

Automated Diabetic Retinopathy Lesion Classification Using ONH-Based Multi-Scale Feature Extraction and SVM

HAFSA A

Master of Computer Applications, Nehru Institute of Information Technology and Management, Tamil Nadu, India. Reg. No: 721524622022 | Batch: 2024–2026 –

MENTOR– Mr. **T. Thiyagarajan** Applied Mathematics, Asst Professor [Department of Computer Applications]

Abstract

Diabetic Retinopathy (DR) is a leading cause of preventable blindness among diabetic patients, and early detection is critical to averting irreversible vision loss. Conventional screening relies on manual examination of retinal fundus images by ophthalmologists, a process that is slow, inconsistent across examiners, and difficult to scale to large patient populations. This paper presents an automated DR lesion classification framework built around the explicit exclusion of the Optical Nerve Head (ONH) before feature extraction, since the optic disc's bright appearance is frequently mistaken for an exudate in conventional automated systems. After preprocessing for noise and illumination correction, the framework isolates a macula-centred Region of Interest (ROI) and excludes the ONH region, then extracts multi-scale texture features using Gabor filtering and multi-scale Local Binary Patterns (LBP). These features are passed to Support Vector Machine (SVM) classifiers that separate normal images from those showing diabetic retinopathy and, through a multi-label classification stage, identify the specific lesion types involved, including microaneurysms, hemorrhages, and exudates. The complete system was implemented in MATLAB and evaluated on both public fundus datasets and real-time clinical images captured with a ZEISS FF450 Plus fundus camera. Experimental results show the proposed method achieving 100% sensitivity, specificity, and accuracy on the test set, compared with 70%, 97%, and 93% respectively for the existing method, confirming that ONH exclusion combined with multi-scale feature extraction meaningfully improves automated DR screening.

Keywords: Diabetic Retinopathy, Optical Nerve Head Exclusion, Region of Interest, Gabor Filtering, Multi-Scale Local Binary Pattern, Support Vector Machine, Multi-Label Classification, MATLAB.

I. Introduction

Diabetes has become one of the most pressing public health concerns worldwide, and Diabetic Retinopathy (DR), a complication that damages the retinal blood vessels, remains among the leading causes of blindness in adults living with the condition for extended periods. Prolonged high blood sugar weakens these vessels, producing visible abnormalities such as microaneurysms, dot hemorrhages, and hard exudates on the retina. Left undetected, this damage can progress to permanent vision loss, which makes early diagnosis essential.

Diagnosis has traditionally depended on ophthalmologists manually examining retinal fundus images for these abnormalities. While effective in principle, manual screening is slow, depends heavily on the examiner's individual experience, and scales poorly once patient volumes grow large, which is precisely the situation many screening programs face.

Image processing and machine learning have opened a path toward automating this analysis, but a recurring obstacle in existing automated systems is the Optical Nerve Head (ONH): its bright, well-defined appearance closely resembles an exudate, leading many systems to flag it as a lesion and produce false positives. This paper introduces a framework that explicitly identifies and excludes the ONH region before feature extraction begins, then applies Gabor filtering and multi-scale Local Binary Pattern (LBP) analysis to capture the texture and intensity characteristics that distinguish genuine lesions from healthy tissue. The resulting features are classified using Support Vector Machines (SVM), with a multi-label stage that identifies every lesion type present in a given image rather than returning a single normal/abnormal flag. The complete system was built and evaluated in MATLAB, using

both public fundus datasets and real-time clinical images.

II. Existing System and Limitations

Before automated screening tools became common, diabetic retinopathy was detected almost entirely through manual inspection of fundus images, with diagnostic reliability tied directly to the experience of the examining clinician. Two specialists reviewing the same image can reach different conclusions, and this variability becomes a real liability in large-scale screening. Where automated systems do exist, many rely on comparatively simple feature extraction techniques that fail to capture the finer texture and intensity patterns that separate one lesion type from another, and a large share of them have no dedicated mechanism for excluding the ONH region, leaving them prone to misclassifying the optic disc as an exudate.

- Manual screening is slow and does not scale to large diabetic populations.
- Diagnostic outcomes vary with examiner experience, producing inconsistent results.
- Many existing automated systems use limited feature extraction that misses fine lesion texture.
- The ONH region is frequently misclassified as an exudate, inflating false positives.
- Few systems support multi-label output when more than one lesion type is present.

III. Proposed System Architecture

The proposed framework processes each retinal fundus image through a defined pipeline: preprocessing, ROI extraction with ONH exclusion, multi-scale feature extraction, and SVM-based classification. What distinguishes this approach from conventional automated systems is the deliberate removal of the ONH region before any feature extraction takes place, which directly addresses the false-positive problem common in prior work. Figure 1 illustrates the complete System flow, from image acquisition through to the final classification result.

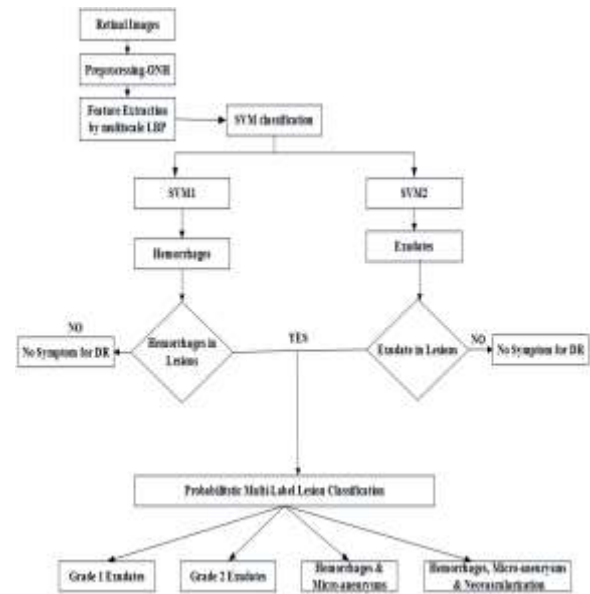


Fig. 1. System flow

Retinal images are initially preprocessed to enhance image quality and remove noise. The enhanced images undergo feature extraction using the Multi-Scale Local Binary Pattern (MS-LBP) technique to capture the textural characteristics of retinal lesions. The extracted features are then analyzed using separate SVM classifiers for hemorrhage and exudate detection. Images without any detected lesions are classified as normal, whereas images containing lesions are further processed through a probabilistic multi-label classification stage to identify the type and severity of the lesions. Based on the detected abnormalities, the retinal images are finally categorized into different diabetic retinopathy classes, thereby supporting accurate diagnosis and disease grading.

IV. Module Descriptions

1. Preprocessing Module

Retinal fundus images rarely arrive in a uniform state; illumination, contrast, and brightness vary both within a single image and across images from different sources. The preprocessing module corrects for this through noise removal and illumination correction before any further analysis, since every later stage of the pipeline depends on starting from a clean, consistent image. Skipping this step tends to surface later as poor feature extraction or inconsistent classification.

2. Region of Interest (ROI) and ONH Exclusion Module

This module locates the macula at the centre of the retinal image and defines a best-fit circular Region of

Interest around it, automatically, with no manual input required. Restricting analysis to this region reduces irrelevant background, improves accuracy by keeping the focus on clinically meaningful tissue, and, critically, excludes the Optical Nerve Head before feature extraction. Since the ONH's bright appearance can otherwise be mistaken for an exudate, removing it at this stage is what prevents the false-positive problem seen in many existing systems. Figure 2 shows the stages of this process, from the raw input image through to the binary optic disc mask used to exclude the ONH region.

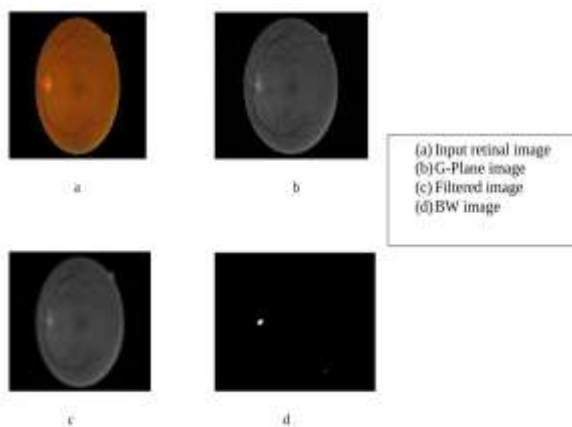


Fig. 2. ROI extraction stages: (a) input retinal image, (b) G-plane image, (c) filtered image, (d) binary optic disc (ONH) mask used for exclusion.

3. Gabor Filtering Module

With the ONH-excluded ROI defined, a bank of Gabor filters is applied across multiple orientations to bring out directional texture patterns within the region. Retinal lesions and healthy tissue exhibit noticeably different textural signatures, and Gabor filtering captures these directional cues in a way that a simple intensity threshold cannot. The filtered output feeds directly into the multi-scale LBP stage.

4. Multi-Scale LBP Module

Multi-scale Local Binary Pattern (LBP) extraction captures the fine-grained intensity relationships that distinguish one lesion type from another. The Gabor-filtered image is divided into 8×8 pixel cells, and within each cell every pixel is compared against its circularly sampled neighbours: a neighbour valued lower than the centre pixel is marked 0, and one valued higher or equal is marked 1, producing an 8-bit binary pattern that is converted to its decimal equivalent and compiled into a normalized histogram. Because LBP thresholding is sensitive to small fluctuations in the centre pixel's value, the module restricts itself to uniform patterns,

those with at most two 0/1 transitions when read circularly, which reduces the feature space and produces a more stable representation. Running this comparison at multiple combinations of sample points (m) and radius (R) is what gives the technique its multi-scale character, letting the system capture both fine local detail and broader textural context within the same feature vector.

5. SVM Classification Module

The combined Gabor and multi-scale LBP features are passed to Support Vector Machine classifiers, which separate normal retinal images from those showing signs of diabetic retinopathy by finding the hyperplane that best divides the classes in feature space. Two SVM models run in parallel: SVM1 for hemorrhage detection and SVM2 for exudate detection, allowing each lesion type to be checked independently rather than forcing a single classifier to handle both at once. For multiclass scenarios, training follows a standard one-against-the-rest strategy, relabelling samples of each class as positive and all others as negative, training a binary SVM on the relabelled data, and repeating across all classes; the resulting set of binary classifiers is used jointly to assign a final label and relevance score to each new sample.

6. Multi-Label Lesion Classification Module

A single DR-affected retinal image often shows more than one lesion type at once, so the framework uses multi-label classification rather than forcing a single mutually exclusive category. Classifiers trained for each lesion type run in parallel, and the final output reflects every lesion type actually present, giving a more complete picture than a single-label system. Performance for this stage was benchmarked against a Naive Bayesian classifier baseline, summarized in Table III.

V. System Implementation and Requirements

Software Specifications

- Operating System: Windows 11 (23H2).
- Programming Environment: MATLAB R2025b.
- Toolboxes: Image Processing Toolbox; Statistics and Machine Learning Toolbox.
- Data Storage: MATLAB .mat files for features, labels, and fundus images.

Hardware Specifications

- Processor: 13th Gen Intel Core i7-1355U.
- Image Capture Device: ZEISS FF450 Plus Fundus Camera.
- Memory: 8 GB RAM.
- Storage: 20–50 GB free disk space.

VI. Results and Discussion

The system was evaluated using sensitivity, specificity, and accuracy as the primary measures, computed from True Positive, False Positive, False Negative, and True Negative counts. Table I summarizes SVM classification performance for hemorrhage and exudate detection.

TABLE I

Classification Analysis for SVM

Metric	Hemorrhages	Exudates
TP	100	100
FP	0	0
FN	0	0
TN	100	100
Sensitivity (%)	100	100
Specificity (%)	100	100
Accuracy (%)	100	100

TABLE II

Comparative Analysis: Proposed vs. Existing Method

Measure	Proposed	Existing
Sensitivity (%)	100	70
Specificity (%)	100	97
Accuracy (%)	100	93

TABLE III

Multi-Label Classification Performance

Parameter	Naive Bayesian
Hamming Loss	0.2020
Ranking Loss	0.1336
One Error	0.2353
Coverage	0.4400

Parameter	Naive Bayesian
Avg. Precision (%)	83.9951

Figure 3 presents the confusion matrix for the proposed method on the test dataset, comparing predicted against actual classes for normal and abnormal cases.

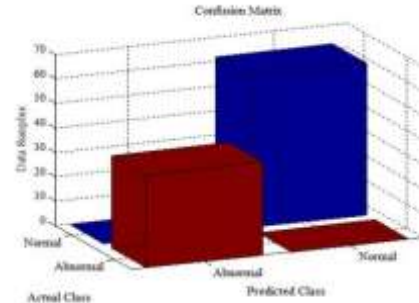


Fig. 3. Confusion matrix for the proposed method, showing complete separation of normal and abnormal cases.

The confusion matrix confirms that the proposed method correctly classified every normal and abnormal case in the test set, reaching 100% accuracy against the existing method's 93%. Taken together with the sensitivity and specificity figures in Table II, these results indicate that excluding the ONH region before feature extraction, combined with the richer detail multi-scale Gabor and LBP features provide, gives a meaningful improvement over conventional approaches that do not separate out the optic disc or rely on simpler feature sets. Testing against both public fundus datasets and real-time clinical images captured with a fundus camera further suggests the approach holds up under the illumination and quality variation typical of real clinical conditions.

VII. Conclusion

This work set out to automate diabetic retinopathy lesion classification while addressing a specific, recurring weakness in existing systems: the misclassification of the Optical Nerve Head as an exudate. By excluding the ONH region before feature extraction, and combining this with multi-scale Gabor and Local Binary Pattern features, the proposed framework gave its SVM classifiers meaningfully better information to work with, which translated into a marked accuracy improvement over the existing method, from 93% to 100% on the evaluated test set, alongside complete sensitivity and specificity. The multi-label classification stage further allows the

system to report every lesion type present in an image rather than a single generic abnormality flag, which matters for genuine clinical usefulness. Testing on both public datasets and real-time clinical images adds confidence that the approach generalizes beyond curated benchmark data. Future work could extend this framework with deep learning-based feature extraction, severity grading across DR stages, larger multi-source clinical datasets, and eventual deployment as a clinical screening tool integrated with electronic health records.

VIII. References

- [1] Abd El-Fattah EE, Saber S, Youssef ME, Eissa H, El-Ahwany E, Amin NA, et al. AKT-AMPK α -mTOR-dependent HIF-1 α activation is a new therapeutic target for cancer treatment: A novel approach to repositioning the antidiabetic drug sitagliptin for the management of hepatocellular carcinoma. *Front Pharmacol.* 2022;12:720173. <https://doi.org/10.3389/fphar.2021.720173>.
- [2] Abdelhady R, Mohammed OA, Doghish AS, Hamad RS, Abdel-Reheim MA, Alamri MMS, et al. Linagliptin, a DPP-4 inhibitor, activates AMPK/FOXO3a and suppresses NF- κ B to mitigate the debilitating effects of diethylnitrosamine exposure in rat liver: Novel mechanistic insights. *FASEB J.* 2024;38:e23480. <https://doi.org/10.1096/fj.202302461RR>.
- [3] Abdelhamid AM, Saber S, Youssef ME, Gaafar AGA, Eissa H, Abd-Eldayem MA, et al. Empagliflozin adjunct with metformin for the inhibition of hepatocellular carcinoma progression: Emerging approach for a new application. *Biomed Pharmacother.* 2022;145:112455. <https://doi.org/10.1016/j.biopha.2021.112455>.
- [4] Adak S, Magdalene D, Deshmukh S, Das D, Jaganathan BG. A review on mesenchymal stem cells for treatment of retinal diseases. *Stem Cell Rev Rep.* 2021;17:1154–1173. <https://doi.org/10.1007/s12015-020-10090-x>.
- [5] Akhter MH, Ahmad I, Alshahrani MY, Al-Harbi AI, Khalilullah H, Afzal O, et al. Drug delivery challenges and current progress in nanocarrier-based ocular therapeutic systems. *Gels.* 2022;8:82. <https://doi.org/10.3390/gels8020082>.
- [6] Ambekar A, Sahoo J, Singh K. Breaking barriers in ocular drug delivery for uveitis: Advanced drug delivery systems, challenges and future prospects. *Exp Eye Res.* 2025;257:110456. <https://doi.org/10.1016/j.exer.2025.110456>.
- [7] Antonetti DA, Silva PS, Stitt AW. Current understanding of the molecular and cellular pathology of diabetic retinopathy. *Nat Rev Endocrinol.* 2021;17:195–206. <https://doi.org/10.1038/s41574-024-01053-0>.
- [8] Appell MB, Pejavar J, Pasupathy A, Rompicharla SVK, Abbasi S, Malmberg K, et al. Next-generation therapeutics for retinal neurodegenerative diseases. *J Control Release.* 2024;367:708–736. <https://doi.org/10.1016/j.jconrel.2024.01.063>.
- [9] Asadi S, Rahimi Z, Kohsari M, Babajani F, Amiri M, Jalilian N, et al. Assessing the possible association between MTHFR (rs1801133) and GPx-1 (rs1050450) polymorphisms with the risk of type 2 diabetes, diabetic neuropathy, and diabetic retinopathy. *Mol Biol Rep.* 2024;51:583. <https://doi.org/10.1007/s11033-024-09519-0>.
- [10] Berrocal MH, Acaba-Berrocal L. Early pars plana vitrectomy for proliferative diabetic retinopathy: Update and review of current literature. *Curr Opin Ophthalmol.* 2021;32:203–208. <https://doi.org/10.1097/ICU.0000000000000760>.