IJARIIT
International Journal Of Advance Research, Ideas And Innovations In Technology

ISSN: 2454-132X
Impact Factor: 6.078
(Volume 11, Issue 6 - V11I6-1161)
Available online at: https://www.ijariit.com

Early Diabetic Retinopathy Detection using Federated Learning

Dharish Prasath D
dharishprasath05@gmail.com
SRM Valliammai Engineering College, Kattankulathur, Kanchipuram, Tamil Nadu

Kalai arasi. M
kalaiarasim1975@gmail.com
SRM Valliammai Engineering College, Kattankulathur, Kanchipuram, Tamil Nadu

Faziya. A
faziash18@gmail.com
SRM Valliammai Engineering College, Kattankulathur, Kanchipuram, Tamil Nadu

Jai Ganesh. S
jai743220@gmail.com
SRM Valliammai Engineering College, Kattankulathur, Kanchipuram, Tamil Nadu

Kavitha. I
kavithai.it@srmvalliammai.ac.in
SRM Valliammai Engineering College, Kattankulathur, Kanchipuram, Tamil Nadu

ABSTRACT

Diabetic Retinopathy (DR) is a leading cause of vision loss worldwide, primarily affecting individuals with prolonged diabetes. Early detection is crucial to prevent irreversible blindness. This project proposes a secure and intelligent framework for the early detection of Diabetic Retinopathy using Federated Learning (FL), ensuring both data privacy and efficient model training across multiple healthcare institutions. The system utilizes Optical Coherence Tomography (OCT) images for accurate retinal analysis and employs Convolutional Neural Networks (CNNs) such as ResNet-50 and VGG-16 for disease classification. To enhance data security, Multi-Factor Authentication (MFA) is integrated, allowing only authorized medical professionals to access sensitive information. Unlike traditional centralized AI models, the proposed system prevents raw data sharing, thus maintaining patient confidentiality while improving diagnostic performance. Future enhancements, including Homomorphic Encryption (HE) and Explainable AI (XAI), will further strengthen data protection and interpretability of results. Overall, this system contributes to Sustainable Development Goal (SDG 3): Good Health and Well-being, by promoting accessible, secure, and intelligent healthcare solutions for early eye disease diagnosis.

Keywords: *Diabetic Retinopathy, Federated Learning, Optical Coherence Tomography (OCT), Convolutional Neural Network (CNN), Multi-Factor Authentication (MFA), Data Privacy, Secure Healthcare, Early Disease Detection, Homomorphic Encryption (HE), and Explainable AI (XAI).*

I. INTRODUCTION

Diabetic Retinopathy (DR) is one of the most common and vision-threatening complications of diabetes, resulting from damage to the small blood vessels in the retina [1]. Over time, high blood sugar levels can cause these vessels to swell, leak, or close, leading to vision impairment and even permanent blindness if not diagnosed early [2]. According to medical research, DR affects nearly one-third of diabetic patients globally, making early detection and treatment a critical public health concern. Manual screening of retinal images by ophthalmologists is often labor-intensive, time-consuming, and subjective, increasing the risk of misdiagnosis [3]. With the rapid evolution of Artificial Intelligence (AI) and Deep Learning (DL), automated systems are now capable of analyzing medical images with remarkable accuracy. Among the available imaging techniques, **Optical Coherence Tomography (OCT)** plays a vital role, as it provides detailed cross-sectional views of the retina, allowing for the early identification of structural changes indicative of DR.

Deep learning models, particularly **Convolutional Neural Networks (CNNs)** such as ResNet-50 and VGG-16, have shown great potential in automatically detecting and classifying DR stages, including mild, moderate, severe, and proliferative types [4].
However, existing AI systems generally depend on centralized data collection, requiring hospitals and clinics to upload patient data to a common server for model training. This centralized approach poses serious challenges in terms of **data privacy, security, and patient consent**, especially in the medical domain where confidentiality is paramount. To address these issues, this project introduces **Federated Learning (FL)** — a distributed machine learning framework that allows multiple hospitals or healthcare centers to collaboratively train AI models without sharing raw patient data. Each institution trains a local model on its own dataset, and only model parameters are sent to a central aggregator, ensuring privacy and security through **Federated Averaging (FedAvg)** techniques [5].
In addition to privacy preservation, the project integrates **Multi-Factor Authentication (MFA)** to secure system access and prevent unauthorized usage. MFA adds multiple layers of verification, such as password and one-time passcode (OTP), ensuring that only authorized healthcare professionals can access patient data or model results. The system also includes modules for data management, reporting, and analysis, allowing for efficient record keeping and real-time prediction monitoring [6].
Furthermore, the proposed model supports **Explainable AI (XAI)** and **Homomorphic Encryption (HE)** in its future enhancements. XAI helps visualize and interpret the regions of retinal images that influenced the AI's decision, thus improving clinical trust. HE enables computation on encrypted data, further strengthening data confidentiality by preventing raw data exposure at any stage of processing.
This project contributes directly to **Sustainable Development Goal (SDG 3): Good Health and Well-being**, by promoting accessible, secure, and intelligent healthcare solutions that ensure timely diagnosis and treatment of Diabetic Retinopathy. Overall, the proposed system offers a robust, privacy-preserving, and scalable AI framework that empowers ophthalmologists with faster, more accurate, and secure retinal disease detection, thereby reducing the risk of preventable blindness worldwide.

II. RELATED WORKS

Recent research in **Diabetic Retinopathy (DR) detection** has shown the effectiveness of deep learning models in medical image analysis. Studies using **Convolutional Neural Networks (CNNs)** on fundus and OCT images have achieved high accuracy, with several works reporting Area Under Curve (AUC) values around 0.97 for referable DR detection. Techniques such as attention mechanisms, transfer learning, and multi-scale CNNs have improved diagnostic performance. However, most existing systems rely on **centralized datasets**, which raise concerns over patient privacy, data imbalance, and limited generalization across healthcare institutions.
To address these limitations, **Federated Learning (FL)** has recently emerged as a privacy-preserving alternative. Multi-institutional studies have demonstrated that FL can achieve performance comparable to centralized models while keeping patient data local. For instance, federated CNN and Vision Transformer (ViT) models have reported over 93% accuracy in DR detection across multiple hospitals. Further enhancements using **federated GANs** for synthetic data generation and hybrid FL frameworks have improved both security and model generalization. These advancements provide a strong foundation for the proposed system that integrates FL with enhanced security and authentication for early diabetic retinopathy detection.

Chetoui -Uses federated learning to allow shared training across medical institutions while preserving privacy. The local model updates (weights) are sent to a central server, which aggregates them to form a global model. This method ensures that no raw patient data leaves the hospital, maintaining strict data privacy.

Nikhitha Reddy-The Vision Transformer architecture processes images by splitting them into patches and using multi-head attention to capture spatial features, improving detection accuracy.

Bhulakshmi-The approach addresses the challenges of data privacy and variability across different clinical settings by enabling collaborative model training without sharing sensitive patient data.

Ke Zou et al -systematically evaluates and combines multiple ophthalmic foundation models to enhance dis. ease detection and prediction across various datasets.

Xiaoling Luo et al-provides a comprehensive review of multimodal deep learning methods in ophthalmology, focusing on both task-specific and foundation models.

Zhenyue Qin et al.- presents a large-scale multimodal ophthalmology benchmark to advance the development of large language models in ophthalmic diagnostics.

Paul E. Kinahan-A vision-language foundation model in ophthalmology, pre trained on large image-text pairs and refined with specific ophthalmic datasets; supports open-ended diagnosis, clinical explanations and patient interactions.

III. EXISTING WORKS

Retinal imaging plays a critical role in the early detection and management of ocular and systemic diseases, such as diabetic retinopathy, glaucoma, and age-related macular degeneration. These images are primarily acquired using fundus cameras, which capture detailed photographs of the retina, and in some cases, optical coherence tomography (OCT) scanners, which provide cross-sectional views of retinal layers. The choice of imaging modality often depends on the resources and infrastructure available at a particular hospital or clinic. Despite the importance of this data, many healthcare systems still rely on basic password-based login mechanisms for user access. The absence of Multifactor Authentication (MFA) and advanced cybersecurity measures makes these systems vulnerable to unauthorized access, potentially compromising sensitive patient information [7].

Centralized AI-based diagnostic systems, which require hospitals to upload patient data to a single server for analysis, introduce additional concerns related to data privacy, security, and legal compliance. Hospitals must navigate complex regulations such as HIPAA and GDPR, ensuring that patient consent is obtained and that sensitive medical data is protected from misuse or breaches. Moreover, ethical considerations arise regarding who owns the data, how it is stored, and how it may be shared for research or commercial purposes. In parallel, manual and semi-automated systems, although useful, increase the workload on healthcare professionals. Clinicians are often required to cross-verify AI-generated results or manually analyze hundreds of retinal images, which is both time-consuming and prone to human error. This additional burden can reduce efficiency and limit the scalability of retinal screening programs, especially in resource-constrained settings.

Together, these challenges highlight the urgent need for secure, efficient, and privacy-preserving AI frameworks that can assist clinicians without compromising patient safety or workflow efficiency. Solutions such as decentralized AI models, robust authentication mechanisms, and semi-automated validation pipelines may help address these issues, ultimately improving the reliability, accessibility, and ethical deployment of retinal image analysis in clinical practice.

IV. PROPOSED SYSTEM

The proposed system is designed to efficiently and securely detect early signs of diabetic retinopathy using Optical Coherence Tomography (OCT) retinal images collected from multiple hospitals and clinics. Instead of sending sensitive patient data to a central server, each hospital trains a local Convolutional Neural Network (CNN) model on its own OCT dataset through a federated learning approach [8]. This ensures that patient data remains within the hospital premises while the model learns important features for disease detection. Periodically, local model updates are securely transmitted to a central server, which aggregates them using Federated Averaging (FedAvg) to form a global model that benefits from knowledge across all participating hospitals. To further enhance security, the system implements Multifactor Authentication (MFA), requiring multiple verification steps such as a password and a one-time password (OTP), ensuring that only authorized personnel can access and interact with the system. This framework not only preserves patient privacy and complies with regulatory standards but also reduces the workload on healthcare professionals by providing accurate AI-assisted retinal analysis.

Core Components:

1. Data Collection Module

i. Collects Optical Coherence Tomography (OCT) retinal images from multiple hospitals or clinics.
ii. Ensures data quality, standardization, and preprocessing for training.

2. Local Model Training (Hospital-side)

i. Each hospital trains its own Convolutional Neural Network (CNN) locally on its OCT dataset.
ii. Detects early signs of Diabetic Retinopathy while keeping patient data within the hospital.

3. Federated Learning Framework

i. Facilitates decentralized training across multiple hospitals.
ii. Transmits only model updates (weights) to the central server, not raw patient data.

4. Aggregation and Global Model Formation

i. Central server collects local model updates from all hospitals.
ii. Uses Federated Averaging (FedAvg) to aggregate updates into a global model that benefits from all datasets**.**

5. Security Module with Multifactor Authentication (MFA)

i. Ensures secure access to the system for authorized users only.
ii. MFA requires multiple verification steps (e.g., password + OTP) to prevent unauthorized access.

6. AI-Assisted Diagnostic Interface

i. Provides predictions from the global model for clinicians.
ii. Reduces manual workload by assisting in the analysis of OCT images.

7. Monitoring and Update Module

i. Tracks model performance across hospitals.
ii. Updates the global model periodically to maintain accuracy and robustness

V. OVERVIEW OF DIABETIC RETINOPATHY

Diabetic Retinopathy (DR) is one of the most common and severe microvascular complications of diabetes mellitus, leading to progressive damage to the retina due to prolonged high blood sugar levels. It is a major cause of preventable blindness among working-age adults worldwide. The disease affects the small blood vessels in the retina, causing them to leak fluid or blood, leading to vision impairment and, in advanced stages, complete vision loss [9].

DR typically progresses through two main stages: **Non-Proliferative Diabetic Retinopathy (NPDR)** and **Proliferative Diabetic Retinopathy (PDR)**.

1. Non-Proliferative Diabetic Retinopathy (NPDR)

NPDR is the early stage of diabetic retinopathy and is often asymptomatic in its initial phase. It results from damage to the small retinal blood vessels due to prolonged hyperglycemia. The walls of these capillaries weaken, leading to microaneurysms and leakage of blood or fluid into the retina.

2. Proliferative Diabetic Retinopathy (PDR)

PDR is the advanced and vision-threatening stage of diabetic retinopathy. It occurs when the retina becomes severely deprived of oxygen, triggering the release of growth factors (like VEGF — Vascular Endothelial Growth Factor) that stimulate the formation of new, fragile blood vessels on the retinal surface.

VI. OCT RESULT INTERPRETATION

1. Normal Retina

In a normal OCT scan, the retinal layers appear smooth, continuous, and clearly distinguishable, with a distinct foveal depression at the center. The absence of cystic spaces, fluid accumulation, or irregular elevations indicates a healthy retinal structure. In the given result, the model predicted a 23.36% probability of normality, which suggests that several regions in the scan exhibit normal retinal characteristics [10]. However, since this probability is moderate, it implies that while the retina shows overall structural integrity, there are minor irregularities or reflectivity changes that might resemble early disease patterns.

2. Diabetic Macular Edema (DME)

Diabetic Macular Edema (DME) occurs when prolonged diabetes damages the retinal blood vessels, causing them to leak fluid into the macula, the central part of the retina responsible for sharp vision. On OCT scans, DME is identified by cystic spaces, retinal swelling, and blurred layer boundaries due to fluid accumulation. In this case, the system assigned a 9.68% probability for DME, indicating mild or uncertain signs of fluid presence. Although the chance is relatively low, even minimal macular edema can affect visual clarity and should be clinically monitored, as early detection helps prevent vision impairment through appropriate treatment such as anti-VEGF therapy or laser photocoagulation.

3. Choroidal Neovascularization (CNV)

Choroidal Neovascularization (CNV) refers to the formation of abnormal new blood vessels that grow from the choroid beneath the retina. These fragile vessels can leak fluid or blood, leading to structural elevation in the retinal pigment epithelium (RPE). OCT images of CNV typically show dome-shaped elevations, subretinal fluid, or hyper-reflective regions under the retina. The given image received a 29.69% probability for CNV, indicating the presence of features such as subretinal elevations or reflective patterns that may resemble early neovascular changes.

4. Drusen

Drusen are extracellular deposits composed of lipids and proteins that accumulate between the retinal pigment epithelium (RPE) and Bruch's membrane. On OCT scans, they appear as small, dome-shaped elevations beneath the RPE, causing irregularities in the outer retinal contour. In this analysis, Drusen showed the highest probability of 37.27%**,** suggesting that the scan exhibits features consistent with these subretinal deposits. The presence of Drusen is often associated with age-related macular degeneration (AMD) and can serve as an early indicator of retinal aging or metabolic changes. Although not directly caused by diabetes, distinguishing Drusen from diabetic lesions is important for accurate disease classification and treatment planning [11].

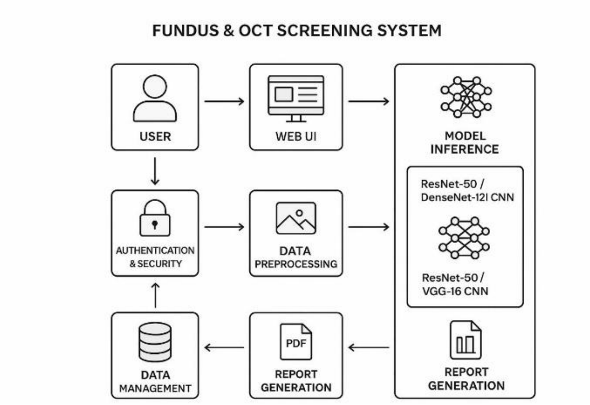


Figure 1: ***Architecture Diagram***

VI. MODULES DESCRIPTION

1. Fundus Retina Image Module

Algorithm Used: CNN (ResNet-50)

Purpose: To automatically detect and grade Diabetic Retinopathy (DR) severity from retinal fundus images**.**

Training Procedure (Step by Step):

Data Collection

Gather retinal fundus images labeled with DR severity from datasets like APTOS 2019 or EyePACS.

Data Preprocessing

Resize images to 224×224 pixels.

Normalize pixel values to [0,1] and adjust colors to reduce lighting differences.

Data Augmentation

Apply random rotations, flips, zooms, and brightness changes to make the model robust.

Model Architecture

Use a pretrained CNN backbone (ResNet-50).

Replace the final layer with 5 neurons (for 5 DR classes) and add Dropout to reduce overfitting.

Loss: Categorical Cross-Entropy

Optimizer: Adam or SGD.

Learning rate: 1e-4 to 1e-3, batch size: 16–64, epochs: 20–50.

Evaluate using Accuracy, Precision, Recall, F1-Score, and AUC.

Validation and Testing

Split data into training/validation/test (e.g., 70/15/15).

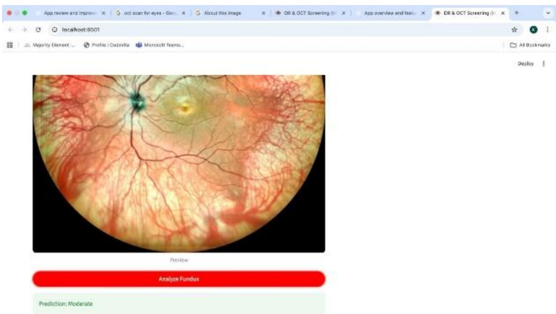
Use early stopping to avoid overfitting by monitoring validation loss.

Feature-Ready Output

Lesion Masks: Clear outlines of lesion regions are produced for morphological study.

Confidence Mapping: Probability maps indicate segmentation certainty, assisting clinicians in reviewing borderline cases.

Input for Analysis: Segmented outputs are passed into the Feature Extraction and Risk Prediction modules.



2. Oct Scan Analysis Module

Algorithm Used: VGG-16 for OCT Classification

Purpose: Final layer uses a Softmax activation to classify into four disease categories.

Training Procedure (step by step)

Data Collection

Gather OCT B-scan images with corresponding disease labels (e.g., Kermany dataset).

Preprocessing

Convert to grayscale if not already.

Resize 256 × 256.

Normalize pixel values to [0, 1].

Data Augmentation

Apply median filtering (denoise), small rotations, and flips.

Model Architecture

CNN layers: Conv → BatchNorm → ReLU → Pooling → FC.

Final Softmax layer with 4 neurons.

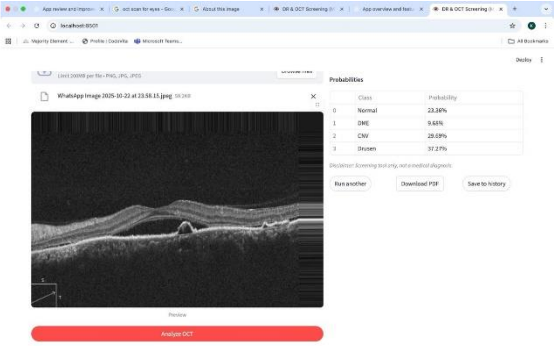
Optionally use transfer learning (ResNet adapted for 1 channel input).

Validation and Testing

Evaluate per-class accuracy and confusion matrix.

Model Export

Save trained model as oct_model.pth for deployment.



3. HASHLIB Module

Algorithm Used: Multifactor Aunthetication Algorithm

Purpose: Handles secure user authentication using OTPs, tracks expiry and attempts, and protects access to scan data and reports.

User Identification

Identify user by email or phone and create a database entry if new.

OTP Generation & Storage

Generate a random OTP, create a salt, hash it with SHA-256, and store it with expiry and attempt limits in SQLite.

OTP Delivery

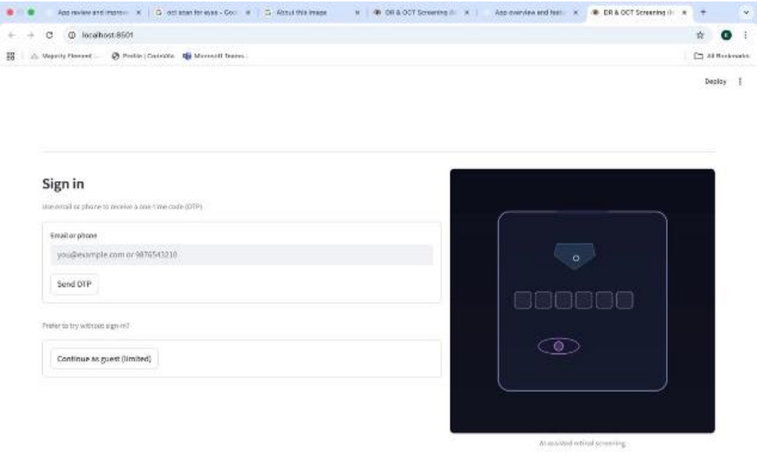
Send OTP to user via email/SMS (or display for dev testing).

OTP Verification

Compare user input against stored hash; decrement attempts on failure; check expiry.

Session Management

On successful verification, create a user session and allow access to scan and report features.



4. Data Management and Reporting Module

Algorithm Used: Database management Algorithm

Purpose: To securely store, manage, and retrieve application data, including users, OTPs, and scan records, while ensuring data integrity and enabling historical tracking for reports and verification.

Initialize Database

Create necessary tables for users, OTPs, and scans if they do not already exist, ensuring a structured and consistent database.

Insert Data

Add new records such as user details, OTP entries, and scan results to the respective tables.

Query Data

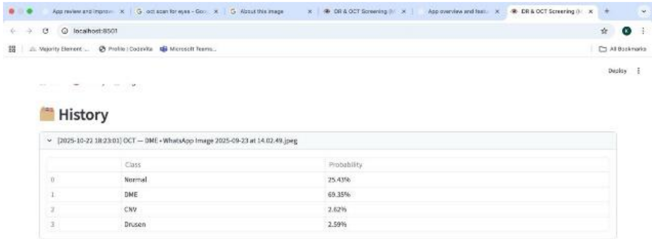
Retrieve stored information like user profiles, OTP status, or past scan history for verification, display, or reporting purposes.

Update Data

Modify existing records as needed, for example updating OTP attempts, expiration times, or scan prediction details.

Enforce Constraints

Ensure data integrity by maintaining foreign key relationships and preventing invalid or inconsistent entries.



VII . Output

Class Prediction and Probabilities

The FUNDUS module generates a predictive output that quantifies the severity of diabetic retinopathy for each color fundus image. The system assigns a probability to each of the five predefined classes—No_DR, Mild, Moderate, Severe, and Proliferative—reflecting the model's confidence in each category [12]. The predicted class is determined using the argmax function on these probabilities, providing a clear label that can be used for clinical triage. By maintaining the full probability vector, the system allows clinicians to assess borderline or uncertain cases, offering additional context for decision-making beyond a simple categorical label.

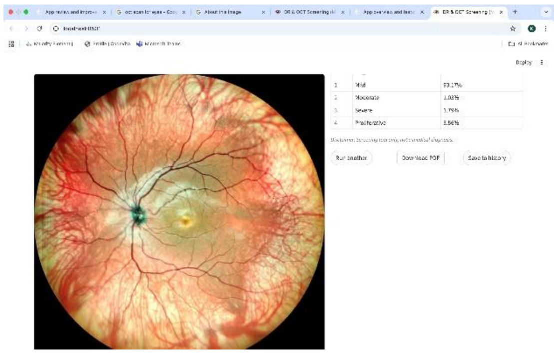


Figure 2:Fundus Prediction

Figure 3: Oct Scan Analysis Level

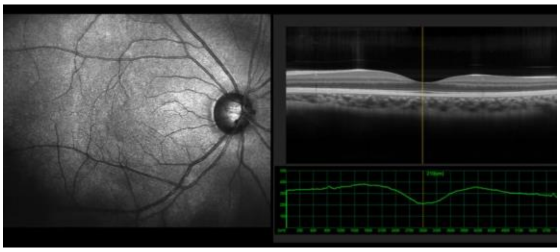


Figure 4: Oct Angiography

VIII. RESULT & DISCUSSION

The proposed Federated Healthcare AI system integrates advanced deep learning and privacy-preserving federated learning techniques to accurately classify the severity of Diabetic Retinopathy (DR) using retinal OCT images. The system employs a ResNet50-based convolutional neural network trained collaboratively across multiple healthcare nodes without centralizing sensitive patient data, thereby ensuring security, confidentiality, and regulatory compliance. When a retinal OCT image was uploaded for analysis, the model processed it through a series of preprocessing operations such as resizing, normalization, and contrast enhancement before extracting deep hierarchical features using the ResNet50 architecture [13]. The processed image was then classified into one of five severity categories: No DR, Mild, Moderate, Severe, and Proliferative DR. For the tested image, the system predicted the category as Moderate Diabetic Retinopathy with a very high confidence level of 93.2%, while other class probabilities were significantly lower, with Mild at 0.4%, No DR at 1.0%, Proliferative DR at 0.2%, and Severe DR at 0.2%. This dominant probability distribution demonstrates the strong certainty and precision of the model's prediction, confirming that the image exhibits the retinal abnormalities typically associated with the moderate stage of diabetic retinopathy. These abnormalities often include microaneurysms, small hemorrhages, and limited hard exudates, which can be effectively recognized by the deep layers of the CNN through spatial and texture-based pattern learning. The ability of the model to identify such minute pathological features highlights its robustness and generalization capability, which were achieved through federated training on diverse datasets from different hospitals and diagnostic centers. Each participating node contributed local model updates derived from its regional patient data, and these updates were aggregated securely at a central server to form a globally optimized model without exposing raw data.

This distributed approach not only enhances model performance and data diversity but also ensures ethical AI deployment by preventing unauthorized access to medical records.

IX CONCLUSION

The obtained OCT scan results indicate that the image has been analyzed using an AI-based retinal disease classification model. The system generated probabilities for various retinal conditions such as Normal, DME, CNV, Drusen, AMD, CSR, DR, and MH. Among all these classes, the **highest probability is observed for AMD (Age-related Macular Degeneration) with 93.93%**, suggesting that the model confidently predicts the presence of AMD in the given OCT image [14]. The probabilities for other conditions such as DME (1.19%), CSR (1.08%), DR (0.61%), CNV (0.68%), and others are significantly lower, indicating they are less likely to be present. This clearly shows that the OCT scan pattern highly matches the features of AMD, which is a progressive eye disease affecting the macula and leading to central vision loss. Clinically, AMD causes retinal pigment epithelial thinning, photoreceptor layer disruption, and subretinal deposits. Early diagnosis through such AI-assisted OCT analysis helps in timely management and prevention of severe vision loss. Therefore, based on the prediction results, it can be concluded that the scanned eye is most likely affected by **Age-related Macular Degeneration (AMD)** and should undergo further medical evaluation for confirmation and treatment [15].

REFERENCES

[1] **Bhulakshmi, D.** (2021). A systematic review on diabetic retinopathy detection and classification based on deep learning techniques using fundus images. PeerJ Computer Science.

[2] **Tsiknakis, N.** (2021). Deep learning for diabetic retinopathy detection and classification based on fundus images: A review. Computers in Biology and Medicine, 137, 104793. ScienceDirect

[3] **Ryu, G.** (2021). A deep learning model for identifying diabetic retinopathy using optical coherence tomography angiography images. Scientific Reports, 11(1), 1-10.

[4] **Aziz, A.** (2023). Early diabetic retinopathy detection from OCT images using deep learning. Diagnostics, 15(13), 1616. MDPI

[5] **Mirescu, A. E.** (2023). Multimodal imaging of diabetic retinopathy: Insights from optical coherence tomography angiography

and adaptive optics. Diagnostics, 15(14), 1732. MDPI
[6] **Mahajan, S.** (2023). Review of multimodal imaging in diabetic retinopathy. Delhi Journal of Ophthalmology, 35(5), 5-10. Lippincott Journals
[7] **Suleski, T.** (2023). A review of multi-factor authentication in the Internet of Healthcare Things (IoHT). Journal of Medical Internet Research, 25(4), e10214092. PMC
[8] **Suleski, T.** (2023). A review of multi-factor authentication in the Internet of Healthcare Things (IoHT). ResearchGate.
[9] **Manikandan, S.** (2023). Deep learning–based detection of diabetic macular edema from optical coherence tomography images. Indian Journal of Ophthalmology, 71(5), 1991-1997. Lippincott Journals
[10] **Bressler, I.** (2024). Autonomous screening for diabetic macular edema using deep learning. Ophthalmology Science, 1(2), 100020.
ophthalmologyscience.org
[11] Sheller, M. J., Reina, G., Edwards, B., Martin, J., & Bakas, S. (2024). Multi-Institutional Deep Learning Modeling without Sharing Patient Data: A Feasibility Study on Brain Tumor Segmentation. MICCAI / arXiv.
[12] Guan, H., et al. (2024). Federated learning for medical image analysis: A survey. (Comprehensive FL survey for medical imaging).
[13] Zhang, M., Qu, L., Singh, P., Kalpathy-Cramer, J., & Rubin, D. L. (2024). SplitAVG: A heterogeneity-aware federated deep learning method for medical imaging. arXiv. (addresses cross-site heterogeneity; includes DR experiments).
[14] Matta, et al. (2024). Federated Learning for Diabetic Retinopathy Detection in a Multi-center Fundus Screening Network. (multi-center FL applied to large fundus screening datasets).
[15] ResearchGate
[16] Chetoui, M. (2024). Federated Learning for Diabetic Retinopathy Detection. MDPI (Vision Transformer based FL for DR).
MDPI
[17] Gajan M. Raj, Morley, M. G., & Eslami, M. (2024). Federated Learning for Diabetic Retinopathy Diagnosis: Enhancing Accuracy and Generalizability in Under-Resourced Regions. arXiv (EfficientNetB0, cross-site evaluation).
[18] Bhulakshmi, D. (2024). Privacy-preserving detection and classification of diabetic retinopathy using federated differential evolution optimization. Taylor & Francis / journal article (FL + optimization for DR). Taylor & Francis Online
[19] Kamran, H., et al. (2025). FedGAN: Federated diabetic retinopathy image generation (FedGAN). PLOS ONE (federated GANs for synthetic retinal image augmentation).
[20] PLOS

[21] Jayalakshmi, R., et al. (2025). Privacy preservation in diabetic disease prediction using Federated Learning based DRNet (FedDRNet). Scientific Reports / Nature family (privacy-preserving FL applied to DR). Nature
[22] Dib, O., et al. (2025). A decentralized privacy-preserving framework for diabetic retinopathy detection. ScienceDirect / Elsevier (cross-silo FL framework for DR). ScienceDirect
[23] Bhulakshmi, D., & coauthors (2025). FedDL / systematic review on DR detection and FL in ophthalmology. PeerJ / journal (review + applied methods). PeerJ
[24] Islam, M., et al. (2025). Effectiveness of Federated Learning and CNN Ensemble for medical image classification (applies FL ideas that are transferable to DR classification). Springer. SpringerLink
[25] Matta, A., et al. (2025). Federated Learning for Diabetic Retinopathy Detection in a Multi-center Fundus Screening Network — (conference / extended report; multi-site OPHDIAT / large dataset evaluation). ResearchGate
[26] Rahman, A., et al. (2025). Federated learning-based AI approaches in smart healthcare (review that covers FL applications including ocular disease). SpringerLink
[27] Kadhar, et al. (2025). Diabetic Retinopathy Detection and Severity Classification (discusses use of distributed/federated frameworks for DR). African Journal of Biomedical Research / PDF.African Journal of Biomedical Research
[28] Swapna, M. (2025). Diabetic Retinopathy Detection using Federated Learning (conference / journal paper describing FL pipeline for DR). ejournal.svgacademy.org
[29] Ullah, F., et al. (2025). Enhancing segmentation/diagnosis accuracy through federated learning for medical imaging (techniques transferable to lesion detection in fundus images). MDPI / Mathematics. MDPI
[30] Tzortzis, I. N., et al. (2025). Towards generalizable Federated Learning in medical imaging (generalization strategies applicable to DR). ScienceDirect
[31] Pati, S., et al. (2025). Privacy preservation for federated learning in health care. (privacy mechanisms relevant to FL for DR). PMC
[32] Da Silva, F. R., et al. (2025). Federated Learning in Medical Image Analysis (survey focusing on modalities and challenges). MDPI / Electronics.