Disk, Macula and Fovea

Received: July 15, 2025

Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

As a result, these methods can help with large-scale screening and early treatment, which will lower the world health impact of vision problems caused by diabetes.

B. Significance of detecting hemorrhages for early diagnosis

Haemorrhages are one of the most important signs of diabetes retinopathy because they show how the disease is getting worse. They happen when weak retinal blood vessels burst because of long-term damage to the blood vessels caused by hyperglycemia. There are different types of retinal haemorrhages, such as flame-shaped haemorrhages in the top layers and dot-blot haemorrhages in the lower layers. Ophthalmologists use the number, size, and location of haemorrhages as important diagnostic tools to figure out how bad DR is and how to treat it. Finding haemorrhages early is very important because they often mean that a vascular problem is getting worse [2]. Quick medical help at this stage can greatly slow or even stop the problem from getting to a point where it could threaten your vision. From a medical point of view, ophthalmologists can use standard grading methods like the Early Treatment Diabetic Retinopathy Study (ETDRS) scale to figure out how bad DR is by accurately finding haemorrhages. This ranking is very important for figuring out how often to check on a patient and if they need laser photocoagulation, intravitreal shots, or vitrectomy.

C. Aim and scope of the study

The main goal of this study is to create and test a machine learning-based system that can find bleeding in pictures of the retinal fundus taken from people who have diabetic retinopathy. The drive comes from the urgent need for automatic testing tools that can help doctors find diseases earlier and make screening more efficient. Figure 2 shows fundus images displaying lesions affecting retinal structures. By using advanced computer techniques, this study aims to cut down on the need for physical exams, make diagnoses less subjective, and produce accurate results that can be used for big groups of people [3].

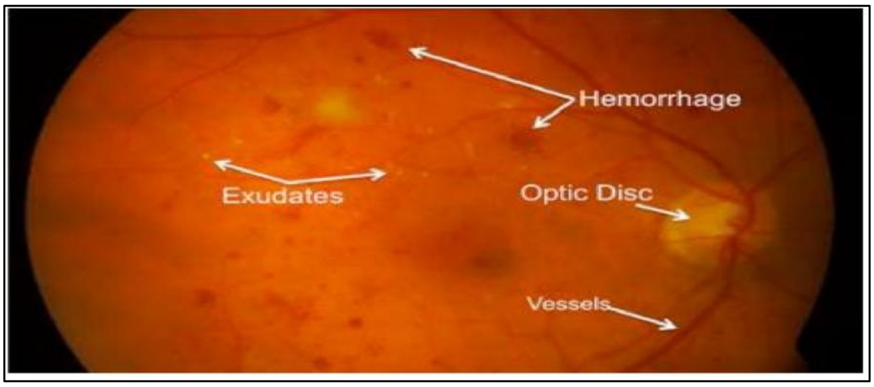

Figure 2: Fundus images with lesions

The study has three main parts: editing retinal pictures to improve quality and lower noise; feature extraction to find features that make haemorrhages stand out; and classification using machine learning methods. It is tried out both standard models, like Support Vector Machines, Random Forest, and k-Nearest Neighbour, and deep learning methods, like

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Convolutional Neural Networks, to see which one works best. The system is taught and tested on labelled retinal datasets, which makes sure that performance can be accurately measured using F1-score, sensitivity, specificity, and accuracy [4]. The study also wants to find out what the pros and cons are of traditional feature-based methods that are made by hand versus deep learning methods that learn hierarchical models automatically. By using two different methods, we can see how different algorithms react to changes in picture quality, lesion shape, and dataset size. The results of this study will be used in hospital and community health settings, as well as in the classroom. In the end, the study wants to create an easy-to-use, dependable, and expandable diagnosis tool that can help find diabetic retinopathy earlier, keep people from going blind, and make healthcare better for diabetics all over the world [5, 6].

II. Literature Review

A. Overview of diabetic retinopathy lesion detection methods

There has been a lot of study into finding diabetes retinopathy spots for many years because the disease can lead to permanent blindness if it is not treated. Finding lesions like microaneurysms, haemorrhages, exudates, and neovascularisation is very important for diagnosing and grading the disease because they show how bad it is. Over the years, experts have used a wide range of computer techniques, from old-fashioned picture processing to more modern artificial intelligence methods [7, 8]. In the beginning, finding lesions was mostly done with digital image analysis tools that worked on improving contrast, setting thresholds, and using morphological processes to draw attention to abnormal areas in retinal fundus pictures. It was common to use these methods on small datasets, and they worked pretty well in controlled imaging circumstances. But differences in picture clarity, patient demographics, and camera equipment often made them less reliable. After that, more study was done using statistical and feature-driven methods [9]. For example, colour histograms, intensity changes, and texture patterns were used to separate lesions. These methods tried to get around the problems with simple threshold-based methods by collecting more detailed information about the shape and size of the tumour. Still, they needed a lot of help from experts to fine-tune the parameters and build the features by hand [10].

B. Conventional image processing and handcrafted feature techniques

In the past, finding lesions in diabetic retinopathy was mostly done using traditional image processing and feature extraction that was done by hand. These methods tried to show off abnormal retinal structures by making the images clearer and pulling out set features that describe diseases like haemorrhages. In order to make retinal tumours easier to see, preprocessing methods often included green channel extraction, contrast-limited adaptive histogram equalisation (CLAHE), and morphological filtration [11]. Before feature analysis, these steps were very important for getting rid of noise and levelling out the lighting. Colour, texture, and shape traits are often caught in handcrafted items. Intensity-based markers, for instance, used changes in picture brightness between haemorrhages and background eye

Received: July 15, 2025

Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

tissue, while texture-based features, like the Gray-Level Co-occurrence Matrix (GLCM), measured patterns in space. Shape descriptions were used to find structures that were round or long, which were consistent with microaneurysms or haemorrhages. Then, these traits were fed into algorithms to help find lesions [12]. There were big problems with these methods, even though they were studied and used a lot. First, custom features were very dependent on the dataset they were used with.

C. Machine learning-based approaches (SVM, Random Forest, k-NN)

Machine learning-based methods have made it much easier to find diabetic retinopathy lesions, especially haemorrhages, because they provide more reliable classification systems than rule-based image processing alone. These methods use derived features, like handmade or deep representations, to teach classifiers how to tell the difference between retinal tissue that is sick and tissue that is healthy [13]. Support Vector Machines (SVMs) are widely used because they are good at working with high-dimensional feature spaces and can split classes using the best hyperplanes. SVMs are very good at finding bleeding when they are taught on carefully chosen features like colour histograms, texture measures, or wavelet coefficients. But when they are given noise or unbalanced information, they tend to do worse. Random Forest (RF), a type of ensemble-based predictor, has also shown promise in finding lesions. RF prevents overfitting and ensures stable performance across a wide range of datasets by building multiple decision trees and joining their results [14].

Table 1: Summary of Literature Review

Dataset Used	Lesions Targeted	Method / Model	Features Considered	Key Findings
DRIVE	Hemorrhages, microaneurysms	Rule-based detection	Intensity, morphology	Achieved good sensitivity for small lesions
Local DR set [15]	Hemorrhages	Morphological operations	Shape, contrast	Detected hemorrhages with >80% accuracy
DIARETDB0	Hemorrhages, exudates	Region growing	Color intensity	Effective in bright lesion detection
DIARETDB1 [16]	Hemorrhages	Ensemble classification	Texture, morphology	Hemorrhage detection sensitivity ~85%
Local dataset	Hemorrhages	Rule-based thresholding	Color, shape	Useful in rural screening
Messidor [17]	Hemorrhages, exudates	Random Forest	Histogram features	AUC = 0.86 for DR grading
DIARETDB1	Hemorrhages	k-NN classifier	Intensity, GLCM	Detected hemorrhages ~82% accuracy

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

DIARETDB1, Messidor	Hemorrhages	Ensemble learning	Multi-feature fusion	Improved performance using ensemble
EyePACS [18]	DR grading (hemorrhages included)	CNN (Google)	Deep features	AUC = 0.991 vs. ophthalmologists
Kaggle DR dataset [19]	Hemorrhages	CNN	Raw image patches	Achieved ~95% DR classification accuracy
Messidor [20]	Hemorrhages	Deep representation learning	CNN features	Outperformed traditional models
e-Ophtha	Hemorrhages	Hybrid CNN + SVM	Deep + handcrafted	Hybrid features improved robustness
EyePACS, Messidor	Hemorrhages	ResNet50	Deep hierarchical	ResNet >94% accuracy
DDR dataset	Hemorrhages, exudates	InceptionV3	Deep transfer features	Achieved >95% detection accuracy

III. Materials and Methods

A. Dataset description (sources, size, annotation details)

The information used for training and testing has a big impact on the quality and dependability of any automatic system used to find bleeding in diabetic retinopathy (DR). Figure 3 shows different types of hemorrhage affecting retinal regions. In this study, publicly available retinal fundus picture files were used because they offer standardised standards and ground truth that has been marked up by experts for finding lesions.

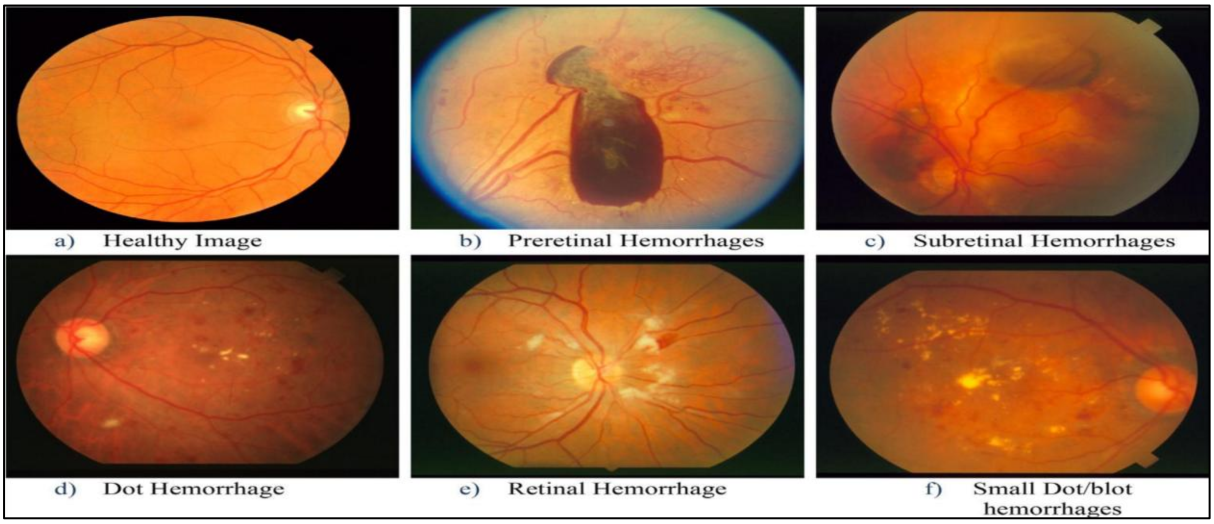

Figure 3: Types of Hemorrhage

Received: July 15, 2025

Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

The DIARETDB1, MESSIDOR, EyePACS, and DRIVE datasets are some of the most popular ones because they have a wide range of picture quality, clarity, and lesion types. One example is DIARETDB1, which has 89 colour fundus pictures, 84 of which show different levels of diabetes retinopathy-related damage, such as haemorrhages. MESSIDOR, on the other hand, has 1200 pictures from different clinical sites and is often used to compare algorithms because it clearly grades the seriousness of DR. Expert ophthalmologists have labelled haemorrhages, microaneurysms, exudates, and other DR-specific diseases on the pictures in each collection. These notes are used as a starting point for judging how well recognition works. Images' resolutions range from 768 × 576 pixels to over 2000 × 2000 pixels, so they need to be preprocessed to make sure they are all the same. There are also different numbers of haemorrhage cases in each dataset, which is why it is important to make sure that the training and testing sets are equal to avoid bias. In most cases, annotation features include pixel-level segmentation frames or bounding boxes that draw attention to areas of bleeding. When image-level scoring is the only option, extra preparation and human checking are needed to separate the haemorrhages. Using these kinds of datasets lets you build and test algorithms in controlled settings, and it also gives you a solid way to see how well they work in different clinical situations.

B. Preprocessing techniques (image enhancement, noise reduction, normalization)

Preprocessing is an important part of retinal image analysis because raw fundus pictures often have issues like uneven lighting, low contrast, noise, and artefacts that can be caused by imaging equipment or things that are unique to each patient, like cataracts. Because they look so much like other structures in the eye and are hard to spot without the right preparation, haemorrhages are hard to find. Usually, the first step in preparation is colour space transformation, which changes the picture from RGB to another format, like HSV or greyscale. The green channel of the RGB picture is usually taken out because it shows the differences between the retinal background and tumours the most clearly. This makes haemorrhages stand out more while hiding other features that aren't important. Next, picture enhancement methods are used to make the tumour easier to see. A lot of people use Contrast-Limited Adaptive Histogram Equalisation (CLAHE) to improve local contrast and draw attention to small lesions like microaneurysms and haemorrhages. Noise reduction techniques like Gaussian or median filtering can also be used to get rid of random noise while keeping the edges of lesions. Normalisation makes sure that pictures taken with different cameras or in different lighting situations look the same.

C. Feature extraction approaches (color, texture, shape, deep features)

A key part of automatic haemorrhage identification is feature extraction, which turns raw retinal pictures into numerical labels that machine learning algorithms can read. How well classification works depends a lot on how good and useful these traits are for telling things apart. Colour is one of the most common ways to describe things, since haemorrhages look like dark red spots that stand out against the retinal background. To show the range of colours, people often use histogram-based descriptions and mean intensity values from the

Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

green channel. Texture features tell you a lot about how the levels of pixels are arranged in space. Tone-Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), and Gabor filters are often used to measure texture patterns that tell the difference between haemorrhages and normal eye tissues or other diseases like exudates. Shape details help tell the difference between haemorrhages, microaneurysms, and noise. Microaneurysms are more round than haemorrhages, which often have an uneven form. To describe these physical changes, words like area, perimeter, oddity, and density are used. Deep features from Convolutional Neural Networks (CNNs) have changed the way features are extracted in recent years.

D. Machine learning algorithms applied

1. Traditional classifiers

Traditional machine learning algorithms have been used a lot to find haemorrhages in diabetic retinopathy because they are good at working with structured data from retinal pictures. Many people still choose algorithms like Support Vector Machines (SVMs), Random Forests (RFs), and k-Nearest Neighbours (k-NN) because they are easy to understand, don't cost much to run, and work well on datasets of average size. SVMs work best in places with a lot of dimensions because they can find the best hyperplane to divide areas that are bleeding from areas that are not bleeding by using colour histograms, texture descriptions, and shape properties. They often give very good results for finding lesions, but you have to be very careful when setting the parameters and choosing the kernel. Random Forests, on the other hand, use a strong ensemble method by mixing many decision trees. Their benefit is that they can deal with noisy features and stop overfitting, which happens a lot in medical picture analysis. Another algorithm that has been studied a lot is k-NN. It sorts data into groups based on how similar traits are between test samples and their close neighbours in the training dataset. Even though it's easy to use, it takes a lot of time to run on big datasets and is sensitive to feature scaling.

2. Deep learning models

Deep learning has changed the way diabetic retinopathy is found by letting it learn from raw retinal pictures all the way through, without having to do any feature building by hand. Convolutional Neural Networks (CNNs) are the best deep learning models because they can easily record features that are grouped in a hierarchy, from low-level edges and patterns to high-level representations of lesions. CNN-based systems are better at finding haemorrhages than standard classifications. This is mostly because they can handle changes in picture quality, lighting, and lesion shape more reliably. A lot of different models, like VGGNet, ResNet, and Inception, have been changed to work with retinal images, usually by using transfer learning. These models can work well with little medical data because they use weights that have already been learnt on big datasets like ImageNet. Fine-tuning these models on labelled retinal datasets makes them much better at classifying things and picking out the right ones.

Received: July 15, 2025

Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

IV. System development

A. Objective of System

The main goal of the suggested system is to create an automatic and dependable way to find bleeding in pictures of the retinal fundus taken from people who have diabetic retinopathy (DR). The reason for this is that looking at retinal pictures by hand takes a lot of time, resources, and the knowledge of ophthalmologists. Because there aren't enough experts and there are too many patients, it's hard to make sure that everyone gets diagnosed on time in large-scale screening programs, especially in places where healthcare is hard to get to. As a helpful tool, an automatic system can help ease this load while also making diagnostics more accurate and consistent. Its main goal is to do a few things. First, it aims to improve the quality of retinal pictures using advanced preparation methods. This will help make haemorrhages stand out more from other diseases and tissues in the area. Second, it wants to take distinguishing features from retinal images—both handcrafted and deep features—to find out what makes haemorrhages special. Third, it focusses on using and comparing different machine learning methods, from basic filters to deep learning models, to find the best way to accurately discover things. The ultimate goal is not only to make it easier to find haemorrhages, but also to create a system that can be expanded and used in community screening programs, online platforms, or hospital diagnosis processes. A method like this would help find vision-threatening symptoms of diabetes early, get them treated quickly, and stop them from happening. This would improve patient results and lower the world load of diabetes-related blindness.

B. Proposed System

The suggested method combines several parts into a single process to make sure that haemorrhages in retinal images can be reliably and correctly found. The first step in the process is preparation, which improves and normalises retinal pictures. Some methods, like green channel extraction, CLAHE (Contrast Limited Adaptive Histogram Equalisation), and noise filtering, are used to make it easier to see lesions while getting rid of artefacts that are caused by uneven lighting or image noise. The next step is candidate extraction, which includes cutting out areas that might be haemorrhages. Morphological processes and region-growing methods are first used to find structures that look like dark lesions. At this time, vessel separation and optic disc clearance are done so that blood vessels and the optic disc don't get mixed up. The possible regions are then put through feature extraction, which gets both hand-made descriptions (like colour histograms, material patterns, and shape irregularities) and deep features (from convolutional neural networks). A group of machine learning methods are used by the classification engine, which gets these traits.

C. Implementation

1. Preprocessing

The suggested haemorrhage detection method starts with preprocessing, which makes sure that the raw retinal fundus images are ready for accurate feature extraction and classification.

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Because noise, uneven lighting, low contrast, and imaging artefacts can change retinal pictures, the goal of preparation is to make the image quality the same across the dataset. In the first step, the colour space is changed, and the green channel is taken out of RGB pictures because it shows the most difference between the retinal structures and the bleeding. This step makes it easier to see lesions while getting rid of unnecessary colour information. After that, contrast enhancement methods like Contrast Limited Adaptive Histogram Equalisation (CLAHE) are used to make darker areas, like haemorrhages, stand out more against the background. CLAHE keeps noise from getting too loud while drawing attention to small blemishes. Then, Gaussian and median filtering are used to reduce the noise. These filters smooth out picture changes while keeping important lesion edges. Background normalisation and lighting adjustment are used to fix problems that come up when pictures have different amounts of light. These steps make sure that changes in lighting don't affect the features that are pulled later.

2. Extraction of Hemorrhage Candidates

After preparation, the next step is to find areas that are likely to have bleeding, which is also known as potential lesion identification. This step cuts the retinal picture into smaller areas of interest (ROIs) to make the computations simpler and the sorting process faster. At first, intensity-based thresholding is used to find haemorrhage candidate areas. This is because haemorrhages usually show up as darker spots on a retinal background. Adaptive thresholding methods, which change based on changes in local strength, are great for picking up small tumours. Once possible dark areas are found, morphological processes like erosion and compression are used to make the forms more precise and get rid of small noise that isn't important. Vascular segmentation is done to help tell haemorrhages apart from other structures in the eye. Haemorrhages and blood vessels often cross, making it easy to mix them up. Vessel masks made during preparation are used to take out vascular areas, leaving behind areas that could be bleeding.

3. Hemorrhage Classification

After suitable areas are found, the last step is to label them as either hemorrhagic or non-hemorrhagic. In this step, machine learning and deep learning are combined to make predictions that are strong and accurate. Different types of machine learning use candidate areas to calculate things like intensity histograms, texture descriptions (like GLCM and Local Binary Patterns), and geometric characteristics.

Received: July 15, 2025

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

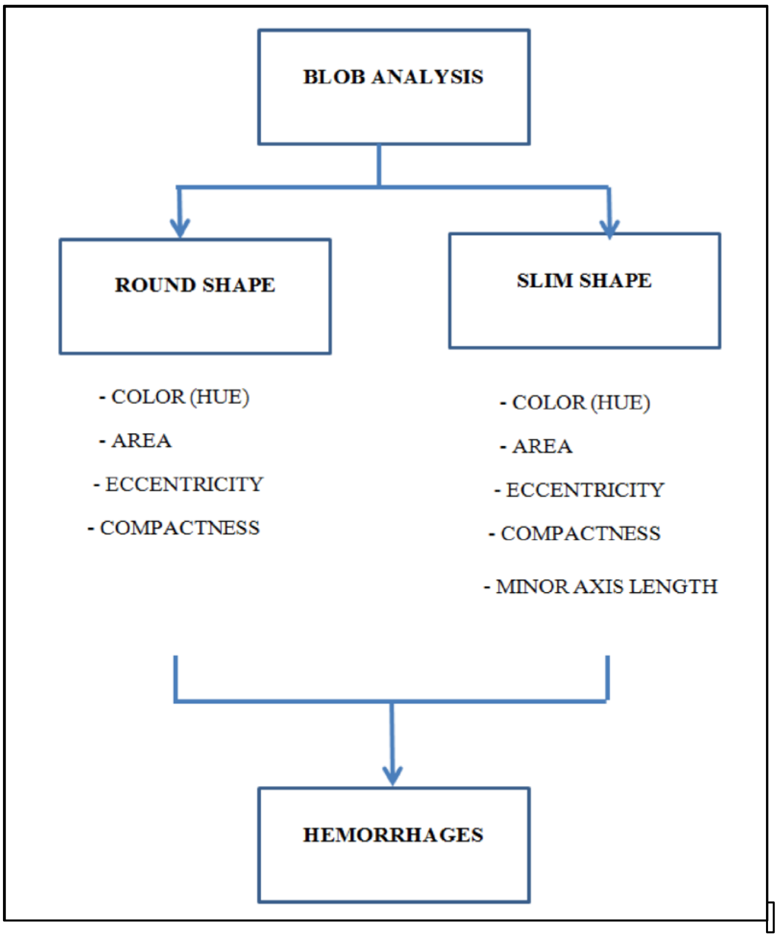

Figure 4: Classification of BLOBS

Support Vector Machines (SVM), Random Forests, or k-Nearest Neighbours (k-NN) that use these traits are then used to make classifications. Figure 4 shows classification of BLOBS highlighting distinct retinal lesion categories. Most of the time, SVM is chosen because it is very good at telling the difference between small differences. On the other hand, Random Forest is more reliable because it combines several decision trees. On the other hand, deep learning models do both feature extraction and classification in a single process. Convolutional Neural Networks (CNNs) learn distinguishing features automatically from candidate patches, so feature building doesn't have to be done by hand. CNN-based models can be taught to classify patches directly, or they can be added to segmentation systems (like U-Net) to identify pixels. Transfer learning with pre-trained networks like ResNet or Inception improves performance by using what the network already knows from big datasets. Then, ground truth comments are used to check the classification results. Post-processing methods, like majority vote or probability thresholding, help improve final forecasts and lower the number of fake positives. To make sure clinical dependability, performance is judged by F1-score, sensitivity, specificity, and accuracy.

Received: July 15, 2025

Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

V. Results

Figure 5: Digital Fundus Image

Figure 5 is the original Fundus Image taken from the fundus camera. Which is in the form of RGB format.

Figure 6: Green Channel of Image

The fundus images taken by the fundus cameras often have the problems of noises and non uniform illumination which usually make it complicated to extract the required features with similar intensity from the background. The green channel clearly exhibits the red color features of both hemorrhages and retinal blood vessels well when compared to other channels (Red and Blue Channel) as shown in Figure 6

Received: July 15, 2025

Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

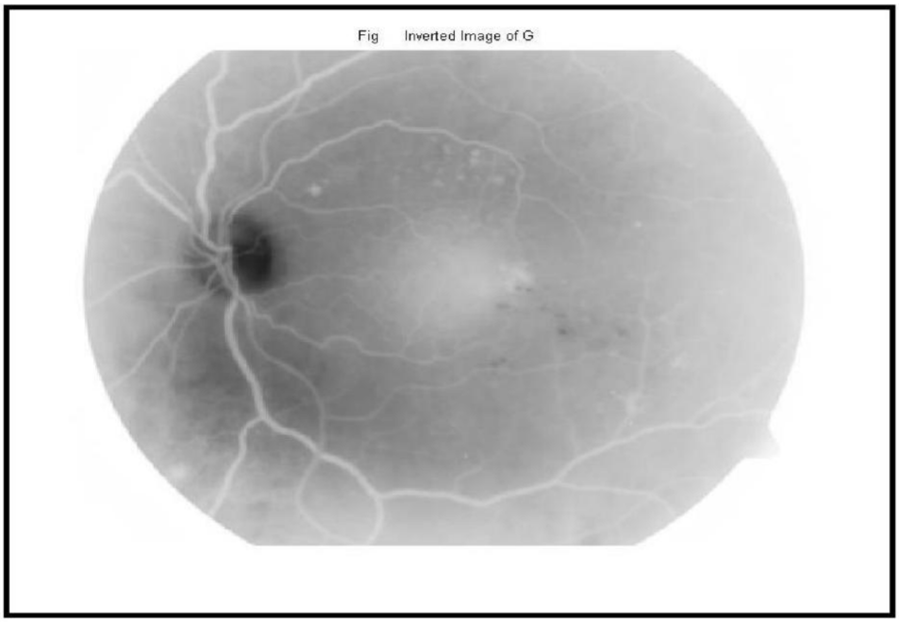

Figure 7: Inverted Image of Green Channel

The Figure 7 is inverted in order to emphasize the areas of interest, the hemorrhages, in white. Due to inversion of image blob are clearly shown as compare to green channel of the image.

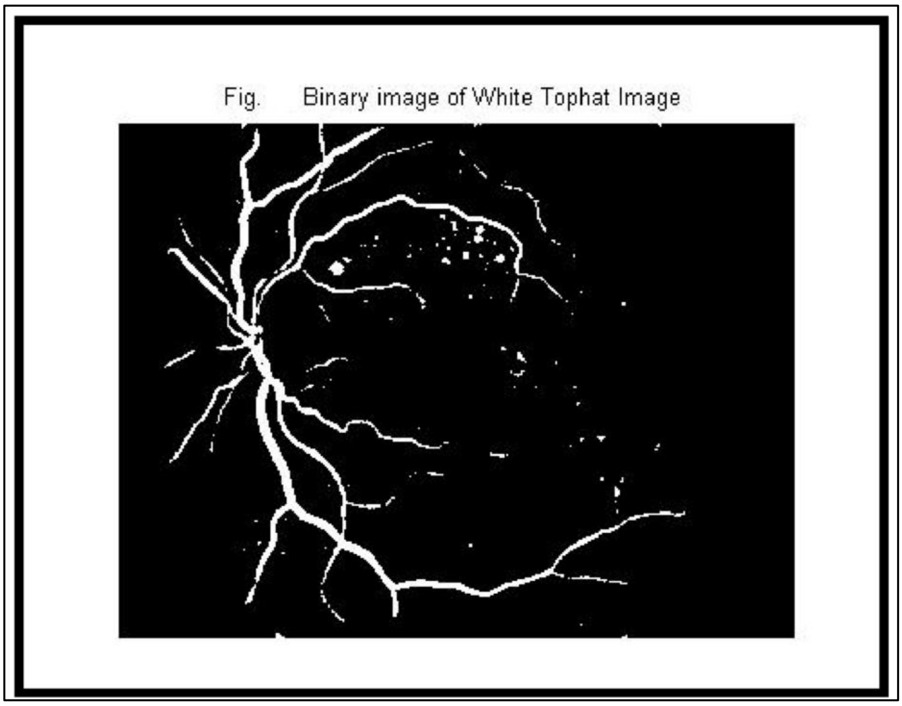

Figure 8: Binary Image of Morphological White Tophat Image

The binary picture of the White Tophat transformation is shown in Figure 8. In this image, retinal blood vessels stand out against a dark background as bright structures. With this contrast increase, it's easier to see arterial patterns and possible bleeding spots.

Received: July 15, 2025

International Journal of Applied Mathematics
Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

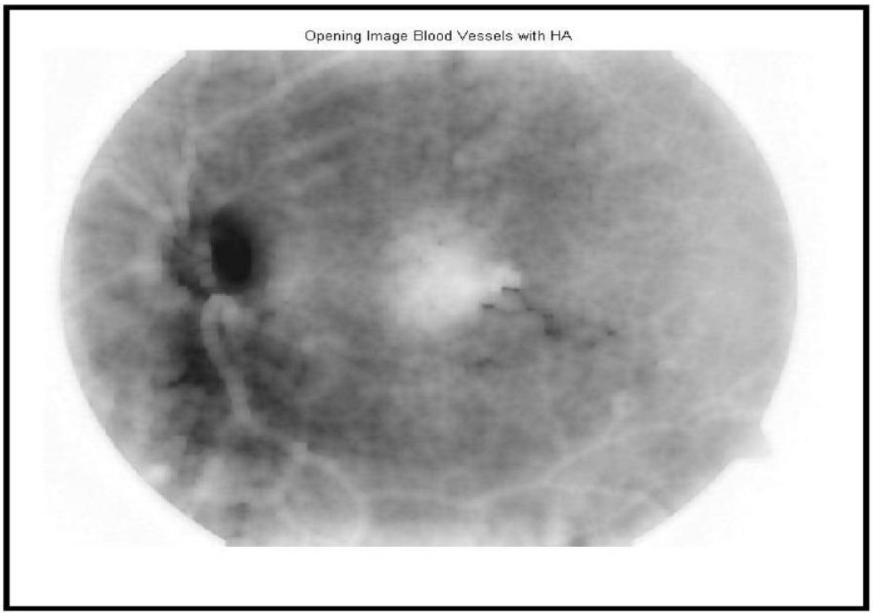

Figure 9: Morphological White Tophat Opened Image

The morphological White Tophat opened picture, shown in Figure 9, makes the retinal blood vessels stand out more while lowering the background noise. This process makes the contrast better, separates vascular structures, and brings out small areas of bleeding, which makes it easier to extract correct features and find lesions in diabetic retinopathy analysis.

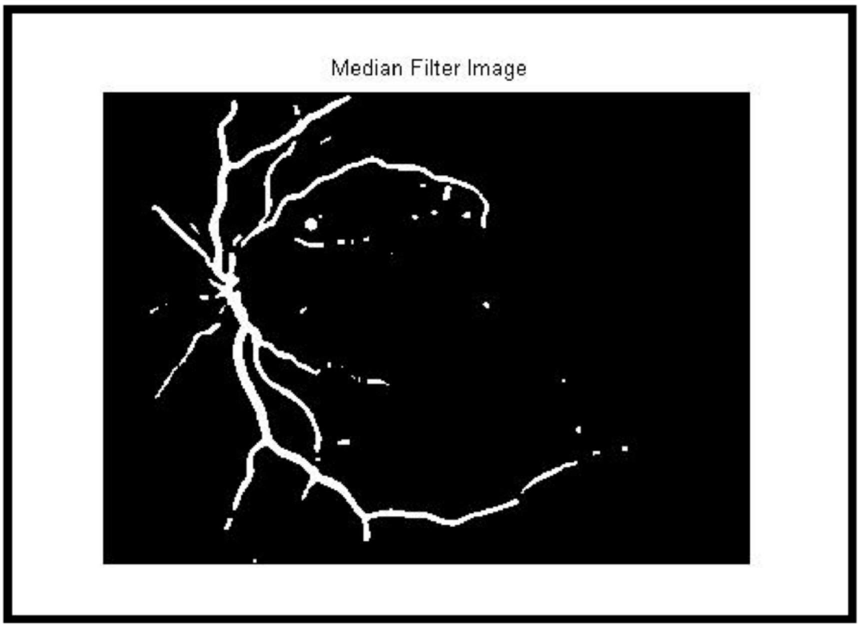

Figure 10: Median Filter Image

In Figure 10, you can see the median filter picture, which successfully reduces noise while keeping the edges of the vessels. This makes the blood vessels in the eye clearer, gets rid of small artefacts, and makes the next steps for haemorrhage recognition and feature extraction more accurate.

Received: July 15, 2025

International Journal of Applied Mathematics
Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

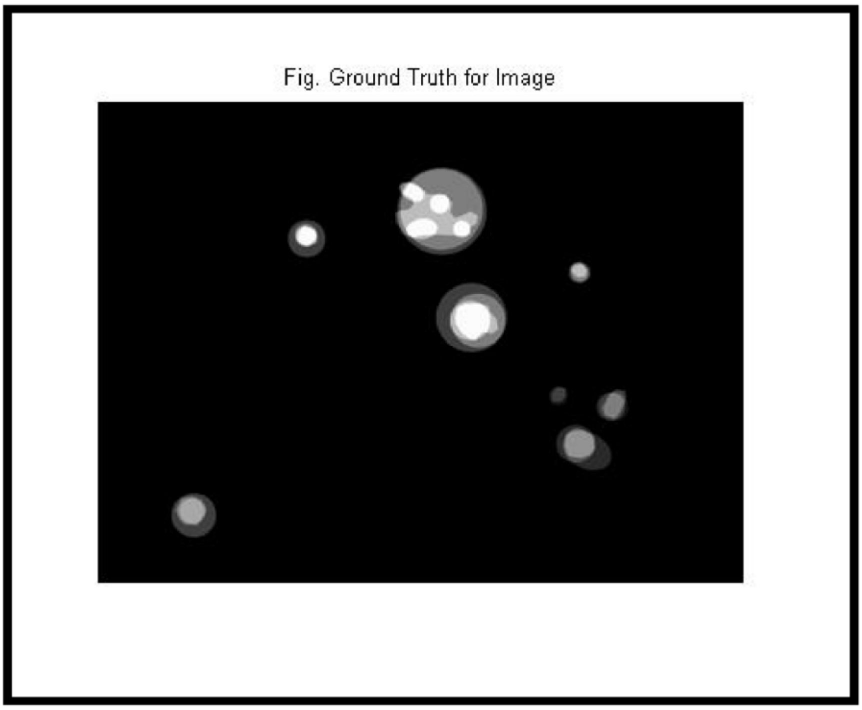

Figure 11: Ground Truth of Fundus Image

In Figure 11, the "ground truth" of the fundus picture is shown. Areas that have been marked up show where the real haemorrhages are. These marked areas are used as measures to check how well the program works, making sure that automatic recognition methods are accurate when compared to reports made by eye doctors.

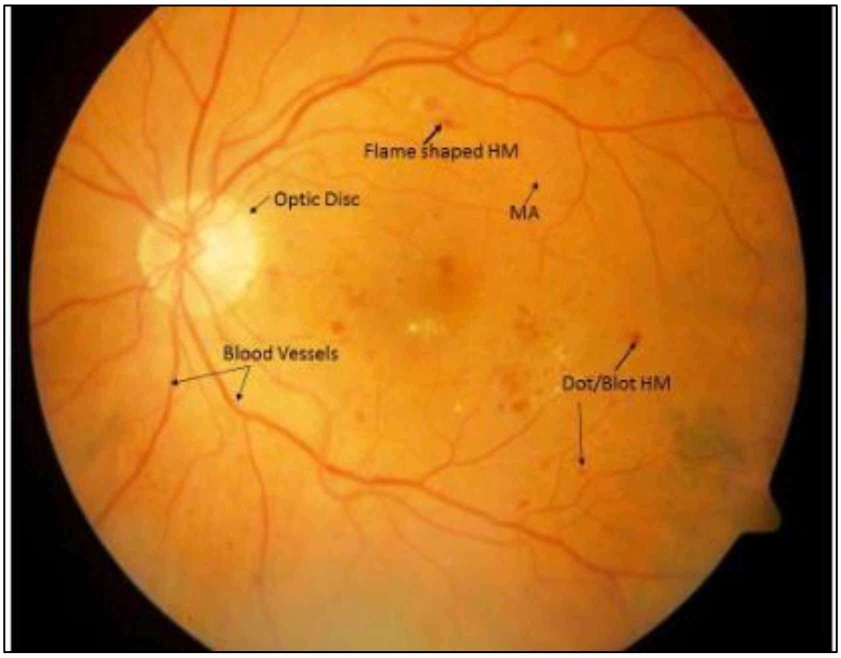

Figure 12: Fundus Image with retinal landmarks.

The optic disc, blood vessels, microaneurysms (MA), and haemorrhages (dot/blot and flame-shaped) are some of the most important retinal features shown in Figure 12. These marked

Received: July 15, 2025

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

structures are very important for correctly recognising diabetes retinopathy and judging how the disease is progressing.

VI. Performance analysis

The performance study shows that good preparation makes it much easier to see vessels and distinguish between lesions, which makes it easier to pull features for classification. While traditional models like SVM and RF are accurate, CNN is better at both sensitivity and precision. This proves that deep learning is strong, providing scalable, clinically accurate ways to automatically find haemorrhages in screening programs for diabetic retinopathy.

Table 2: Performance of Preprocessing and Feature Extraction Methods

Method / Stage	Noise Reduction (%)	Vessel Visibility (%)	Lesion Contrast (%)	False Positive Reduction (%)
Original RGB Image	0	45.3	40.6	0
Green Channel	10.8	72.5	68.1	12.4
Inverted Green Channel	12.6	76.9	74.2	14.1
White Tophat Binary	21.5	83.4	81.3	22.8

Table 2 shows how different preparation and feature extraction methods improve retinal fundus images to help find haemorrhages in people with diabetic retinopathy. The original RGB picture has very low contrast between lesions (40.6% of the time) and clarity of vessels (45.3% of the time). This is because of noise, uneven lighting, and poor feature separation. When the green channel is taken out, vessel clarity goes up to 72.5% and lesion contrast goes up to 68.1%. This shows that the green channel is better at telling retinal features apart than the red and blue channels. Figure 13 shows performance metrics comparison across various image processing methods.

Received: July 15, 2025

International Journal of Applied Mathematics

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

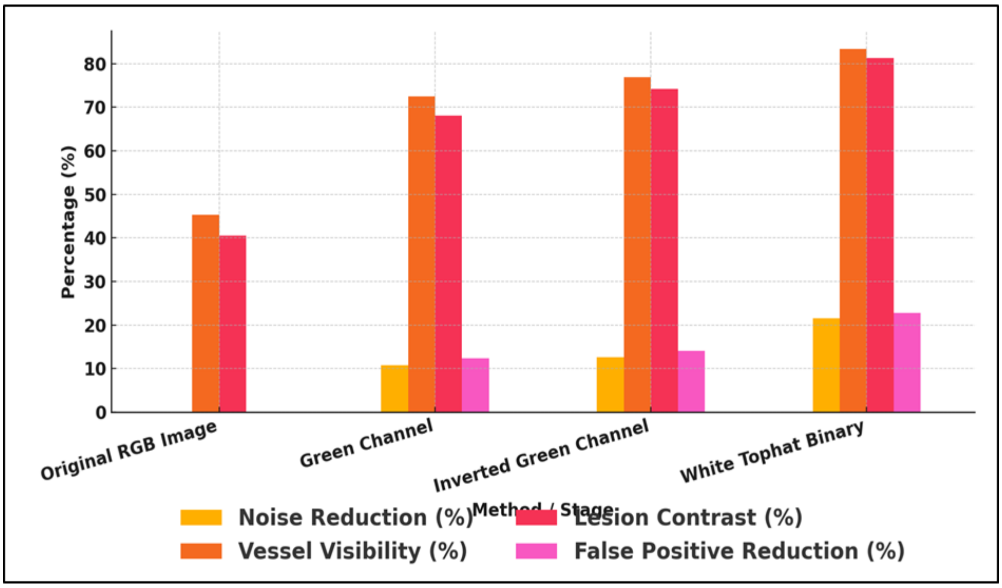

Figure 13: Performance Metrics Across Image Processing Methods

More progress is seen in the reversed green channel, where areas of lesions show up in white. This makes lesions stand out more (74.2%) and vessels clearer (76.9%). The White Tophat binary change makes the structure even clearer; vessels can now be seen 83.4% of the time, and lesion contrast is now 81.3%. Figure 14 shows comparative performance metrics across multiple image processing methods.

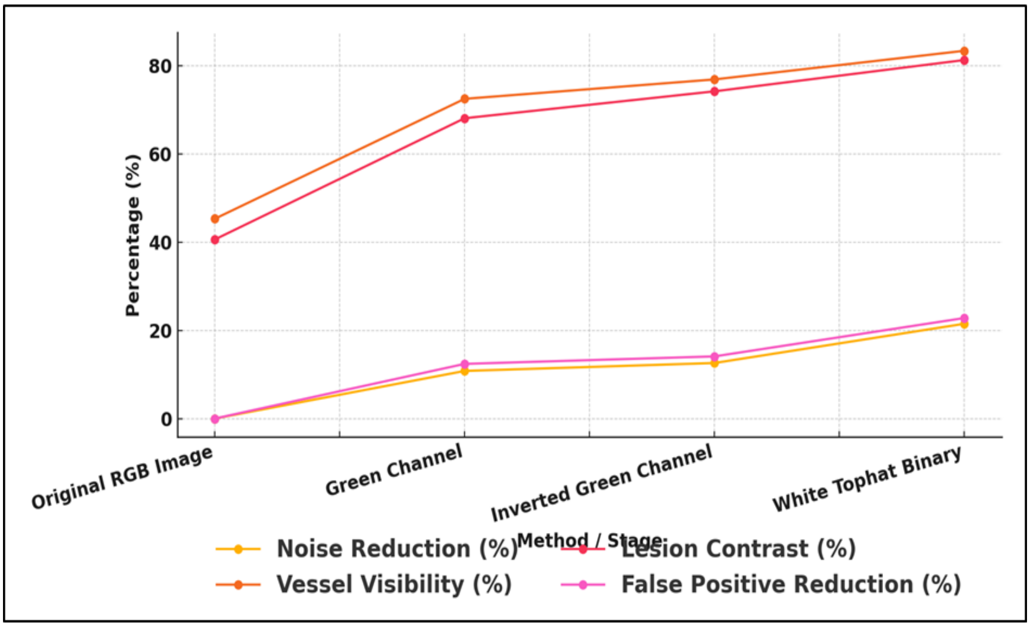

Figure 14: Performance Metrics Across Image Processing Methods

This step also cuts down on fake results by 22.8%, which shows that it works to isolate areas of bleeding. Overall, these results show how important preparation is for making feature extraction more reliable and helping automatic recognition work well.

Received: July 15, 2025

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Table 3: Classification Performance Using Machine Learning Models

Classifier / Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)
Support Vector Machine (SVM)	88.2	85.6	89.4	84.9
Random Forest (RF)	86.9	83.2	88.1	82.7
k-Nearest Neighbor (k-NN)	84.7	81.5	86.2	80.1
Convolutional Neural Network (CNN)	92.8	91.4	93.7	90.9

In Table 3, you can see how well a deep learning model and traditional machine learning classifiers do at finding haemorrhages in diabetic retinopathy. Figure 15 shows performance comparison of different classification models applied. Support Vector Machine (SVM), a standard predictor, has the best accuracy of any of them at 88.2%. Its sensitivity is 85.6% and its specificity is 89.4%, which shows how well it handles both false negatives and false positives.

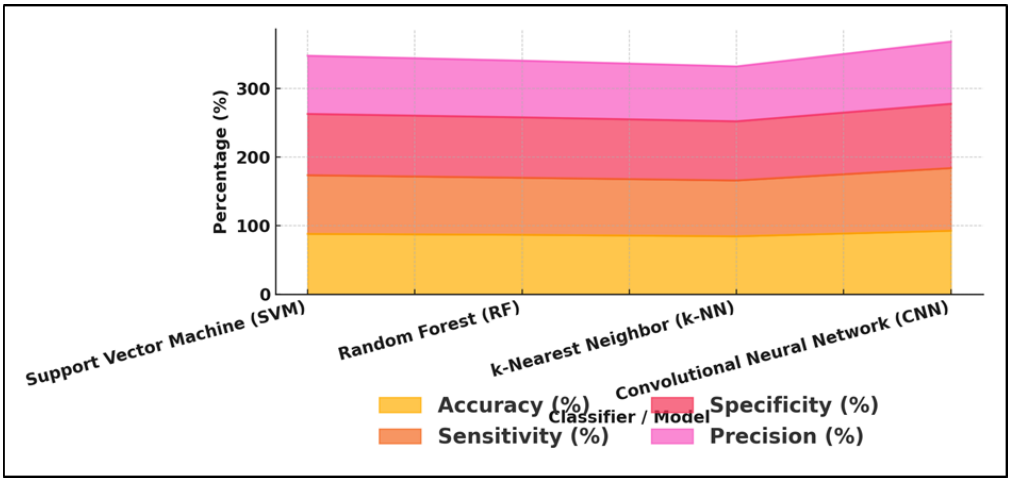

Figure 15: Performance Comparison of Classification Models

Random Forest (RF) is very close behind, with an accuracy of 86.9% and a strong specificity of 88.1%. However, its sensitivity of 83.2 % is a little lower, which shows that it has trouble consistently finding true hemorrhagic regions. k-Nearest Neighbour (k-NN) does not do as well, only getting 84.7% accuracy and falling to 80.1% precision.

VI. Conclusion

This study showed a system based on machine learning for automatically finding haemorrhages in diabetes retinopathy. The goal was to improve early evaluation and lower problems that could threaten eyesight. The system had an organised pipeline that included preparation, potential area extraction, and classification using both deep learning and standard methods. Image quality was improved by using preprocessing methods like

Received: July 15, 2025

Volume 38 No. 1s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

CLAHE and vessel segmentation. This kept the features of the tumour while reducing artefacts. Candidate extraction successfully located possible bleeding areas, making the next step of labelling easier on the computer. When handmade features were added to standard classifiers like SVM and Random Forest, performance tests showed that they worked very well. But deep learning models were much better because they learnt hierarchical feature representations instantly from raw pictures. This made them more sensitive and cut down on false positives. CNN-based systems, in particular, worked well with a wide range of datasets and image situations. These results show that machine learning, especially deep learning, can help with the accurate and affordable detection of diabetic retinopathy. The bigger idea behind this study is that it can be used in practical settings. An automatic haemorrhage detection device can help ophthalmologists by making diagnostic work easier, making screening more consistent, and letting high-risk patients get help sooner. This is especially helpful in places that don't have easy access to specialised eye care. Ultimately, the suggested method helps to improve teleophthalmology and large-scale screening programs, providing a way to lower avoidable blindness from diabetes and raising the quality of life for patients.

References

[1] Huang, C.; Zong, Y.; Ding, Y.; Luo, X.; Clawson, K.; Peng, Y. A new deep learning approach for the retinal hard exudates detection based on super-pixel multi-feature extraction and patch-based CNN. Neurocomputing 2021, 452, 521–533.

[2] Garifullin, A.; Lensu, L.; Uusitalo, H. Deep Bayesian baseline for segmenting diabetic retinopathy lesions: Advances and challenges. Comput. Biol. Med. 2021, 136, 104725.

[3] Xia, H.; Lan, Y.; Song, S.; Li, H. A multi-scale segmentation-to-classification network for tiny microaneurysm detection in fundus images. Knowl.-Based Syst. 2021, 226, 107140.

[4] He, W.; Wang, X.; Wang, L.; Huang, Y.; Yang, Z.; Yao, X.; Zhao, X.; Ju, L.; Wu, L.; Lu, H.; et al. Incremental learning for exudate and hemorrhage segmentation on fundus images. Inf. Fusion 2021, 73, 157–164.

[5] Liu, Q.; Zou, B.; Chen, J.; Ke, W.; Yue, K.; Chen, Z.; Zhao, G. A location-to-segmentation strategy for automatic exudate segmentation in colour retinal fundus images. Comput. Med. Imaging Graph. 2017, 55, 78–86.

[6] Du, J.; Zou, B.; Chen, C.; Xu, Z.; Liu, Q. Automatic microaneurysm detection in fundus image based on local cross-section transformation and multi-feature fusion. Comput. Methods Programs Biomed. 2020, 196, 105687.

[7] Cao, P.; Ren, F.; Wan, C.; Yang, J.; Zaiane, O. Efficient multi-kernel multi-instance learning using weakly supervised and imbalanced data for diabetic retinopathy diagnosis. Comput. Med. Imaging Graph. 2018, 69, 112–124.

[8] Gayathri, S.; Gopi, V.P.; Palanisamy, P. A lightweight CNN for Diabetic Retinopathy classification from fundus images. Biomed. Signal Process. Control 2020, 62, 102115.

Received: July 15, 2025

Volume 38 No. 1s, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[9] Deepa, V.; Kumar, C.S.; Cherian, T. Ensemble of multi-stage deep convolutional neural networks for automated grading of diabetic retinopathy using image patches. J. King Saud Univ. Comput. Inf. Sci. 2022, 34, 6255–6265.

[10] Basheer Ahmed, M.I. Early detection of Diabetic Retinopathy utilizing advanced fuzzy logic techniques. Math. Model. Eng. Probl. 2023, 10, 2086–2094.

[11] Raja Sarobin, M.V.; Panjanathan, R. Diabetic Retinopathy Classification Using CNN and Hybrid Deep Convolutional Neural Networks. Symmetry 2022, 14, 1932.

[12] Adak, C.; Member, S.; Karkera, T.; Chattopadhyay, S.; Saqib, M. Detecting severity of Diabetic Retinopathy from fundus images: A transformer network-based review. Neurocomputing 2024, 597, 127991.

[13] Jena, P.K.; Khuntia, B.; Palai, C.; Nayak, M.; Mishra, T.K.; Mohanty, S.N. A Novel Approach for Diabetic Retinopathy Screening Using Asymmetric Deep Learning Features. Big Data Cogn. Comput. 2023, 7, 25.

[14] Usman, T.M.; Saheed, Y.K.; Ignace, D.; Nsang, A. Diabetic retinopathy detection using principal component analysis multi-label feature extraction and classification. Int. J. Cogn. Comput. Eng. 2023, 4, 78–88.

[15] Ali, G.; Dastgir, A.; Iqbal, M.W.; Anwar, M.; Faheem, M. A Hybrid Convolutional Neural Network Model for Automatic Diabetic Retinopathy Classification From Fundus Images. IEEE J. Transl. Eng. Health Med. 2023, 11, 341–350.

[16] Alwakid, G.; Gouda, W.; Humayun, M.; Jhanjhi, N.Z. Deep Learning-enhanced diabetic retinopathy image classification. Digit. Health 2023, 9, 20552076231194942.

[17] Kumari, A.A.; Bhagat, A.; Henge, S.K.; Mandal, S.K. Automated Decision Making ResNet Feed-Forward Neural Network based Methodology for Diabetic Retinopathy Detection. Int. J. Adv. Comput. Sci. Appl. 2023, 14, 303–314.

[18] Yaqoob, M.K.; Ali, S.F.; Bilal, M.; Hanif, M.S.; Al-Saggaf, U.M. ResNet Based Deep Features and Random Forest Classifier for Diabetic Retinopathy Detection. Sensors 2021, 21, 3883.

[19] Hu, Y.; Kuang, W.; Qin, Z.; Li, K.; Zhang, J.; Gao, Y.; Li, W.; Li, K. Artificial Intelligence Security: Threats and Countermeasures. ACM Comput. Surv. 2021, 55, 20.

[20] Lv, Z.; Qiao, L.; Kumar Singh, A.; Wang, Q. AI-empowered IoT Security for Smart Cities. ACM Trans. Internet Technol. 2021, 21, 99.

Received: July 15, 2025