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"Smart Diagnosis of Diabetic Retinopathy Using AI"

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Abstract: In this project, we developed a hybrid modeling technique models K-Nearest Neighbors (KNN), Random Forest, and Support Vector Machine (SVM) models to estimate the severity of diabetic retinopathy using the APTOS dataset. By merging the strengths of these three algorithms, the model delivers more stable, accurate, and dependable predictions compared to individual classifiers. Such precise severity grading can support healthcare professionals by providing early warnings and timely insights, helping them plan proactive treatment for patients at risk. Beyond improving accuracy, the proposed ensemble method also reduces inconsistencies between different diagnostic systems, making it easier to integrate into existing medical workflows. This enhances overall diagnostic reliability and promotes better clinical decision-making. The study plays a vital role in applying machine learning in real-world healthcare settings, ultimately aiming to support clinicians and result that enhanced outcomes for patients with diabetic retinopathy. Diabetic retinopathy doesn't manifest as a singular entity but progresses through stages of severity. These stages, which include mild non-proliferative, moderate non-proliferative, severe non-proliferative, and proliferative DR.

Keywords: KNN, SVM model, Diabetic Retinopathy, APTOS, Healthcare professionals, Leveraging machine.

I. INTRODUCTION

Diabetic Retinopathy (DR) is a health challenge, increasingly recognized as a a major reason people lose vision among adults. As the worldwide prevalence among patients with diabetes mellitus, it continues to surge, the imperative to understand, diagnose, and effectively manage this relentless complication becomes paramount. the majority of patients with type 1 diabetes and 60% many individuals with type 2 diabetes develop retinopathy. In younger patients, diabetic retinopathy accounts for about 86% of blindness cases, while in older patients, nearly one-third of legal blindness is due to diabetic retinopathy. retinopathy. The disease finally leads to visual impairment due to neovascularization from retinal detachment, hemorrhage, retinal capillary nonperfusion and macular edema. DR, essentially a microvascular disease, takes root within the intricate vasculature of the retina, primarily due to the systemic effects of diabetes. imperative. However, the impact of DR is profound, potentially leaving a trail of sight loss in its wake.

1.1 Anatomy of Eye

Fig 1.1 indicates the anatomy of Eye, To understand Diabetic Retinopathy, is important to understand the functioning of the eye and its different parts eye,

- Most of the outer layer of the eye is covered by a strong white layer called the sclera, which is covered by a thin clear layer called as the conjunctiva. At the eye's front portion is the cornea, a transparent surface that protects the ocular pupil and iris.
- The front part of the eye contains a clear fluid called aqueous humor, produced by the ciliary body. This fluid flows through the pupil and drains through structures such as the trabecular meshwork and small canals.
- The iris is the colored muscle of the eye that modulates light entry enters. At its center is the pupil, an the aperture that allows light into the eye.

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- The lens directs incoming light onto the retina located at the posterior part of the eye. The retina then converts this light into electrical impulses, which travel to the brain via the optic nerve. The optic disc represents the location where the nerve fibers converge to form the optic nerve.

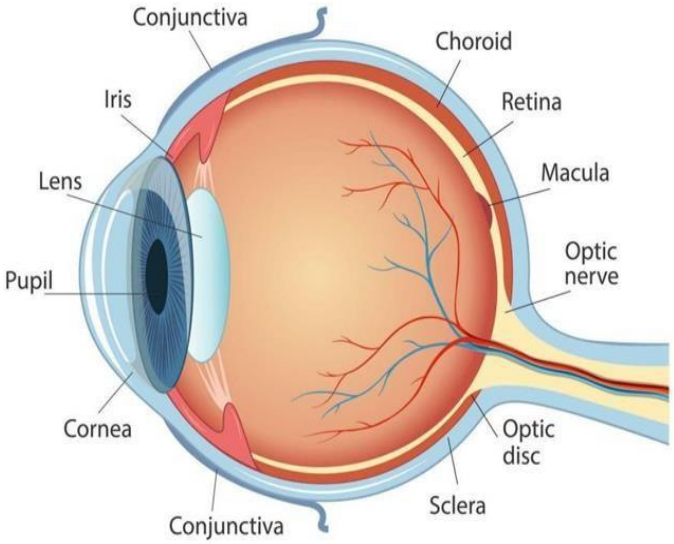

Fig 1.1 Anatomy of Eye

1.2 Retinal Fundus Image

Fig 1.2 refers to the retinal fundus image, The Retinal fundus image consists of the interior lining of the eyeball, including the retina (the light-sensitive screen), optic disc (the head of the nerve to the eye), and the macula (the small spot at the level of the retina where vision is keenest). The fundus is the region at the back of the inner eye that can be affected seen during an eye inspection done by looking through the opening in the iris. "Fundus" is the Latin word for the bottom. In medicine, fundus refers to the:

1.2.1 **Optic Disc**: The circular area in the rear of the eye, where the visual nerve connects toward the retina. Also called optic nerve head. It contains no photoreceptor cells, so it cannot detect light. The central retinal artery and vein also run through this part region.

1.2.2 **Macula:** The macula is a darker, slightly depressed area of the retina near the centre (but slightly temporal to the side of the optic disc) responsible for central, detailed vision (like reading, recognizing faces).

1.2.3 **Fovea:** The fovea is a tiny central pit in the macula in the retinal region that contains only cone cells for sharp, detailed, and colour vision. It is responsible for high-acuity vision, like reading or recognizing faces. The foveola, its centre, gives the sharpest vision, but it works best in bright light. Harm to the fovea causes loss of central vision.

1.2.4 **Central Retinal Vein**: The central retinal vein main blood-carrying vein without oxygen from the retina. It runs alongside the central retinal artery through the optic nerve and exits the eye at the optic disc. It carries blood departing from the retina to sustain proper circulation and retinal health. Blockage of this vein can cause vision problems like retinal hemorrhages.

1.2.5 **Central Retinal Artery:** The central retinal artery is the primary vessel that enters the eye through the optic nerve. It supplies oxygenated blood to the inner layers of the retina. This artery is crucial for maintaining the health and function of retinal cells. Any blockage in this artery can lead to vision problems or sudden loss of vision.

1.2.6 **Retinal Venules:** Retinal venules are small veins which drain deoxygenated blood from the retina. They collect blood draining from the capillary networks and eventually merge into larger veins to exit the eye. These venules play an important role in removing waste products and maintaining proper circulation within the retina.

1.2.7 **Retinal Arterioles:** Retinal arterioles are tiny branches of the central retinal artery that spread blood throughout the retina. They deliver oxygen and nutrients to specific regions of the retina. These vessels help regulate retinal blood flow and maintain tissue health. Narrower than veins, arterioles help keep the retina healthy function and vision.

1.2.8 **Optic Cup:** The optic cup is the white, cup-like area.

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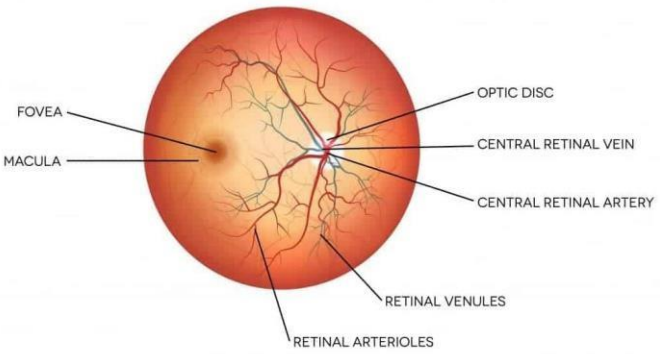
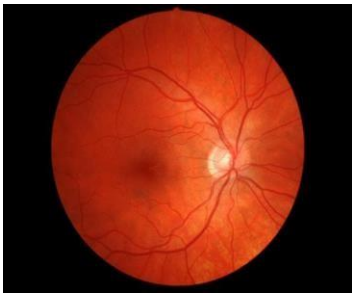


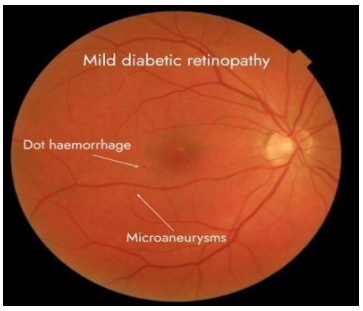
Fig 1.2 Retinal Fundus Image

1.3 Phases of Diabetic Retinopathy

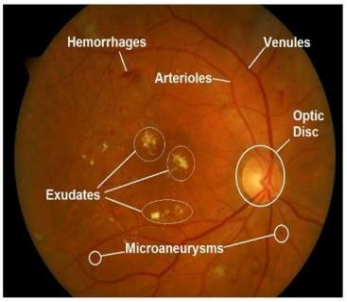
Fig 1.3 (a) refers to Normal eye, Fig (b) refers to Mild Diabetic Retinopathy, Fig (c) Moderate Diabetic Retinopathy, Fig (d) Severe Diabetic retinopathy, It is a common problem of diabetes that affects the blood vessels of the retina, the light-sensitive tissue at the rear of the eye. Long-term hyperglycemia can damage these vessels, leading to vision problems and, in severe cases, blindness. The course of diabetic retinopathy occurs in distinct phases, starting from mild changes in the retinal blood vessels to the formation of abnormal new vessels and retinal swelling. Understanding these phases is important for early detection, timely treatment, and prevention of vision loss in diabetic patients.



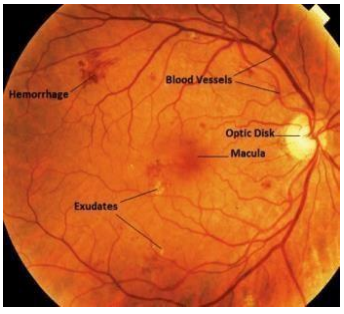
(a)Normal Eye



(b) Mild Diabetic Retinopathy



© Moderate Diabetic Retinopathy



(d) Severe Diabetic Retinopathy

Fig 1.3 (a), (b), (c), (d) Classification of Diabetic Retinopathy

It is mainly chracterised based on the severity and type of retinal changes:

1. **Non-Proliferative Diabetic Retinopathy (NPDR):** It is the early stage of diabetic retinopathy. In this stage, the small blood vessels of the retina become weakened, resulting in the development of tiny swellings called microaneurysms. Other features include retinal haemorrhages, hard exudates, and venous beading. NPDR is divided into mild, moderate, and severe forms stages contingent upon the extent of blood vessel damage and blockage. Vision may not be significantly affected in the early stages, but careful monitoring is essential.
    - **Mild NPDR:** The earliest stage, marked by tiny swellings in the blood vessels called microaneurysms. Vision is usually not affected at this stage.
    - **Moderate NPDR:** More blood vessels are ruptured, causing retinal haemorrhages, hard exudates, and

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venous beading. Some areas of the retina may receive less blood, leading to mild vision changes

- **Severe NPDR:** Extensive blockage of retinal blood vessels occurs, resulting in significant retinal ischemia (lack of blood supply). The retina may start signalling for new vessel growth, increasing the risk of progression to proliferative diabetic retinopathy. Vision may become noticeably impaired.

2. **Proliferative Diabetic Retinopathy (PDR):** It is the advanced period of the disease. It shows the growth of new, abnormal vessels on the retina and optic disk, a process called neovascularization. These vessels are fragile and prone to bleeding, which can lead to vitreous haemorrhage or tractional retinal
3. detachment. PDR is the main cause of severe vision loss in diabetic patients and requires prompt treatment to prevent blindness.

1.4 Causes of Diabetic Retinopathy

Fig 1.4 defines a Difference of Normal Eye and Diabetic Retinopathy Infected Eye, Diabetic retinopathy develops due to long-term persistent high blood glucose linked to diabetes. The condition affects retinal blood vessels, the posterior ocular tissue specialized in light detection.

Chronic Hyperglycaemia: Prolonged periods of prolonged hyperglycemia can compromise the vascular structures of the retina. retina. Elevated glucose levels lead to biochemical changes that affect the structure and function of the retinal blood vessels, leading to to weaken and become more permeable.

Microvascular Changes: Diabetes impacts tiny blood vessels throughout the body, comprising those in the retina. Microvascular changes, for instance endothelial dysfunction, elevated vascular permeability, and abnormal angiogenesis (formation of new blood vessels) are critical for the development of diabetic retinopathy.

Hypertension: Chronic hypertension is a common medical condition comorbidity within the population with diabetes. Hypertension exacerbates the damage to retinal blood vessels, rise the risk and severity of diabetic retinopathy.

Dyslipidemia: Blood limit abnormalities, includes high levels of cholesterol and triglycerides, frequently occur in people with diabetes. Dyslipidemia can cause to atherosclerosis narrowing of blood further compromising perfusion of the retina and exacerbating retinal damage.

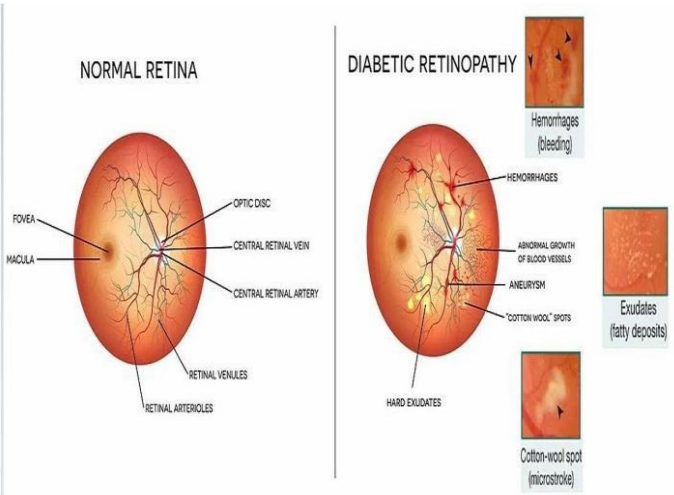

Fig 1.4 Comparison of Normal Eye and Diabetic Retinopathy Infected Eye

1.5 Project Brief

Diabetic Retinopathy (DR) is a long-term degenerative eye disorder that may culminate in irreversible blindness if not detected early. The conventional manual diagnosis process is slow, subjective, andunable to meet the growing demand for diabetic eye screening. This gap in timely and reliable detection results in delayed treatment and preventable vision loss. Therefore, there is a critical need for an automated, precise and expandable diagnostic system capable of analysing eye fundus images and identifying DR at an early stage to support effective clinical decision-making and improve patient outcomes.

1.6 Proposed System

Our proposed system endeavors to redefine the assessment of Diabetic Retinopathy severity through a sophisticated ensemble learning approach. Drawing from the rich ATPOS dataset, we will orchestrate a fusion of Random Forest, KNN, and Voting ensemble methods. Prior to model training, meticulous data preprocessing will encompass image enhancement and feature extraction to optimize the model. By training these models on a diverse dataset, our system

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will yield precise predictions of diabetic retinopathy severity. Our system aims to alleviate the workload on healthcare professionals and enable timely interventions, potentially safeguarding against vision loss in individuals afflicted by diabetic retinopathy.

1.7 Objectives

The primary objectives of this project are:

1.7.1 To preprocess fundus images for extracting key features like nerve patterns and dark spots.
1.7.2 To classify the severity of diabetic retinopathy using ML models such as SVM, KNN, and Random Forest.
1.7.3 To provide accurate predictions of diabetic retinopathy stages ranging from No DR to Proliferative DR.
1.7.4 To utilize Generative AI for generating medical reports, treatment suggestions, and synthetic fundus images.

II. LITERATURE SURVEY SUMMARY

Harun et al. (2025) proposed a robust ResNet-based CNN architecture integrated with attention mechanisms and ensemble learning to enhance diabetic retinopathy (DR) detection. Their model achieved 98.5% classification accuracy and provided better interpretability of lesion regions. However, the model demanded significant computational power, making real-time application challenging. In a similar line, Khan et al. (2024) developed a combined ensemble learning model that enhanced fundus image quality through preprocessing and employed multiple classifiers for better performance. Although the accuracy improved, preprocessing introduced the risk of image artifacts, and the ensemble structure added complexity. Ali et al. (2024) combined EfficientNet with deep CNN layering to extract discriminative features for detecting microaneurysms and hemorrhages. While accuracy was high, the deep architecture increased training and inference time.

Uppamma and Bhattacharya (2023) introduced a multidomain bio-inspired feature extraction approach that mimicked biological visual processing, combined with ensemble classifiers for severity classification. This method resulted in robust classification across datasets, but the feature extraction process was computationally expensive and less suitable for real-time systems. Kale and Sharma (2023) tackled multi-class classification by detecting five DR severity levels utilizing a deep learning ensemble CNN models. The ensemble strategy yielded high exactness and retrieval rate but required a large amount of labeled data, and risked overfitting. Mishra et al. (2022) proposed a two-step pipeline involving lesion segmentation followed by deep neural network-based classification, which significantly improved lesion-level recognition. However, its effectiveness depended heavily on the quality and quantity of annotated segmentation data.
Odeh et al. (2021) explored an ensemble of classical ML classifiers including Random Forest and XGBoost applied to extracted features. The model worked well with relatively low variance but lacked scalability and required extensive feature engineering. Sikder et al. (2021) also used an ensemble learning strategy for severity classification of DR and showed effectiveness across severity levels. However, image quality and preprocessing had a significant impact on results. Bhardwaj et al. (2021) proposed a quadrant ensemble model that divided fundus images into four regions and processed each separately before combining results. This localized grading improved accuracy but ignored global image context and required more computation.

III. SYSTEM REQUIREMENTS

3.1 Hardware Stack

The hardware required for the development of this project is:

- Processor : Intel core i5 or more
- RAM : 8 GB or more

3.2 Software Stack

Thesoftware required for the development of this project is:

- Programming Language: Python, JavaScript
- Libraries: Scikit-learn, OpenCV, Pillow, Pandas, Numpy.
- Front end: React
- Operating System: Linux

3.3 Tools

3.3.1. PYTHON

At the heart of our “Detection of Diabetic Retinopathy” project lies Python, a high-level scripting language known for its versatility and user-friendly nature. With its expansive ecosystem and the capability to process complex data structures effortlessly, Python functions as the cornerstone for writing adaptable ensuring code maintainability. Its widespread use

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in scientific computing, data. analysis, and AI makes it an ideal choice for developing cutting-edge medical diagnostic tools.

3.3.2. SCIKIT-LEARN

The project leverages scikit-learn, a robust Python library developed for implementing machine learning algorithms. Known for its easy-to-use and efficient tools for handling data analysis, sklearn is instrumental in managing and interpreting the retinal images to detect features associated with diabetic retinopathy. It enables a range comprising algorithms designed for classification, regression, clustering, and dimensionality reduction, which hold a central role in the interpretation and categorization of the complex patterns present in medical imagery.

3.3.3 OPENCV

OpenCV stands as the image processing engine of our project, a library tailored for computer vision applications tasks. OpenCV is employed to perform various pre-processing operations on the retinal images like noise reduction, contrast enhancement, and edge detection. These processes are crucial to prepare the images for accurate derivation of features and subsequent analysis, permitting for a detailed assessment of potential retinal damage indicative of diabetic retinopathy.

3.3.4 REACT

The front-end interface of our application is developed using React, a prominent JS library designed for developing dynamic and responsive user interfaces. React's component- architecture facilitates for modular development, enabling efficient rendering and reusability of UI elements. This proves essential for creating an user-friendly interface that allows users to upload retinal images, view diagnostic results, and interact with the system in real time. React's virtual DOM ensures optimal performance, even as the interface dynamically updates based on AI-driven outputs.

IV. SYSTEM DESIGN

4.1 Methodolgy

The Figure 4.1 represents the methodology adopted toward the creation of a Non-Invasive Diabetic Retinopathy (DR) Detection System using AI. The core idea is to analyze fundus images through a well-defined AI pipeline involving machine learning and generative AI to predict the stage of DR and provide meaningful healthcare insights. The entire methodology is executed in six key phases: Planning, Design, Implementation, Testing, Evaluation, and Deployment.

Planning Phase: In the Planning Phase, the first goals of the system are established, focusing on creating an AI-based diagnostic platform that predicts diabetic retinopathy stages without requiring invasive techniques.
The system is designed for a broad audience, including patients, doctors, and health-conscious individuals. The key resources identified include AI models such as SVM, KNN, Random Forest, and generative AI models for image and text generation. Platform decisions are made to support both mobile and web interfaces. A feasibility analysis is conducted to evaluate the practicality of extracting fundus image features and generating personalized medical content using generative AI.

Design Phase: The Design Phase focuses on laying down the blueprint of the system. The architecture is built to accept input in the form of fundus images, which undergo pre- processing to enhance clarity and extract significant features like nerve patterns and dark spots—critical indicators of diabetic retinopathy. These extracted features form the input to a machine learning classification system comprising SVM, KNN, and Random Forest models. The design also incorporates a generative AI module, which is triggered post-classification to enhance system outputs through functionalities like report generation, synthetic image creation, and personalized treatment advice. Simultaneously, a simple and intuitive UI/UX is drafted to ensure accessibility across all age groups and devices, along with a backend architecture for efficient data handling.

Implement Phase: In the Implementation Phase, the designed system is translated into code using modern development frameworks. The frontend is implemented with React, HTML, and CSS, and JavaScript, ensuring a responsive interface. The backend is built with Flask and integrated with Supabase for real-time database operations. During implementation, uploaded fundus images are first processed to highlight relevant structures. Feature extraction algorithms then isolate nerve patterns and dark spots which are fed into the ML models for classification into DR stages. Simultaneously, generative AI is incorporated to interpret predictions and generate user-specific reports, education content, and even synthetic medical images for model training or documentation. An agentic learning system is implemented to periodically retrain the ML models using user feedback, making the system adaptive and continuously improving. A ChatGPT-based chatbot is also embedded to interactively explain prediction results and guide users with

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preventive measures.

Testing Phase: In the Testing Phase, comprehensive validation of the system components is carried out. Functional testing ensures that fundus image uploads, feature extraction, predictions, and chatbot responses work correctly. The prediction pipeline is validated for accuracy, recall, and robustness using standard medical datasets. Usability testing is conducted with sample users for evaluating the efficacy of the interface, clarity of medical reports, and ease of chatbot interactions. Browser and device compatibility is tested to ensure uniform experience across platforms. The data collected as part of this phase is carefully analyzed to drive refinements in model performance and UI enhancements.

Evaluation Phase: The Evaluation Phase focuses on assessing the system's accuracy and reliability. The efficacy of the machine learning models is quantitatively evaluated using metrics such as Accuracy, Precision, Recall, and F1-score. Generative AI outputs are reviewed for relevance, clarity, and personalization value. User feedback and satisfaction surveys are used to evaluate trust in the system, interpretability of predictions, and usefulness of the chatbot guidance. The system's overall efficacy is compared with traditional invasive methods to highlight the benefits of this AI-powered, non-invasive approach in terms of accessibility, user comfort, and cost-effectiveness.

Deployment Phase: Finally, in the Deployment Phase, the system is prepared for real-world usage. The frontend assets are optimized for fast loading and deployed to platforms such as Vercel or Firebase Hosting, while the backend APIs are secured with proper authentication and encryption. Real-time performance and usage data are monitored using analytics tools to identify system bottlenecks and areas of improvement. A continuous deployment strategy is adopted for future updates and patches. Feedback loops are established to ensure that user interactions guide future enhancements in both AI models and UX. By following an agile development methodology, the system remains flexible, scalable, and ready for iterative upgrades based on emerging needs.

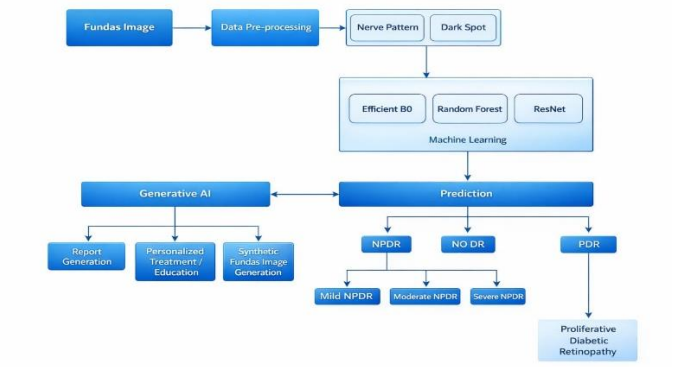

Fig 4.1 define the complete pipeline to detect diabetic retinopathy from fundus images. The system involves data preprocessing to extract nerve patterns and dark spots, which are transmitted to ML models (SVM, KNN, Random Forest) for classification. Derived from the prediction, Generative AI assists in report generation, treatment suggestions, and synthetic image creation.

4.1 Working Process

Step 1: Fundus Image
The process starts with the input of a fundus image of the eye.

Step 2: Data Pre-Processing
The image undergoes preprocessing to extract essential features such as nerve patterns and dark spots.

Step 3: Machine Learning
Extracted features are fed into machine learning models like SVM, KNN and Random Forest for classification.

Step 4: Prediction
The system predicts the Diabetic Retinopathy (DR) stage: No DR, Mild Non-Proliferative DR, Moderate Non-Proliferative DR, Severe Non-Proliferative DR or Proliferative DR.

Step 5: Generative AI
Based on the prediction, Genrative AI is used for:

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- Report Generation
- Personalized Treatment Suggestions/ Education
- Synthetic Fundus Image Generation

V. TESTING

Testing is an essential stage in assessing the precision, consistency, and overall performance of the Diabetic Retinopathy Detection System. Since the system integrates multiple advanced technologies like machine learning, deep learning, Generative AI, and a web-based interface thorough validation guarantees that every component works correctly both individually and within the scope of a unified pipeline.
This chapter explains the different testing strategies used, the test cases executed, evaluation metrics for the ML and deep learning models, validation of the Generative AI outputs, and a summary of the system's final performance.
The overall system includes several interconnected modules:

- Backend APIs (FastAPI)
- Machine Learning Model (Scikit-learn)
- Deep Learning Model (EfficientNet using PyTorch)
- Consensus Engine for final prediction
- Generative AI Module (Gemini 2.5 Flash)
- Frontend Interface (React + Vite)
- Synthetic Fundus Image Generator

Each of these components required specific testing to ensure that the final system is robust, medically reliable, and user-friendly.

VI. TESTING METHODOLOGY

1. Unit Testing

Unit testing was carried out on the smallest functional parts of the system. This included:

- Image preprocessing functions (resizing, normalizing, color correction, augmentation).
- Feature extraction and prediction functions in both ML and DL models.
- Consensus logic, ensuring correct combination of SVM, KNN, Random Forest, and EfficientNet outputs.
- Synthetic fundus image generator, validating that generated images follow correct DR characteristics.

Unit tests helped confirm that individual functions behave as expected before integrating them into larger modules. Individual backend functions such as preprocessing, prediction, consensus logic, synthetic image generator.

2. Module Testing

After individual functions were verified, each major module was tested as a whole. This included:

- Scikit-learn ensemble prediction module Testing accuracy, stability, and handling of edge cases like blurry images.
- PyTorch EfficientNet inference module Checking GPU/CPU compatibility, model loading time, batch processing, and prediction consistency.
- Generative AI Output Testing Ensuring the Gemini 2.5 Flash API returned complete and medically coherent text reports.

Module testing ensures every major block performs correctly under real-world scenarios.

3. Integration Testing

Since this project uses multiple interconnected subsystems, integration testing was crucial. The following interactions were tested:

- **Frontend ↔ Backend**
  Ensured that image uploads, prediction requests, and report generation calls work seamlessly.
- **Backend ↔ ML/DL Models**
  Verified that FastAPI correctly processes images, sends them to models, and returns predictions.
- **Backend ↔ Generative AI**
  Ensured that patient metadata, prediction results, and images are correctly passed to the LLM for report generation.
- **Model Pipeline ↔ Consensus Engine**

Confirmed that ML and DL outputs merge correctly for the final severity score.
This step validated the reliability of the entire workflow.

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4. Functional Testing

Functional testing ensured the system delivered all features according to user requirements are listed below Key functions tested included:

- File Upload: Only valid fundus images accepted; incorrect formats rejected.
- Prediction: System returns DR grade along with confidence score.
- Consensus Output: Final label reflects combined ML + DL judgment.
- Report Generation: Gen-AI produces readable and medically sound summaries.
- Download Option: Reports can be downloaded easily in PDF or text format. Functional testing confirmed the system behaves exactly as a user expects.

5. Performance Testing

The system's responsiveness and efficiency were tested using multiple metrics:

- Model Inference Time:

EfficientNet inference time, KNN/RF/SVM prediction time.

- API Latency:

Checking response time of FastAPI under multiple requests.

- Throughput:

Evaluating how many images can be processed per minute.

- Memory & GPU/CPU Usage:

Verified system stability during high-load scenarios.
Performance testing ensures the system is fast enough for real clinical usage.

6. Usability Testing

Usability testing was performed to ensure the frontend is intuitive and user-friendly. Testers evaluated:

- Layout clarity
- Ease of uploading images
- Navigation simplicity
- Responsiveness on different screen sizes
- Smoothness of animations and transitions
- Readability of results and reports

Feedback from testers helped refine the interface for a better user experience.

7. Validation Testing (LLM Output Verification)

Since the system generates medical reports using Generative AI, validating these outputs was essential. The LLM-generated reports were checked for:

- Medical accuracy: Findings match the model's predictions.
- Completeness: Includes severity, risk factors, and recommended follow-up steps.
- Clarity: Text is easily understandable by healthcare professionals and patients.
- Consistency: No contradictions or incorrect medical claims.
- Bias Prevention: Ensures ethical and unbiased generation.

This step ensures the AI-generated content is safe and reliable for clinical use.

VII. RESULTS AND DISCUSSION

7.1 Model Comparisons

Table 7.1 is the difference between KNN and SVM,The results obtained from the optimized KNN and SVM models highlight the strengths and limitations of each algorithm in predicting various phases of diabetic retinopathy (DR). The graphs demonstrate clearly the evaluation of each model across the five DR classes: No DR, Mild, Moderate, Severe, and Proliferative.

KNN Model

The optimized KNN classifier demonstrates strong and consistent performance for early-stage detection. The model achieves 100% performance accuracy of the No DR category, showing that KNN demonstrates strong performance in identifying healthy retinal images. This is a notable advantage, as detecting "no disease" with high reliability prevents unnecessary medical follow-ups.

Accuracy decreases gradually for disease-positive classes. KNN records 60% accuracy for Mild DR and 40% for Moderate DR, which shows that it can recognize early patterns but struggles as the disease becomes more complex. For

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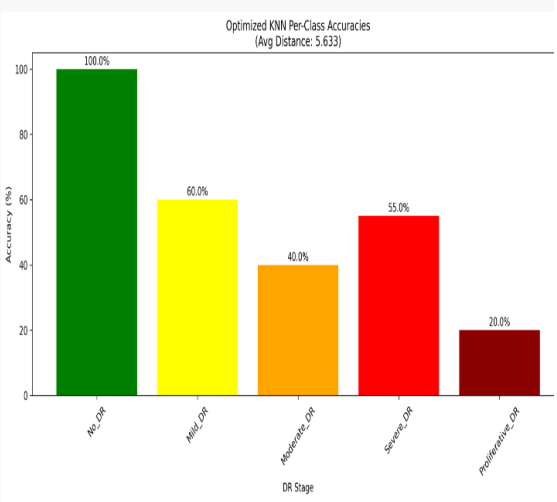
Severe DR, the accuracy rises moderately to 55%, likely because severe lesions are more visually distinct. However, for Proliferative DR, the accuracy drops to 20%, reflecting difficulty in differentiating the most advanced stage where features are highly variable.Overall, KNN performs best in identifying healthy and early-stage cases, but its performance declines as the retinal pathology becomes more complex. This behavior is expected because KNN relies heavily on distance-based similarity, which is less dependable for high-variance disease patterns.

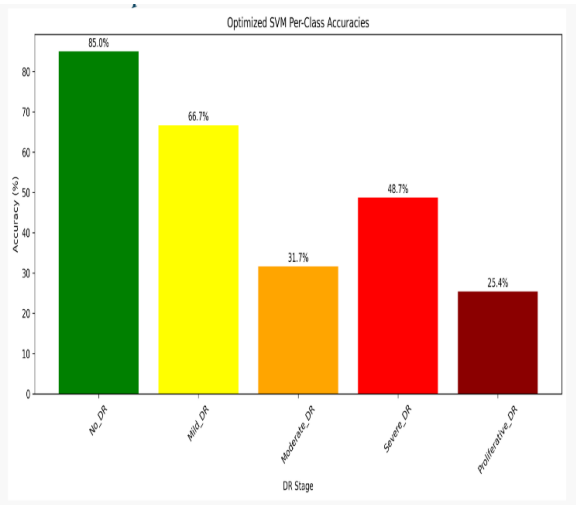


SVM Model

gThe optimized SVM model shows a different performance trend compared to KNN. SVM reaches 85% accuracy for No DR and 66.7% accuracy for Mild DR, demonstrating good capability in detecting non-disease and early-stage abnormalities. The performance then drops for Moderate DR, where accuracy is 31.7%, indicating difficulty in capturing the transitional features between mild and severe stages.

A positive observation is revealing that SVM achieves better results than KNN in the Severe DR category, achieving 48.7% accuracy. This suggests that the SVM decision boundary is better at capturing advanced- stage features compared to KNN. For Proliferative DR, the accuracy is 25.4%, which is slightly higher than KNN, but still low, reflecting the complexity of identifying extreme retinal damage.

In general, SVM shows improved consistency across classes compared to KNN but still faces challenges in higher DR stages due to feature overlap and class imbalance.



Comparison of KNN and SVM

Fig 7.1 refers to comparing the two models, KNN excels at detecting healthy eyes, achieving perfect accuracy for No DR, ensuring high reliability for screening normal cases. In contrast, SVM provides ensuring consistent results across all categories DR stages and handles severe cases slightly better than KNN. Both models show decreasing accuracy as the disease severity increases, particularly struggling with Proliferative DR, highlighting the limitations of individual

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ML models and the need for an ensemble or deep learning approach to improve predictions for advanced stages.

DR Class	KNN Accuracy	SVM Accuracy	Difference (SVM − KNN)
No DR	100%	85%	**−15%** (KNN better)
Mild DR	60%	68.7%	**+8.7%** (SVM better)
Moderate DR	50%	31.7%	**−18.3%** (KNN better)
Severe DR	55%	48.7%	**−6.3%** (KNN better)
Proliferative DR	20%	25.4%	**+5.4%** (SVM better)

Table 7.1 Difference between KNN and SVM Accuracy

7.2 Conclusion

In conclusion this project presents a smart diagnostic approach for detecting and classifying Diabetic Retinopathy (DR) using Artificial Intelligence (AI). Given the rising global prevalence of diabetes and the urgent requirement for early identification of its ocular complications, the study highlights the significance of prompt DR diagnosis to avert vision impairment and blindness. The report explores various AI-driven methodologies, particularly deep learning and hybrid models, to automate and enhance the accuracy of DR classification across its severity stages. Through a detailed literature review and comparative analysis of recent techniques—including convolutional neural networks with attention, and ensemble models—the report identifies both the progress made and the persistent challenges, such as computational overhead and the need for large annotated early, efficient, and scalable DR screening systems. Timely medical interventions such as laser therapy, injections, or surgery help preserve vision. Therefore, awareness, prevention, and early management are crucial aimed at mitigating the burden of DR and improve quality of life.

7.2 Future Scope

- **Integration with Real-Time Clinical Systems:** The system can be connected directly to hospital software and retinal imaging devices so that doctors receive instant predictions during patient checkups. This will make diagnosis rapidly and efficient in practical clinical environments.
- **Detection of Additional Retinal Diseases:** In the future, the platform can be expanded to identify other eye conditions such as glaucoma, cataract, and age-related macular degeneration (AMD). This would transform the model into a complete retinal screening tool rather than focusing only on diabetic retinopathy.
- **Validation on Diverse Populations:** The model should be tested covering patients from a wide age spectrum, ethnic backgrounds, and imaging systems. Such large-scale validation will help improve accuracy, reduce bias, and move the system closer to medical certification or regulatory approval.
- **Scalable Prediction APIs:** The system can be deployed as cloud-based APIs that hospitals, clinics, and telemedicine platforms can easily integrate. This will allow remote diagnosis, rural healthcare support, and large-scale screenings with minimal infrastructure.

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