CONVOLUTED NEURAL NETWORKS (CNN) BASED CLASSIFICATION OF DIABETIC MACULAR EDEMA (DME) IN FUNDUS IMAGES

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Keywords:

Diabetic Macular Edema, Convoluted Neural Networks, Diabetic Retinopathy, Image Processing, Retinal Fundus Images.

Introduction:

Diabetic Macular Edema (DME) is a vision-threatening complication of diabetic retinopathy which involves the macula's swelling due to fluid retention and can lead to figurative or literal vision disability. Grading DME with precision and detecting it timeously is crucial for prompt treatment and management. The purpose of this project is to apply deep learning, specifically CNNs, on retinal fundus images to determine the severity of DME into clinically relevant grades such as: no DME and DME.

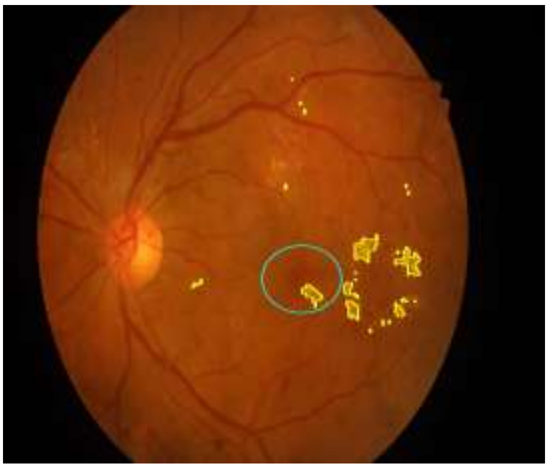


Fig 1. Diabetic Macular Edema (DME) in Fundus images

Objectives:

- Primary Objective:
    1. **Develop** a CNN model to accurately classify Diabetic Macular Edema (DME) in retinal images.

- Secondary Objectives:
    2. **Optimize** the automated extraction of key features from retinal images using CNN layers for effective DME classification.
    3. **Validate** the CNN model's accuracy against established diagnostic standards to ensure clinical applicability.

Methodology:

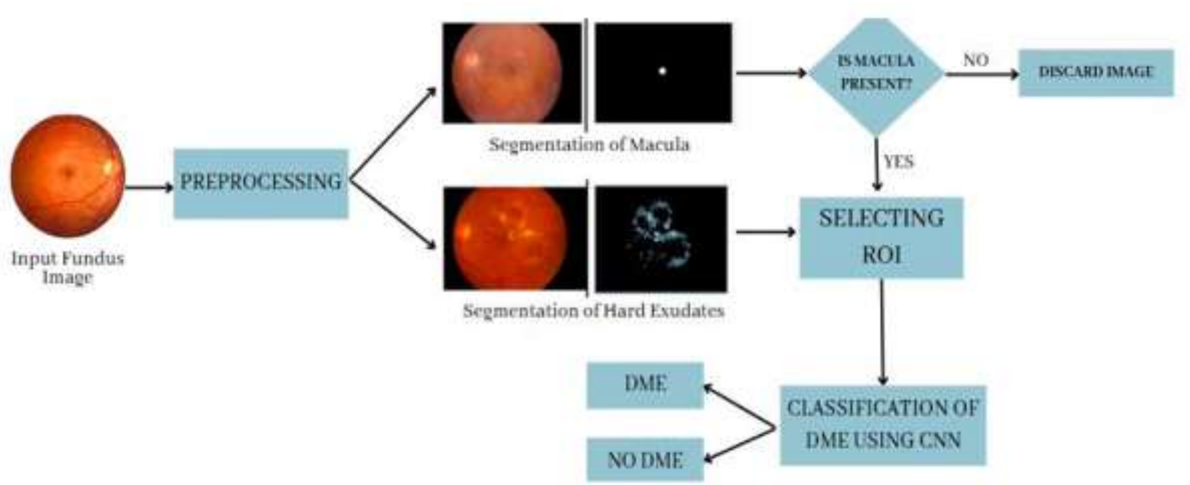


fig 2. High level architecture for the proposed solution

This project focuses on classifying Diabetic Macular Edema (DME) in fundus images using **deep learning** and **image processing**. Fundus images are sourced from Forus Health devices and public datasets like IDRID and DiaRetDB1, labeled as DME or Non-DME. Preprocessing includes normalization, histogram equalization, and Gaussian blur for better image quality. Data augmentation techniques like rotation and flipping address data imbalance challenges. Convolutional Neural Networks (CNNs) segment macula and hard exudates. ROI around the macula is analyzed for DME-specific features, such as hard exudates' shape, size, and intensity, using contour detection and morphological operations. The extracted features enable DME classification without deep learning, ensuring an interpretable, robust approach.

Result and Conclusion:

This is **Phase 1** of the project, where we developed and are fine-tuning algorithms to detect the **macula** and **hard exudates**. Models were trained using a basic **U-Net**, with **binary cross-entropy** loss and the **ADAM optimizer**.

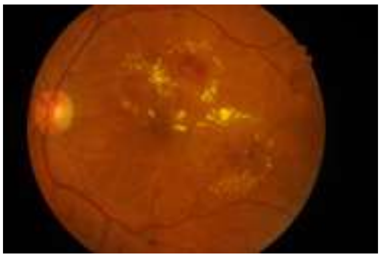
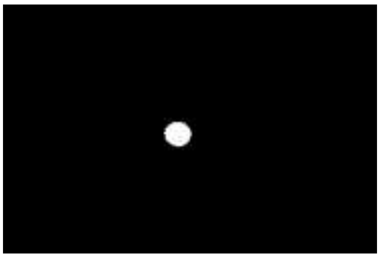
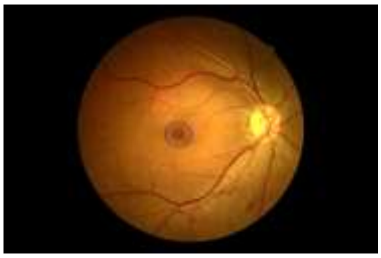
 Original Image	 Predicated Mask	 Predicted Overlay
 Original Image	 Predicated Mask	 Predicted Overlay

Fig 3. Results obtained for segmentation of exudates (row 1) and macula (row 2)

In **Phase 2,** we will focus on integrating the models to classify images as **DME or non-DME**. This phase will also address edge cases and emphasize perfecting the overall model for robust, real-world application.

Project Outcome & Industry Relevance:

- <u>Outcomes and Impacts:</u>
    1. Enables accurate and early detection of Diabetic Macular Edema (DME), reducing the risk of vision loss.
    2. Automates the screening process, reducing reliance on expert ophthalmologists, lowers screening costs, making diabetic eye care more affordable and scalable.
    3. Helps in providing eye care access in rural and underserved regions where medical professionals are scarce.

- Industry Relevance:

Our project, in collaboration with Forus Health, aims to use CNNs to classify macular edema in fundus images, improving early detection and diagnosis. This approach enhances accuracy, reduces the burden on doctors, and ensures faster, more reliable assessments. Integrated with Forus Health's 3nethra device, the system can provide quick, affordable screening, even in remote areas.

Simulation Study:

This project combines **theoretical study and simulation** by integrating medical knowledge of diabetic eye diseases with deep learning-based image analysis. Theoretical research guided the design of segmentation and diagnostic criteria, while simulation through model training and testing on real and public datasets enabled validation and refinement. Together, they form a comprehensive approach to DME detection.

Project Outcomes and Learnings:

Working on this project taught us the value of balancing technology with healthcare needs. Designing and refining the CNN architecture was a journey toward achieving optimal performance with efficiency. Implementing fallback strategies emphasized the need for adaptable solutions in medical imaging, where data quality can vary. Collaboration with Forus Health deepened our understanding of practical healthcare applications, showing how innovation can bridge diagnostic gaps, especially in underserved areas. Analyzing the model using metrics like sensitivity and specificity reinforced the need for thorough validation to ensure real-world effectiveness.

Future Scope:

Once **Phase 2** is complete, we can focus on expanding the system through:

- **Real-Time Screening**: Deploying the model into a mobile or web app for on-site DME detection, improving accessibility in clinical and rural settings.
- **Severity Classification**: Moving beyond binary output to grade DME severity, enabling more tailored and informed treatment decisions.