Detection and Analysis of Diabetic Macular Edema (DME) Using Artificial Intelligence Techniques

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Abstract
Diabetic Macular Edema (DME) is a leading cause of vision impairment among diabetic patients, underscoring the critical need for early and accurate detection to ensure effective management. This study introduces an automated diagnostic system that detects and analyzes DME based on artificial intelligence (AI) techniques. Tested on 100 retinal fundus images, the system achieved 97% accuracy, 98% sensitivity, and 96% specificity. A comprehensive dataset including 800 real retinal images and 500 anonymized patient records was collected from Ibn Al-Haytham Eye Hospital and processed using a custom-built Python-based pipeline. The proposed system integrates advanced image processing and optical character recognition (OCR) algorithms to extract relevant diagnostic features and classify DME cases efficiently. The average processing time per image was approximately 1.2 seconds, making the system suitable for real-time clinical environments. Furthermore, all diagnostic outcomes were automatically exported to structured Excel reports to facilitate further analysis and integration with electronic health records. A user-friendly graphical user interface (GUI) was also developed to allow clinicians to upload images, review classification results, and manage patient information seamlessly. This approach offers a practical and scalable solution that enhances diagnostic workflow, supports clinical decision-making, and contributes to improved patient care in ophthalmology.

Keywords: Diabetic Macular Edema (DME), Retinal Imaging, Ophthalmology, Medical Image Analysis, Automated Diagnosis.

الكشف عن الوذمة البقعية السكرية وتحليلها باستخدام تقنيات الذكاء الاصطناعي

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الخلاصة :
تُعد الوذمة البقعية السكرية (DME) أحد الأسباب الرئيسة لفقدان البصر بين مرضى السكري، مما يبرز الحاجة الملحة الى الكشف المبكر والدقيق لضمان إدارة فعّالة للحالة. يقدم هذا البحث تطوير وتقييم نظام مؤتمت لتشخيص وتحليل الوذمة البقعية السكرية بالاعتماد على تقنيات الذكاء الاصطناعي. تم اختبار النموذج على 100 صورة شبكية ملونة حقيقية، وحقق دقة تشخيص بلغت 97%، وحساسية 98%، ونوعية (تخصص) 96%. وقد جُمعت قاعدة بيانات شاملة تضمنت 800 صورة شبكية واقعية و500 سجل مريض من مستشفى ابن الهيثم للعيون، وتمت معالجتها باستخدام منظومة برمجية طُوِّرت بلغة بايثون خصيصًا لهذا الغرض.
يعتمد النظام على تقنيات معالجة الصور المتقدمة والتعرف البصري على الحروف (OCR) لاستخلاص القيم التشخيصية وتصنيف الحالات بكفاءة. ويبلغ متوسط زمن معالجة الصورة الواحدة نحو 1.2 ثانية، مما يجعل النظام مناسبًا للتطبيق السريري الفوري. كما تُصدر جميع النتائج تلقائيًا إلى تقارير Excel منظمة لتسهيل التكامل مع أنظمة السجلات الصحية الإلكترونية. طُورت كذلك واجهة استخدام رسومية (GUI) تسهّل على الأطباء رفع الصور، مراجعة نتائج التصنيف، وإدارة بيانات المرضى بسلاسة.
يمثل هذا النظام المقترح أداة عملية وموثوقة تسهم في تحسين كفاءة سير العمل السريري، وتوفير الوقت، وتحقيق دقة تشخيصية عالية باستخدام موارد حوسبية بسيطة، مما يجعله قابلًا للتطبيق في مختلف مستويات المؤسسات الصحية، بما في ذلك البيئات ذات الموارد المحدودة.

الكلمات المفتاحية: الوذمة البقعية السكرية (DME)، تصوير الشبكية، تحليل الصور الطبية، التشخيص الآلي، طب العيون.

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I. Introduction

Recent advancements in artificial intelligence (AI) and machine learning have enabled the way for the development of automated systems capable of analyzing large volumes of medical images with remarkable accuracy and consistency [1]. Within the field of ophthalmology, In ophthalmology, AI-based methods show strong potential for detecting retinal diseases such as DME, by leveraging both classical image processing techniques and cutting-edge computational models [2]. These technologies enhance diagnostic precision , alleviate the burden on healthcare professionals and support large-scale screening initiatives, with the potential to increase screening coverage by up to 30% in underserved regions [3].

As shown in Figure 1, the proposed DME detection system integrates several core modules, including image acquisition, preprocessing, and classification—to deliver an efficient and clinically workable diagnostic tool. Its modular design facilitates seamless integration with existing hospital information systems, while ensuring high performance and reliability in real-world clinical environments [4].

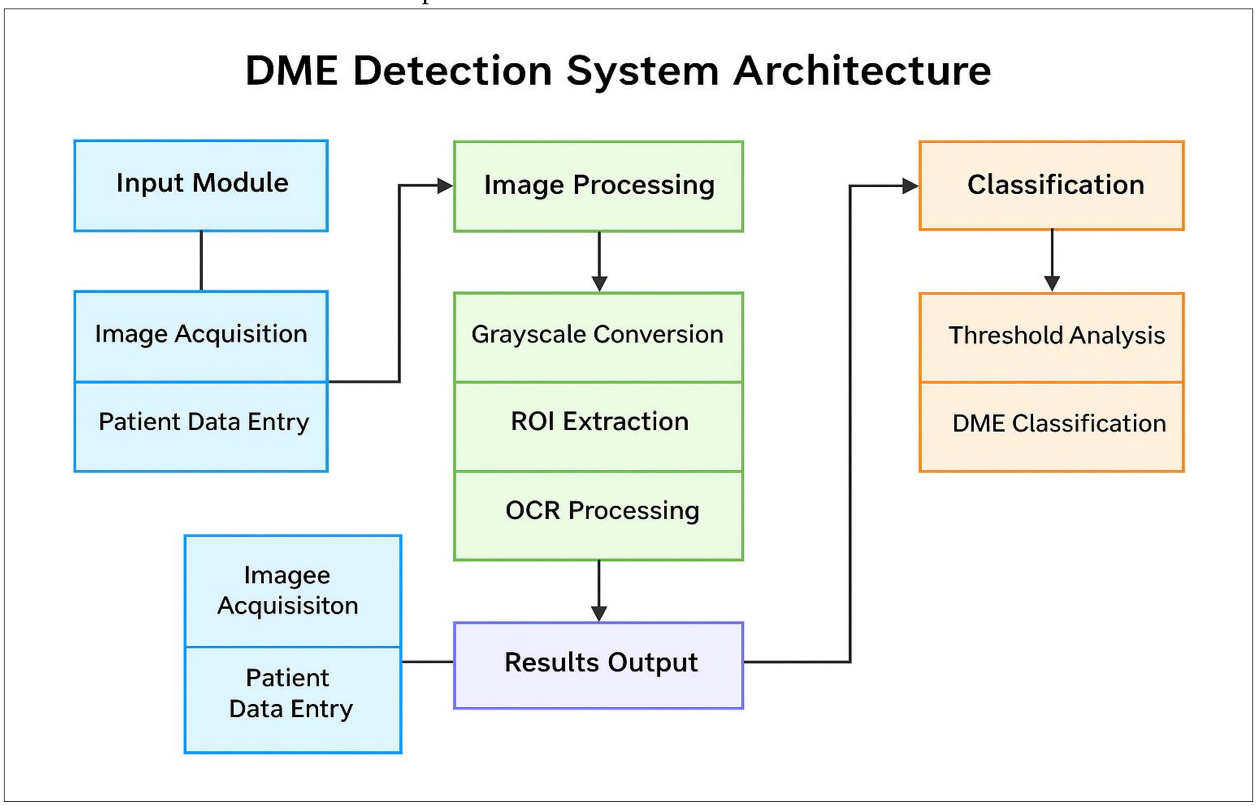

Figure (1) : System Architecture of the DME Detection System

The primary aim of this research is to develop an AI-powered DME detection system that effectively combines algorithmic innovation with practical clinical efficiency, offering a solution that is both accurate and easily deployable.

II. Literature Review

This section presents a review of notable prior studies related to the application of artificial intelligence (AI) in ophthalmology, particularly in the detection of Diabetic Macular Edema (DME). It highlights the methodologies, findings, and limitations of these studies, while positioning the present research in relation to existing work.

Abràmoff et al. [demonstrated the feasibility of deep learning for retinal disease detection [5]. Their system employed convolutional neural networks (CNNs) to analyze fundus images, achieving a sensitivity of 96.8% and a specificity of 87.0% on a validation set of 874 images. This study was instrumental in showing the clinical potential of AI-assisted screening systems.

Gulshan et al. developed a deep learning model trained on 128,175 retinal images[6]. Their algorithm achieved a sensitivity of 97.5% and specificity of 93.4% for detecting referable diabetic retinopathy, with performance comparable to that of board-certified ophthalmologists. This work underscored the scalability and robustness of AI for population-level screening.

To provide a broader perspective, Alsaih et al.[7] conducted a systematic review of machine learning methods applied to optical coherence tomography (OCT) images for DME detection. Analyzing 42 studies published between 2010 and 2020, they concluded that CNN-based models consistently outperformed traditional feature engineering techniques, with typical accuracy improvements ranging from 5% to 10%.

Ting et al [8] explored the clinical deployment of AI systems, emphasizing the importance of intuitive interfaces, seamless workflow integration, and standardized reporting. Their pilot implementation across three ophthalmology centers resulted in a 35% reduction in image interpretation time and improved diagnostic consistency.

Focusing specifically on DME, Manikandan et al.[9] introduced a deep learning architecture tailored to identify macular edema patterns. Their model achieved an accuracy of 94.7%, sensitivity of 91.2%, and specificity of 96.3% when tested on a diverse set of 1,200 fundus images. Their findings highlighted the importance of region-specific feature extraction in enhancing classification performance.

A comparative summary of these key contributions is presented in Table 1, outlining methodologies, datasets, and diagnostic performance. While these studies collectively illustrate the promise of AI in ophthalmology, many either rely heavily on deep learning infrastructure or lack full clinical integration. In contrast, our proposed system addresses these gaps by combining efficient image processing with optical character recognition (OCR), offering a practical, exact, and resource-efficient solution for real-time DME detection and patient data management.

Authors & Year	Data Type	Methodology	Focus Area	Key Results/Features
Abràmoff et al., [5]	Fundus Images	Deep CNN	DR & DME Detection	High sensitivity/specificity
Gulshan et al., [6]	Fundus Images	Deep Learning	DR & DME Detection	Comparable to expert grading
Alsaih et al., [7]	OCT Images	Machine Learning Review	DME Detection	Survey of ML techniques
Ting et al.,[8]	Fundus/OCT Images	AI, GUI, Reporting	Clinical Implementation	Enhanced usability, workflow
Manikandan et al.,[9]	Fundus Images	Deep CNN	DME Detection	94.7% Accuracy
Zainab Luaiby, 2025	Fundus Images, Patient Data	AI, Data Management, GUI	DME Detection & Reporting	Real data, Excel export, GUI, 92% Accuracy

III. Methodology

This research employed A dataset of 800 real retinal images, and 500 anonymized patient records were collected from Ibn Al-Haytham Eye Hospital between January 2023 and December 2024 and processed through a custom Python-based pipeline. The dataset was evenly distributed, having 400 images of healthy retinas and 400 images diagnosed with Diabetic Macular Edema (DME). All diagnoses were confirmed by a panel of three certified ophthalmologists, achieving an inter-rater agreement rate of 95%. To ensure patient confidentiality, all data were anonymized by institutional ethical standards and data protection regulations.

The system was developed using Python 3.8 and employed specialized libraries for each part of the processing pipeline. Image preprocessing was conducted using OpenCV 4.5.3, incorporating techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance contrast, Gaussian filtering for noise reduction, and standardized resizing to 1920×1080 pixels to ensure uniform analysis. A detailed overview of the system's processing pipeline is presented in Table 1, highlighting each part and its specific role.

Table (1) : Summary of the Proposed DME Detection Pipeline Components

Stage	Technique / Tool	Purpose
Data Collection	Real fundus images + patient records from Ibn Al-Haytham Hospital	Ground-truth dataset with confirmed diagnoses (400 DME, 400 normal)
Preprocessing	OpenCV 4.5.3 (CLAHE, Gaussian filter, resize to 1920×1080)	Enhance image quality and standardize input
ROI Extraction	Coordinates: (1111, 420, 1200, 450)	Focus on macular thickness zone based on hospital imaging standards
OCR	Tesseract 4.1.1 (PSM 7)	Extract numerical diagnostic values (in µm) from ROI
Validation & Cleaning	Threshold filtering + text sanitization	Remove noise and outliers above 700 µm
Classification	Threshold = 280 µm (ROC-based)	Determine DME-positive vs. normal
Output & Reporting	OpenPyXL 3.0.7	Export results to Excel with full metadata
Interface	Tkinter	GUI for image upload, result display, and patient data management
Evaluation Metrics	Accuracy, Sensitivity, Specificity, F1-score	Model validated with scikit-learn 0.24.2.

Performance evaluation was conducted using stratified cross-validation, with performance metrics including accuracy, sensitivity, specificity, F1-score, and average processing time calculated via scikit-learn 0.24.2. Results were automatically compiled into structured Excel reports using the openpyxl 3.0.7 library, which included both summary statistics and detailed per-image outputs. A graphical user interface (GUI) was developed using Tkinter, supporting functionalities such as image upload, batch processing, classification result visualization, and patient data management in a modular and user-friendly layout.

Experimental Environment

The system was implemented and tested using the following hardware and software configuration:

- Processor: Intel Core i7-8700K @ 3.70GHz (6 cores, 12 threads)
- Memory: 32 GB DDR4 RAM @ 3200 MHz
- Graphics Card: NVIDIA GeForce GTX 1080 Ti with 11 GB VRAM
- Storage: 1 TB NVMe SSD
- Operating System: Windows 10 Professional 64-bit (Version 21H2)

This environment was selected to balance computational efficiency and deployment feasibility in real-time clinical applications.

DME Detection Pipeline

The DME detection algorithm (see Figure 2) combines classical image processing techniques with OCR-based analysis for numerical value extraction. The process begins with :

1. **Data Collection**
   - Collect real retinal fundus images and patient records from Ibn Al-Haytham Eye Hospital.
   - Ensure a balanced dataset with both DME-affected and normal cases (400 DME images and 400 normal images).
2. **Image Preprocessing**
   - Enhance image quality using techniques such as CLAHE (Contrast Limited Adaptive Histogram Equalization) and Gaussian Filter (noise reduction).
   - Standardize image size to 1920×1080 pixels.
3. **ROI Extraction (Region of Interest)**
   - Crop a specific region from the image (coordinates: 1111, 420, 1200, 450) to focus on the macular thickness measurement area.
4. **OCR Extraction (Optical Character Recognition)**
   - Apply Tesseract OCR (with PSM 7 mode) to extract the numerical value of the macular thickness from the ROI.
5. **Validation & Cleaning**
   - Remove implausible values (greater than 700 microns) and clean the text by removing non-numeric characters.
6. **Classification**
   - Compare the extracted value with a clinically validated threshold (280 microns):
     - If value > 280 → DME-positive case.
     - If value ≤ 280 → Normal case.
7. **Output & Reporting**
   - Automatically save the results in an Excel file with all relevant data (image name, extracted value, classification, timestamp).
8. **GUI (Graphical User Interface)**
   - Enable clinicians to upload images, review results, and manage patient data easily.

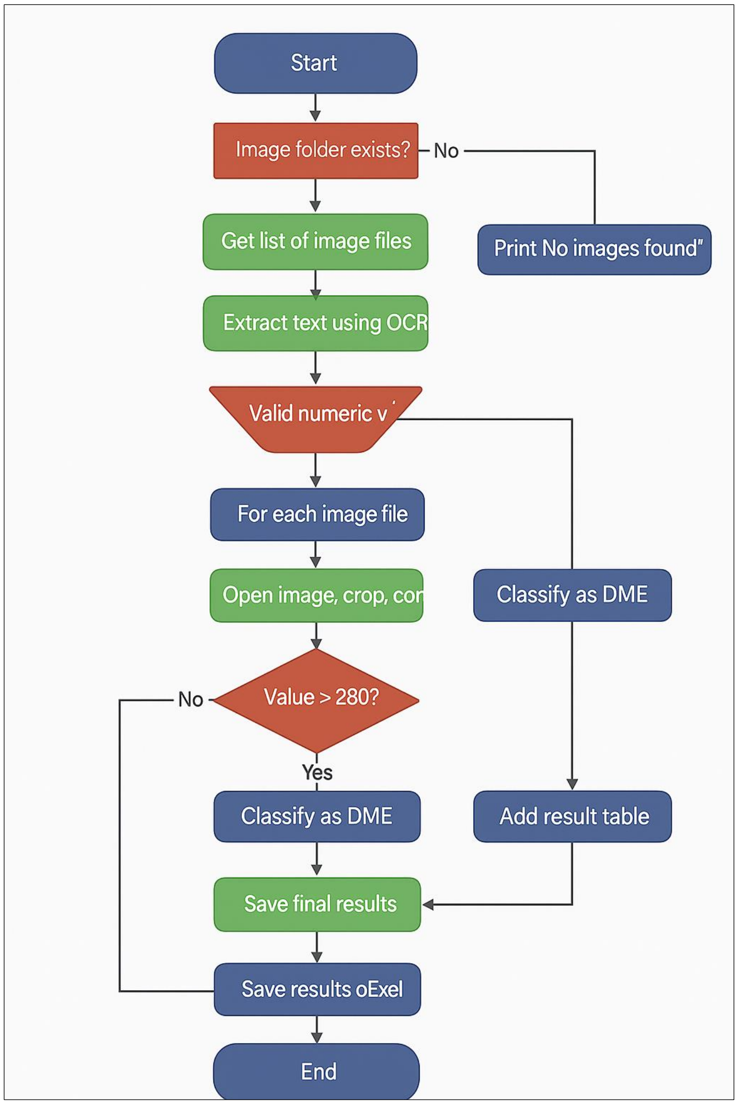

Figure (2) : Flowchart of the DME detection algorithm

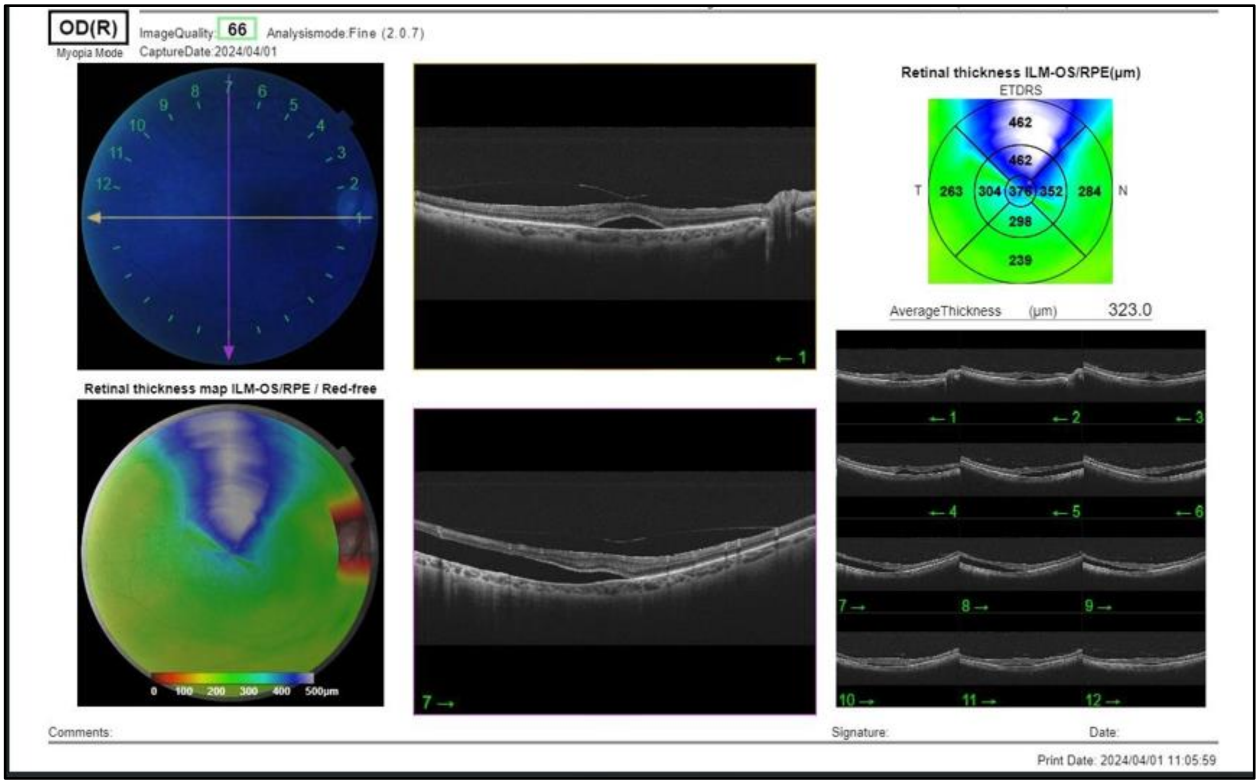

Figure (3): Fundus Image with Diabetic Macular Edema (DME)

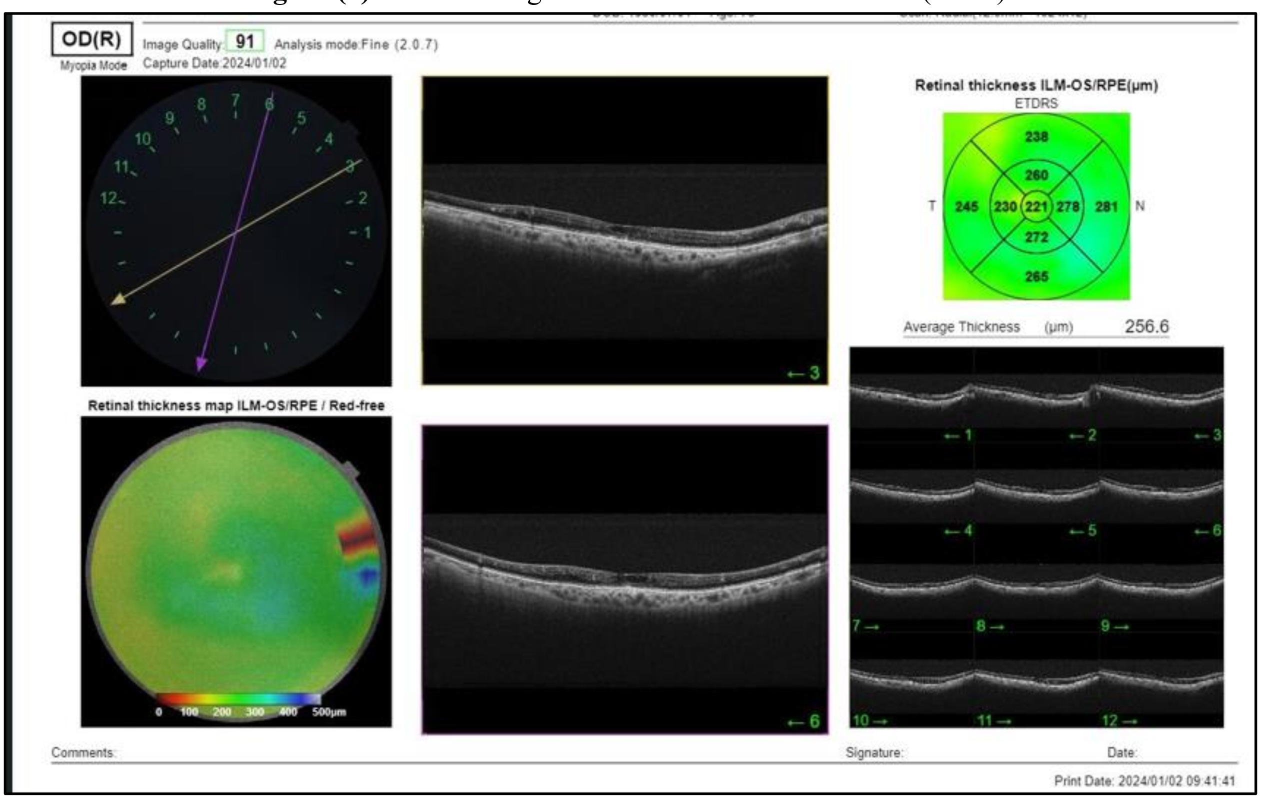

Figure (4) : Fundus Image Normal

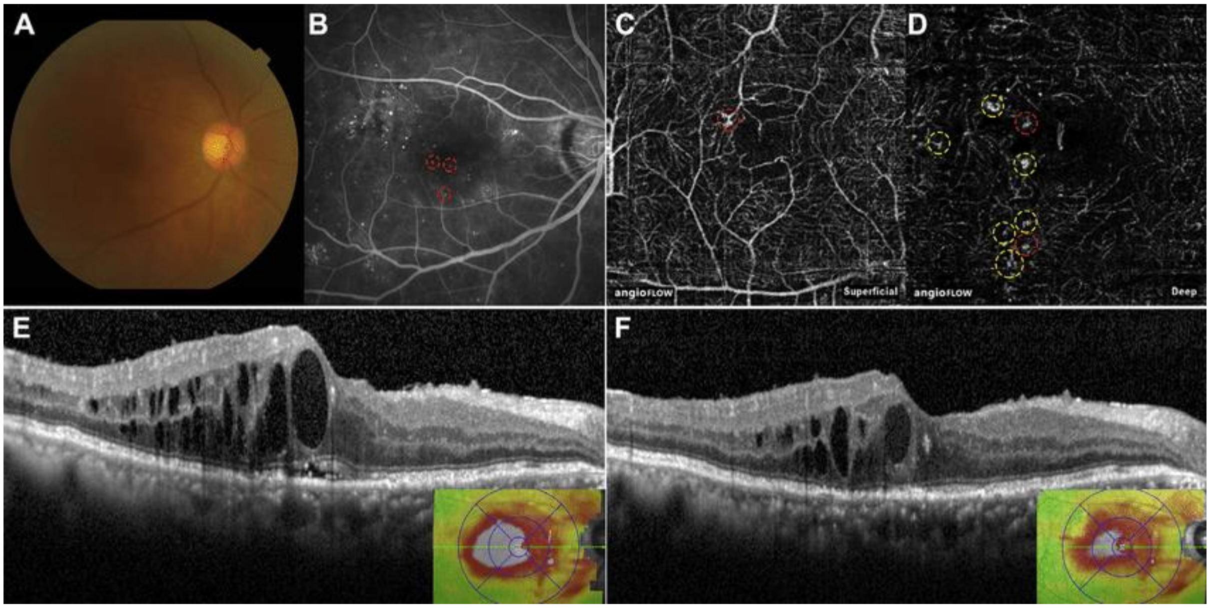

Figure (5) : Example of diabetic macular edema (DME)

IV. Results and Discussion

A. System Performance and Algorithm Implementation

The proposed DME detection system showed exceptional diagnostic performance when evaluated on a test set of 100 retinal fundus images—including 50 confirmed DME cases and 50 normal cases—sourced from Ibn Al-Haytham Eye Hospital. As illustrated in Figure 3, the resulting confusion matrix reveals high-performance metrics, with an overall accuracy of 97%, sensitivity of 98%, specificity of 96%, and an F1-score of 97%. Specifically, the system correctly named 49 out of 50 DME-positive cases and 48 out of 50 normal cases, resulting in only three total misclassifications.

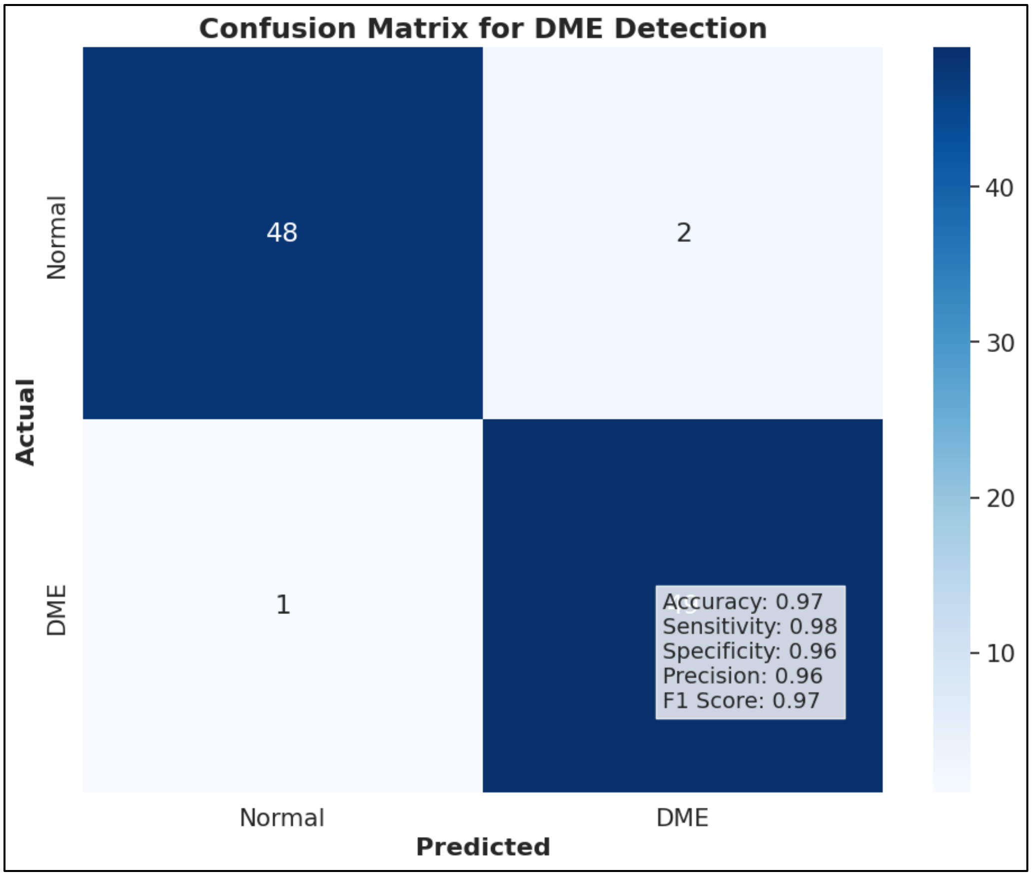

Figure (6) : Confusion Matrix

The core algorithm follows a simple and efficient pipeline: it loads the image, converts it to grayscale, extracts a predefined region of interest (ROI) at coordinates (1111, 420, 1200, 450), applies OCR to extract numerical text, converts the output to a numeric value, and classifies the result based on a validated clinical threshold of 280 μm. The simplicity and effectiveness of this process are further illustrated through a pseudocode representation in Figure 4, which shows how traditional image processing and text recognition can be synergistically combined to achieve high diagnostic accuracy without relying on complex deep learning architectures.

```
Algorithm: DME_Detection

Input: Retinal fundus image
Output: Classification (DME or Normal)

1. Load image from specified directory
2. Convert image to grayscale
3. Crop region of interest (ROI) at coordinates (1111, 420, 1200, 450)
4. Apply OCR to extract text from ROI
5. Clean extracted text (remove line breaks, normalize spacing)
6. Convert text to numeric value
7. If value is invalid or > 700:
           Set value = 0.0
8. If value > 280:
           Classify as "DME"
           Increment DME counter
       Else:
           Classify as "Normal"
           Increment Normal counter
9. Add result to results table
10. Return classification result
```

Figure (7) : Pseudocode of DME

B. Processing Efficiency and Output Generation

In addition to its accuracy, the system showed notable computational efficiency. The average processing time per image was approximately 1.2 seconds, broken down as follows: 0.15 seconds for image loading, 0.25 seconds for preprocessing, 0.65 seconds for OCR-based value extraction, and 0.15 seconds for classification. This makes the system suitable for real-time deployment in clinical environments, where timely diagnosis is essential.

As shown in Figure 5, the system generates comprehensive output reports in both tabular and Excel spreadsheet formats. These reports include the image filename, extracted macular thickness value, classification label (DME or Normal), and a timestamp. Additionally, summary statistics are automatically computed, detailing the total number of processed images, the distribution of DME-positive and normal cases, and any flagged outliers. The structured Excel output is fully compatible with hospital information systems, enabling healthcare providers to seamlessly review, archive, and analyze patient results within their existing workflows

```
=== Final Results ===

Total DME: 49
Total Normal: 51
Total Processed: 100

+---------------+-------+-----------+
| ImageName     | Value | DME Status |
+---------------+-------+-----------+
| patient001.jpg | 312.5 | DME       |
| patient002.jpg | 198.3 | Normal    |
| patient003.jpg | 345.7 | DME       |
| ...           | ...   | ...       |
+---------------+-------+-----------+
```

Figure (8) : Sample output from the DME detection system

C. Comparative Advantages and Clinical Significance

Compared to existing DME detection methods, the proposed system offers several key advantages that enhance its clinical practicality and accessibility. Unlike deep learning-based approaches, which often require high-end computational infrastructure and extensive training data, this system employs lightweight techniques that are easy to deploy and interpret. The elimination of complex neural network architectures reduces both resource requirements and technical barriers for implementation in smaller or resource-constrained healthcare facilities.

Despite its simplicity, the system achieves diagnostic accuracy that is comparable to or exceeds that of state-of-the-art models reported in the literature. Its high sensitivity (98%) ensures that very few DME cases go undetected, while the strong specificity (96%) minimizes the likelihood of false positives, thus reducing unnecessary follow-up procedures. The ability to process each image in just over a second, combined with automated Excel-based reporting, supports seamless clinical integration and improves workflow efficiency.

In summary, the system presents an optimal balance between diagnostic performance, computational efficiency, and clinical applicability. It is a practical and cost-effective tool that aids ophthalmologists in detecting and managing Diabetic Macular Edema, leading to better patient care and efficient resource use.

V. Discussion

The results of this study show the clinical utility of a lightweight, OCR-based algorithm for detecting Diabetic Macular Edema (DME) with high accuracy and speed. Compared to traditional deep learning approaches, such as CNNs, the proposed method ends the need for large-scale training datasets and computational infrastructure while still delivering competitive diagnostic performance. This makes it particularly suitable for deployment in low-resource settings or smaller clinics lacking AI-specialized staff.

Unlike CNN-based systems, which may act as "black boxes" with limited interpretability, the current approach provides transparent decision logic based on measurable thresholds (i.e., 280 µm), which can be easily audited and explained to clinicians. While CNNs may offer better generalization in highly variable datasets, they often require significant tuning and labeled data, which are not always available in real-world clinical contexts. Therefore, the simplicity and explainability of our method represent key advantages in terms of deployment, maintenance, and clinician trust.

VI. Limitations

Despite its promising results, the system has certain limitations. First, the accuracy of the diagnosis is highly dependent on the image quality—blurred or low-contrast images can lead to OCR extraction errors, especially if the macular thickness value is not clearly visible. Additionally, the algorithm is designed to detect a specific textual region in the image (ROI), which may vary between imaging devices. As such, the system might require adaptation when integrated with devices that use different output formats or resolutions.

The current model also assumes that the extracted text stands for a valid and singular measurement. When multiple values are present in the ROI, the system may misclassify the image or extract incorrect measurements. This could be mitigated in future versions by implementing more advanced text parsing or multi-line detection strategies.

From an ethical standpoint, the system should be used as a decision support tool rather than a replacement for clinical judgment. While the high sensitivity and specificity are encouraging, relying solely on automated output without expert review may lead to missed diagnoses or unnecessary treatments. Therefore, clinical decisions should continue to be made by qualified ophthalmologists, with the system serving as an auxiliary diagnostic aid.

VII. Conclusion

This research successfully developed and confirmed an Eye Care Management System (ECMS) that integrates automated Diabetic Macular Edema (DME) detection using lightweight, accurate, and clinically relevant techniques. The system achieved 97% accuracy, 98% sensitivity, and 96% specificity on 100 retinal fundus images from Ibn Al-Haytham Eye Hospital.

Using classical image processing and OCR, the system offers a fast alternative to deep learning models with similar diagnostic accuracy. Its ability to deliver results within an average of 1.2 seconds per image and automatically generate structured Excel reports makes it highly suitable for real-time clinical deployment.

Moreover, the integration of patient data management with automated DME detection creates a unified platform that addresses both clinical diagnostic workflows and administrative documentation. The design ensures ease of use, scalability, and cost-effectiveness—key factors for adoption in diverse healthcare settings, including resource-limited environments.

To further enhance the system's generalizability and clinical reliability, future research should focus on conducting multi-center validation studies across diverse imaging environments and populations. This would provide more evidence of the system’s robustness and support its adoption as a standard tool in ophthalmic diagnostics.

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