Smart Vision: Early Detection of Retinal Diseases Using Deep Learning

Project Members

Arpita Santra (242110602)

Aakriti Sarkar (242110601)

Asit Biswas (241110014)

Aman Kumar Singh (241110007)

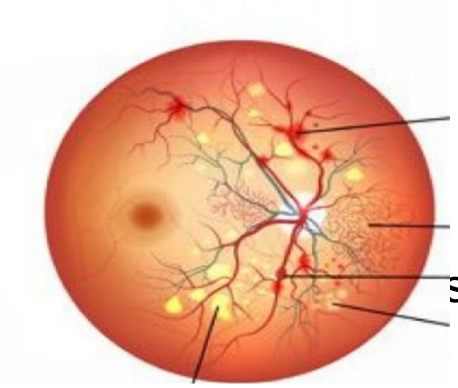
Prabhakar Pandey (241110049)

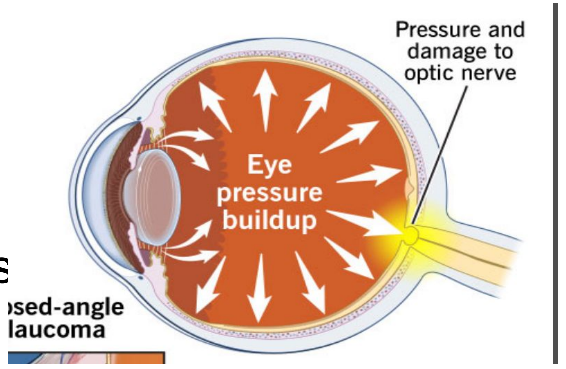
Gautam Raj (241110025)

Severe Eye diseases detected using retina images:-

1.Diabetic Retinopathy – 146 million globally (exp

Damaging r**etinal blood vessels**



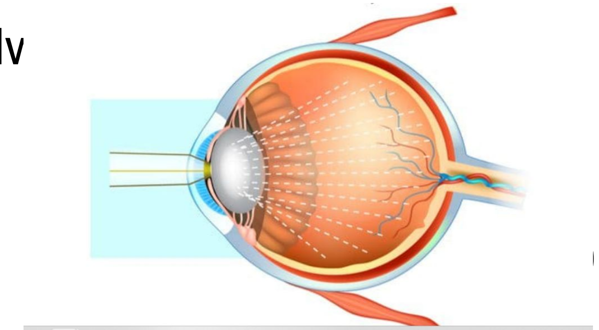


2.Glaucoma – Over 80 million (leading cause of ir

damages the **optic nerves**

3.Cataract – Most common cause of blindness worldv

Damages the lens

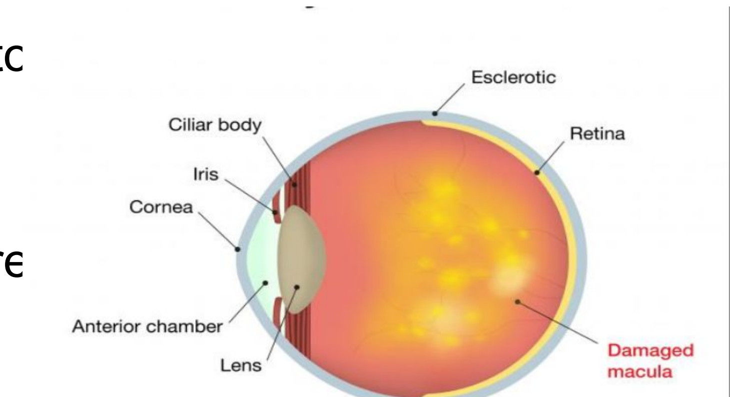


4. AMD – 200+ million

Damages **macula** responsible for sharp central vision

5. Hypertensive Retinopathy – Underdiagnosed, linked tc

Damages the **retina**



6.Pathological Myopia – Increasing due to screen exposure

Damages sclera(white part) ,chroid(middle layer),retina (inner most layer)

Problem Statement

1. **Millions** silently suffer from retinal diseases

2. Shortage of **eye doctor**s and diagnostic resources leads to delayed detection and irreversible vision loss.

3. **Early signs** are missed, as most patients visit doctors only when it's already too late for effective treatment.

4. Traditional eye **screening is costly** and inaccessible — especially in rural and underserved regions.

5. There is an urgent need for an AI-powered, low-cost, fast screening system that can detect multiple eye diseases using just retinal images.

Objective

1. Develop Individual Models:

Create **six state-of-the-art machine learning models**, each accurately diagnose a specific eye disease using just retinal images.

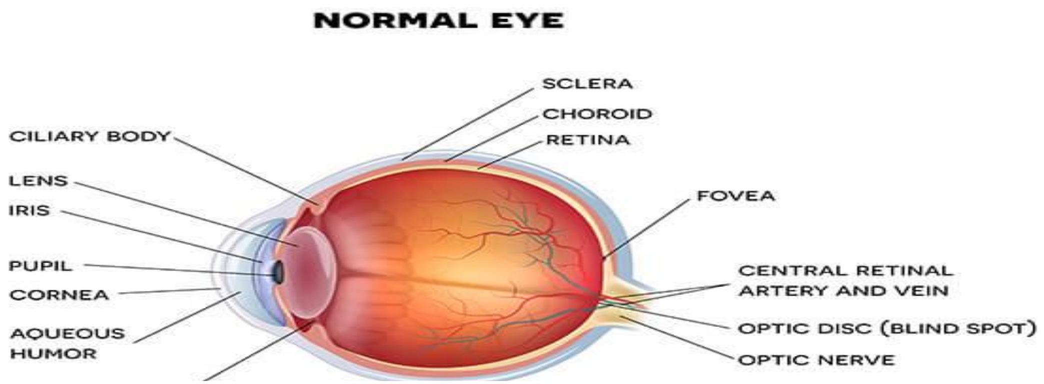
2. Create a Combined Multi-Disease Model:

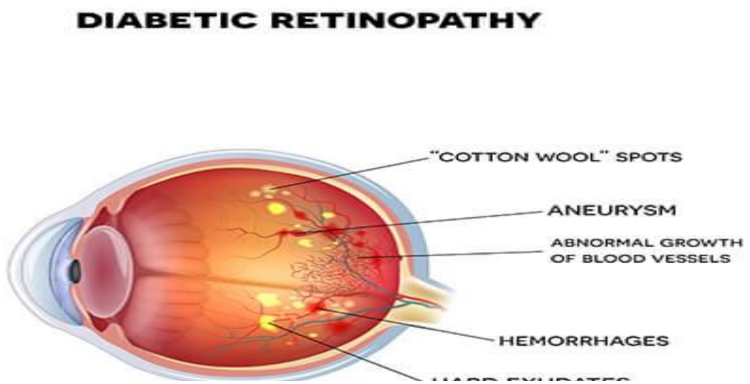
Develop a single unified model capable of simultaneously detecting multiple eye diseases from a single retinal image

3. Apply Knowledge Distillation:

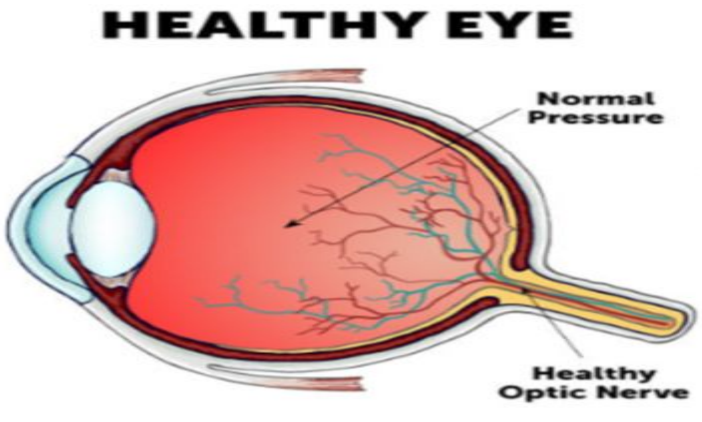
Enhance the performance of the combined model by incorporating knowledge distilled from the individual disease-specific models.

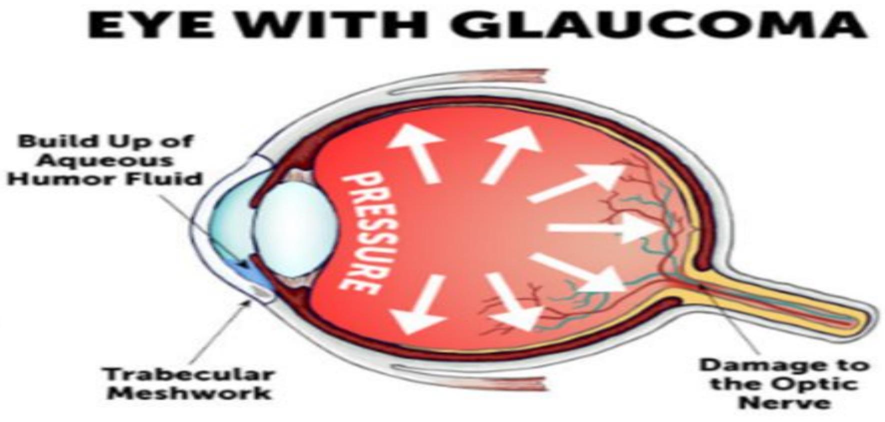
Disease	Description	Prevalence	Impact on Vision
Age-related Macular Degeneration (AMD)	Deterioration of the macula, leading to central vision loss.	196 million (2020); expected to rise to 288 million by 2040	Central vision loss affecting daily activities like reading and driving.
Diabetic Retinopathy (DR)	Damage to retinal blood vessels due to diabetes, can lead to blindness.	Affects about one-third of all individuals with diabetes (~93 million globally).	Progressive vision loss, potentially leading to blindness.
Glaucoma	Eye condition that damages the optic nerve, often due to high eye pressure.	Over 60 million worldwide, a leading cause of blindness after age 60.	Peripheral vision loss initially, potentially progressing to total blindness.
Hypertensive Retinopathy	Damage to the retina caused by high blood pressure.	Common in individuals with chronic and uncontrolled high blood pressure.	Can lead to blurred vision and complete vision loss if untreated.
Pathological Myopia	Severe nearsightedness that worsens over time, increasing risk of serious complications.	Affects about 2% of the global population, more prevalent in Asia.	Risk of retinal detachment, macular degeneration, and glaucoma.
Cataracts	Clouding of the eye's lens, leading to decreased vision.	Very common, especially in the elderly; over half of all Americans aged 80 or older are affected.	Blurred vision, glare, and reduced vision quality, often leading to surgery.



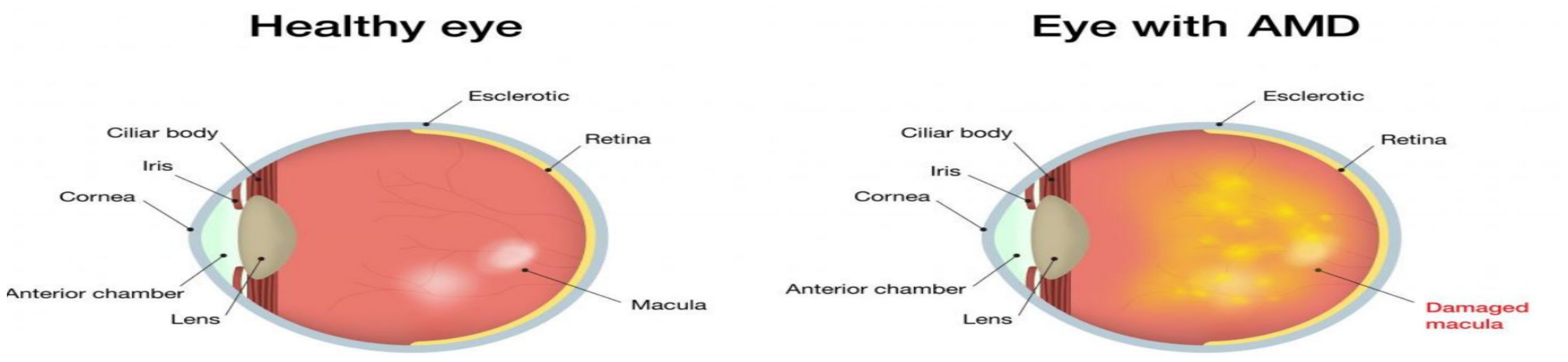


Normal Retina	Diabetic Retinopathy	Hypertensive Retina

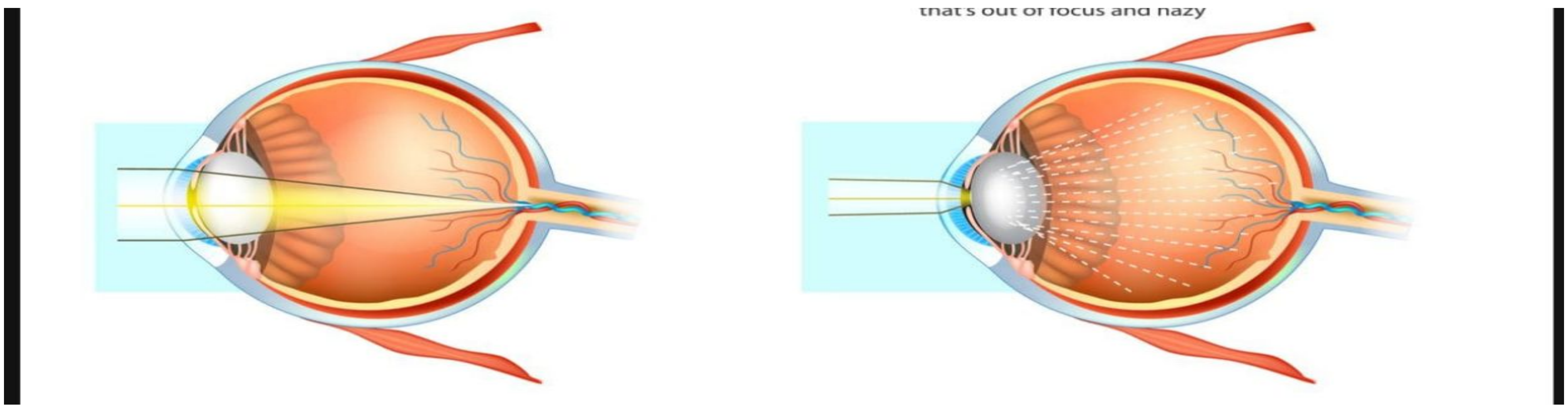




NORMAL EYE VS EYE with AMD



NORMAL EYE VS CATARACT EYE



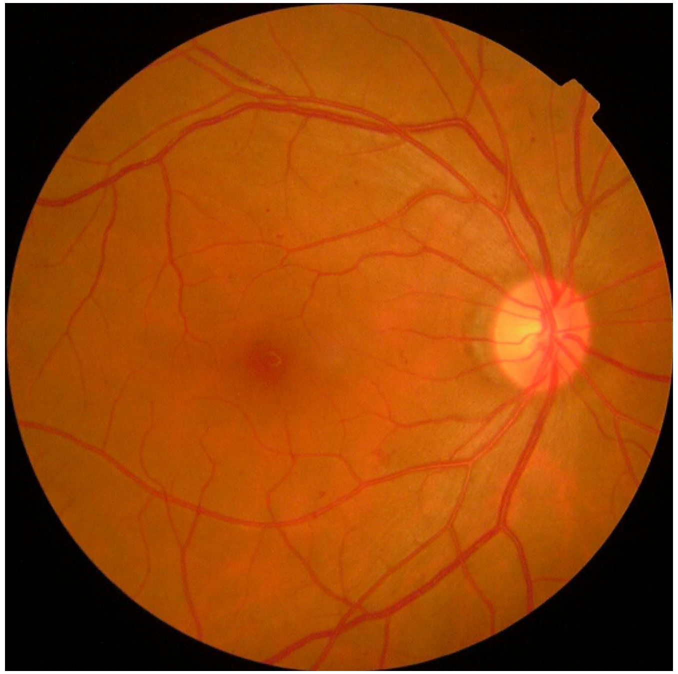
Related Work (Existing Solutions in Literature)

Fundus Images

•Fundus images are high-resolution photographs that capture the back of the eye, specifically the retina, optic disc and blood vessels.

•These images are taken using a special camera called a fundus camera or retinal camera.

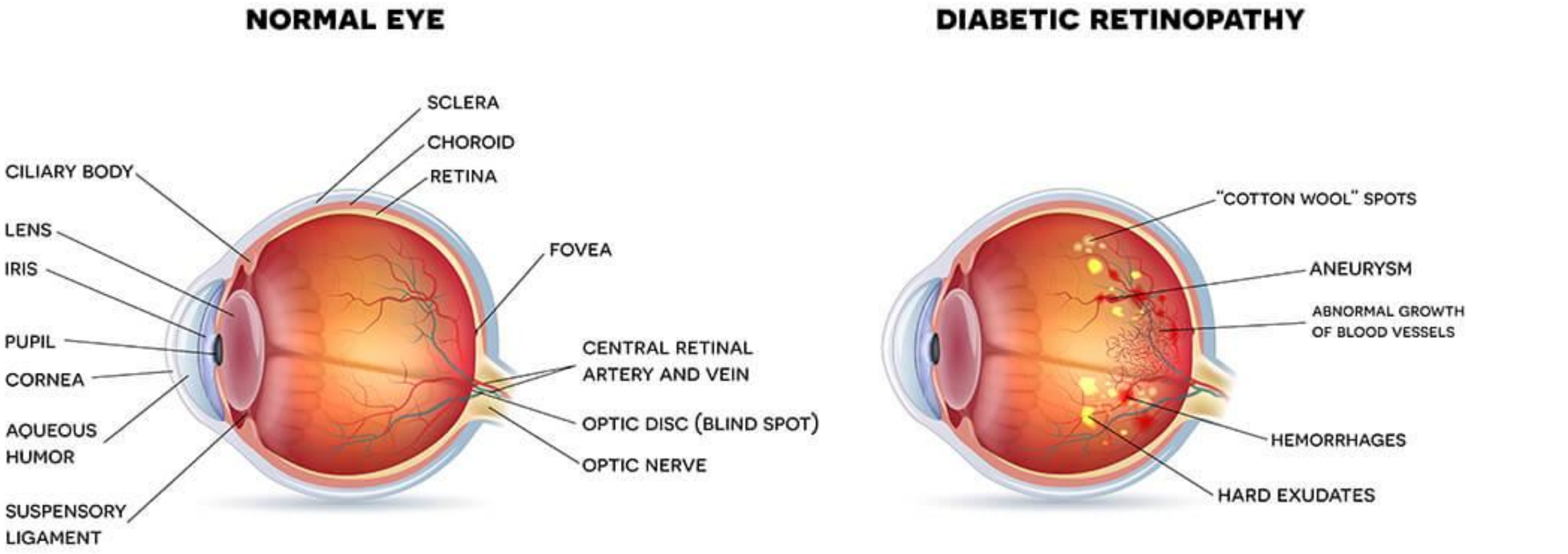
•In diabetic retinopathy, fundus images play a crucial role in assessing the health of the retina, identifying signs of damage such as microaneurysms, hemorrhages, exudates, and abnormal blood vessel growth.



Fundus Image

Diabetic Retinopathy

- Diabetic retinopathy is a condition that affects the eyes of individuals with diabetes.
- It occurs when high blood sugar levels damage blood vessels in the retina, the light-sensitive tissue at the back of the eye.
- In diabetic retinopathy, the damaged blood vessels can cause:
  - **Non-proliferative diabetic retinopathy (NPDR)**: This early stage involves weakened blood vessels, leading to microaneurysms, hemorrhages, and swelling in the retina.
  - **Proliferative diabetic retinopathy (PDR)**: Advanced stage where new, abnormal blood vessels grow on the retina, which can leak blood into the eye, causing vision problems or even blindness.



Comparison between healthy retina and a diabetic retina

Paper 1 - Advancing Diabetic Retinopathy Detection: Leveraging Deep Learning for Accurate Classification and Early Diagnosis

Authors: Aakash Dilip Kolte, Jyotiraditya Sharma, Utkarsh Rai, R.Jansi

Journal: IEEE Xplore (2023) Link

Overview

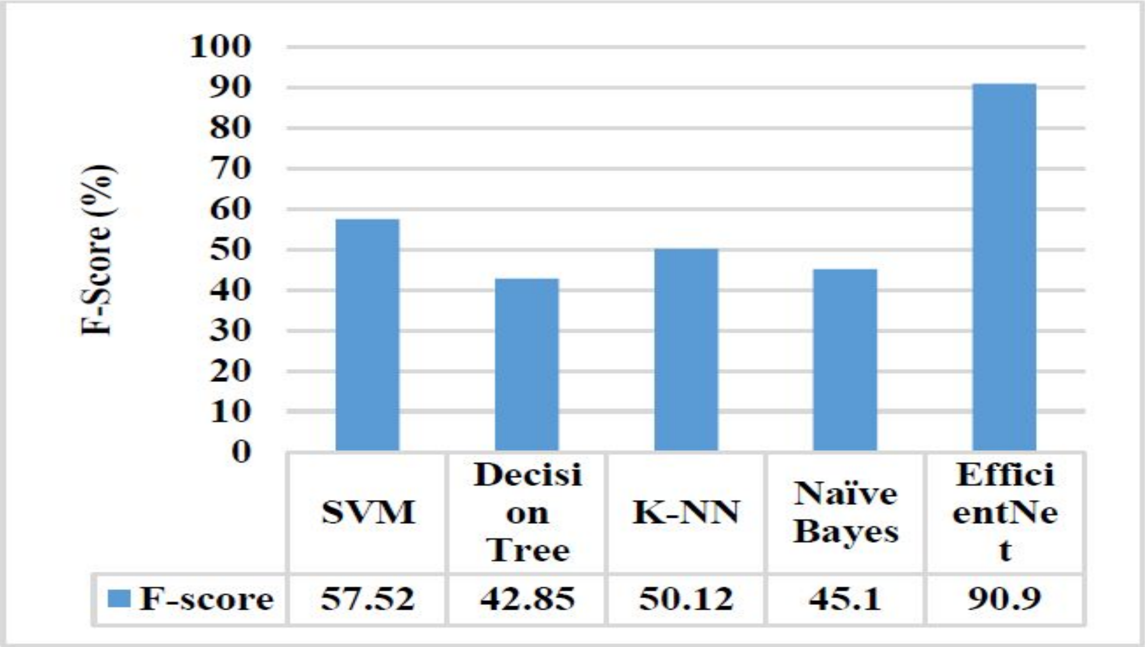
The paper aims to improve **automated detection of Diabetic Retinopathy (DR)** using deep learning, addressing challenges like **limited annotated datasets** and **manual diagnosis variability**.

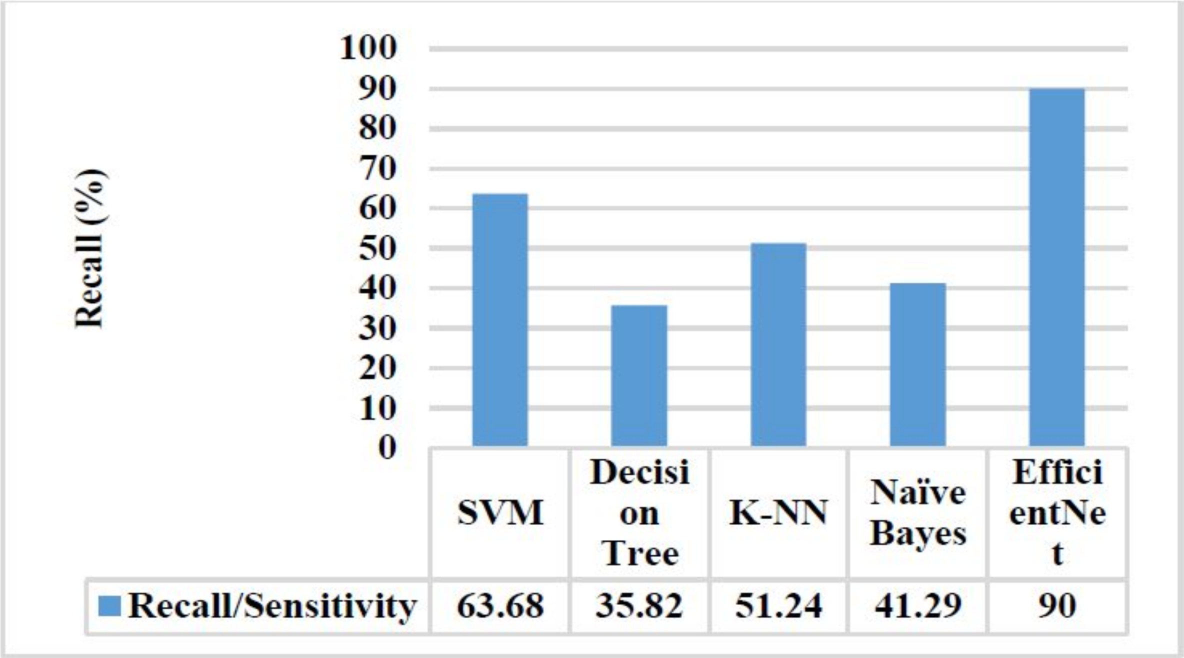
Dataset: Kaggle's Diabetic Retinopathy dataset (1,960 images).

Preprocessing: Image resizing (128×128), feature extraction using **Haralick texture features** and **Hu moments**.

Models Compared:

- Machine Learning: **SVM, Decision Tree, K-NN, Naïve Bayes**.
- Deep Learning: **Efficient-Net**.


F-Score (%)
100
90
80
70
60
50
40
30
20
10
0
SVM
Decision Tree
K-NN
Naïve Bayes
EfficientNet
F-score
57.52
42.85
50.12
45.1
90.9


Recall (%)
100
90
80
70
60
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40
30
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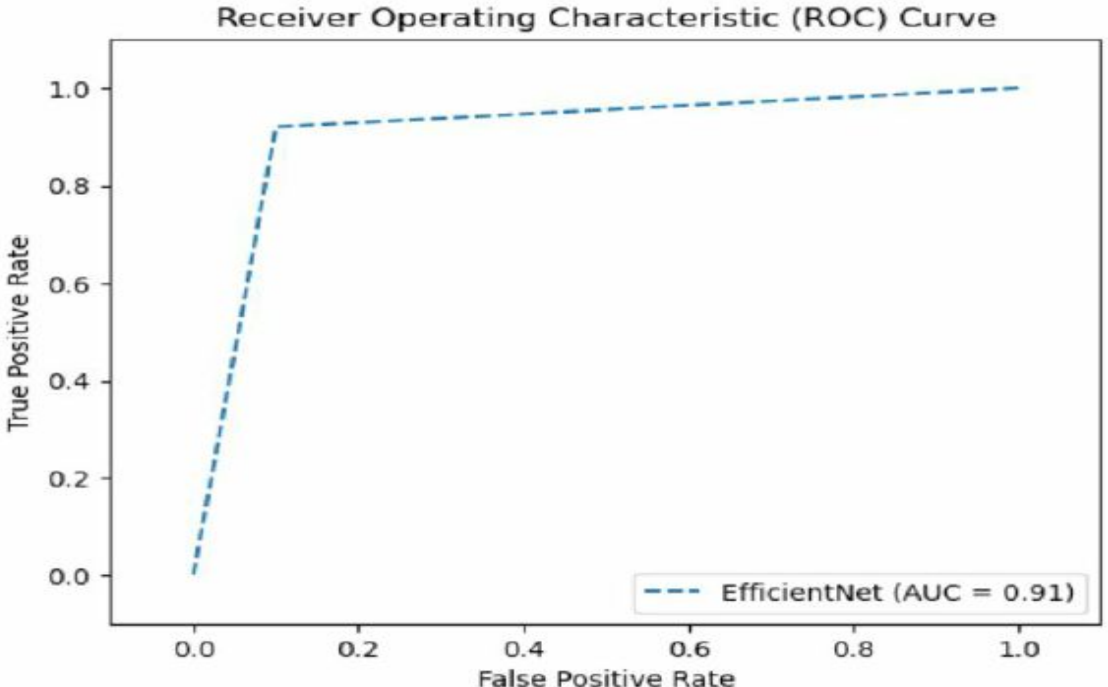
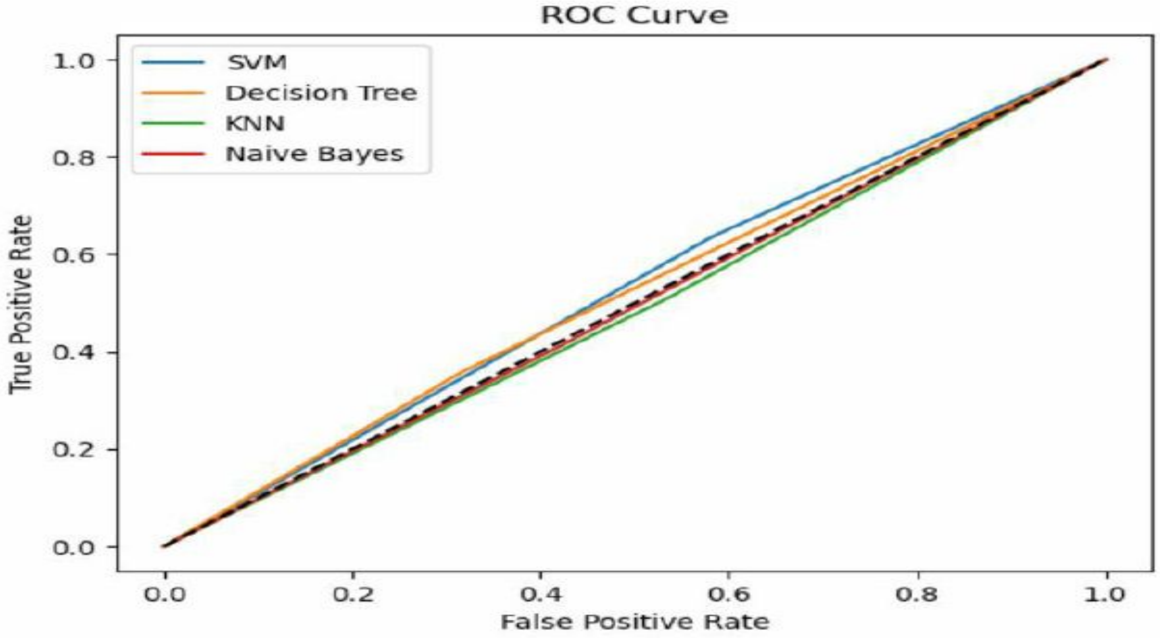
SVM
Decision Tree
K-NN
Naïve Bayes
EfficientNet
Recall/Sensitivity
63.68
35.82
51.24
41.29
90


Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
EfficientNet (AUC = 0.91)


ROC Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
SVM
Decision Tree
KNN
Naive Bayes

Key Findings

Model	Accuracy(%)	Recall(%)	F1-score(%)	Specificity(%)
SVM	52.75	63.68	57.52	41.70
Decision Tree	52.00	35.82	42.85	68.34
K-NN	48.75	51.24	50.12	46.23
Naive Bayes	49.50	41.29	45.10	57.78
Efficient-Net	**91.8**	**90.00**	**90.90**	**90.20**

Efficient-Net outperformed all ML models, achieving 91.8% accuracy and an AUC of 0.91.

Paper 2 - A Deep Learning Framework for the Early Detection of Multi-Retinal Diseases

Authors: Sara Ejaz, Raheel Baig, Zeeshan Ashraf, et al.

Journal: PLoS ONE (July 25, 2024) [Link]

- The paper proposes a **deep learning-based diagnostic system** for detecting **multiple retinal diseases** at an early stage using **fundus images**.
- The focus is on classifying **Diabetic Retinopathy (DR), Media Haze (MH), and Optic Disc Cupping (ODC)** along with normal (WNL) images.
- The study addresses challenges such as **limited annotated datasets, class imbalance, and feature extraction for accurate classification**.

Dataset Used

- Retinal Fundus Multi-disease Image Dataset (RFMiD)
- RFMiD 2.0
- Four disease categories:
  - Diabetic Retinopathy (DR)
  - Media Haze (MH)
  - Optic Disc Cupping (ODC)
  - Healthy (WNL)

Model Used

CNN Architectures

- **12-layer CNN** (Optimal balance of accuracy and efficiency)
- **14-layer CNN** (Deeper feature extraction)
- **20-layer CNN** (Higher accuracy but prone to overfitting)

Strength

Study	Classes	Best Accuracy
EyeDeep-Net (2023)	4	76.04%
InceptionV3 (2023)	4	79.2%
ResNet152 (2024)	2	89.17%
Proposed Model (2024)	4	89.81%

•**Developed a robust deep learning model** for **multi-retinal disease classification**.

•**Data augmentation and model optimization** improve accuracy and generalization.

•**Future Work:**

- Implement **multi-label classification** for multiple disease detection in a single image.
- Explore **Vision Transformers (ViTs)** for improved feature extraction.
- Integrate with **clinical healthcare systems** for real-world applications.

Hybrid Framework for Glaucoma Detection through federated machine learning and deep learning models

Authors: Abeer Aljohani & Rua Y. Aburasain

Journal: BMC Medical Informatics and Decision Making (2024)

Glaucoma:

- Glaucoma is a chronic eye disease that damages the optic nerve, often due to increased intraocular pressure (IOP).
- It is one of the leading causes of irreversible blindness worldwide. The damage to the optic nerve affects peripheral vision first and can eventually lead to complete blindness if untreated. Hence, early detection is crucial.
- Causes:
  - Increased Eye Pressure (Primary Open-Angle Glaucoma)
  - Blocked Drainage Canals (Angle-Closure Glaucoma)
  - Genetic Factors
  - Eye Injury or Trauma
  - Medical Conditions like diabetes, hypertension and migraine
  - Prolonged Use of Steroids

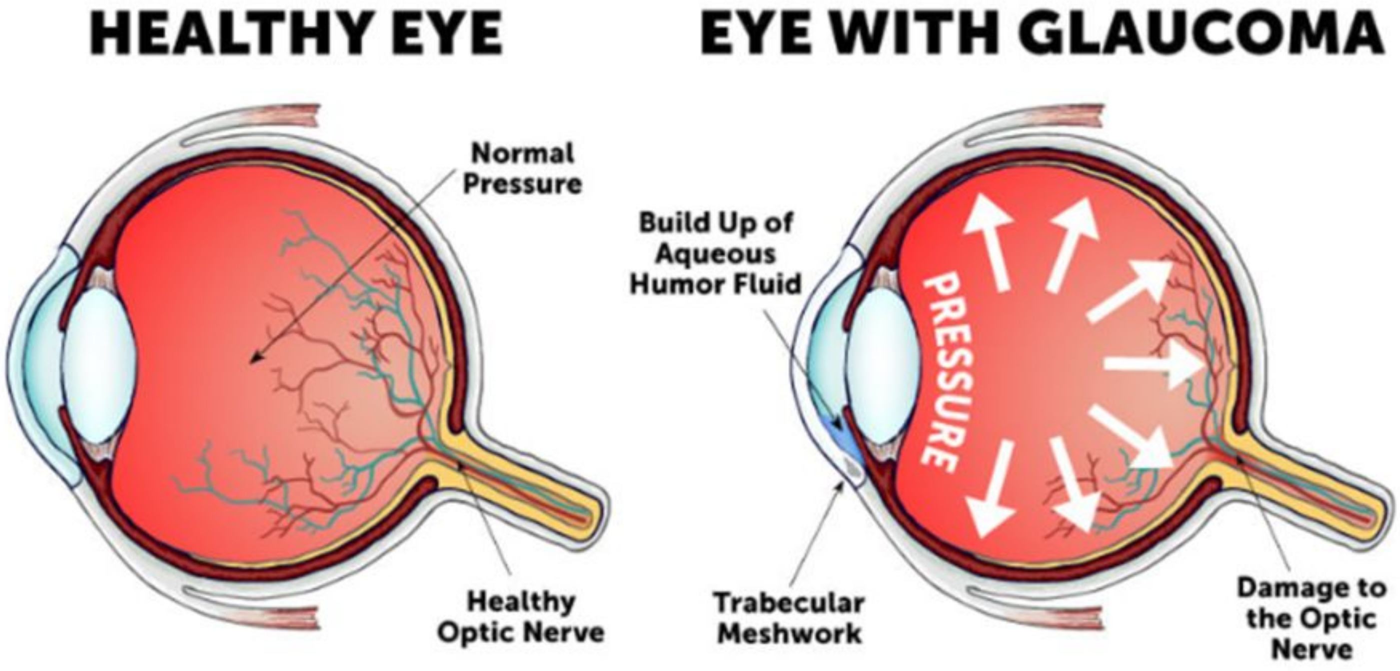


Fig- Schematic diagram showing healthy eye vs eye affected by glaucoma

Objective:

- The study integrates Machine Learning (ML), Convolutional Neural Networks (CNNs), and image processing for early gluacoma detection.
- It aims to surpass previous research efforts with a hybrid approach.

Datasets Used: ACRIMA, ORIGA, REFUGE and G1020

Methodology: The proposed hybrid model uses CNN models- ResNet50 and VGG16 for feature extraction and Random Forest for image classification.

- The fundus images are converted to grayscale from RGB.

Results

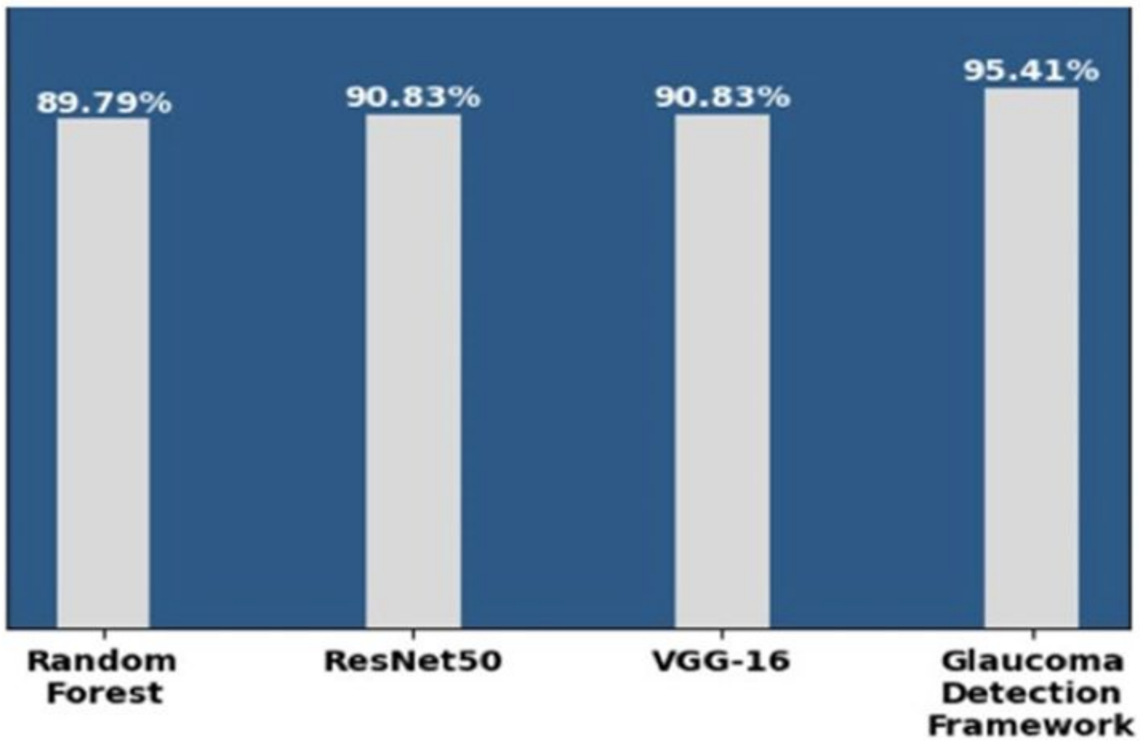


Fig 1- Model and Accuracy

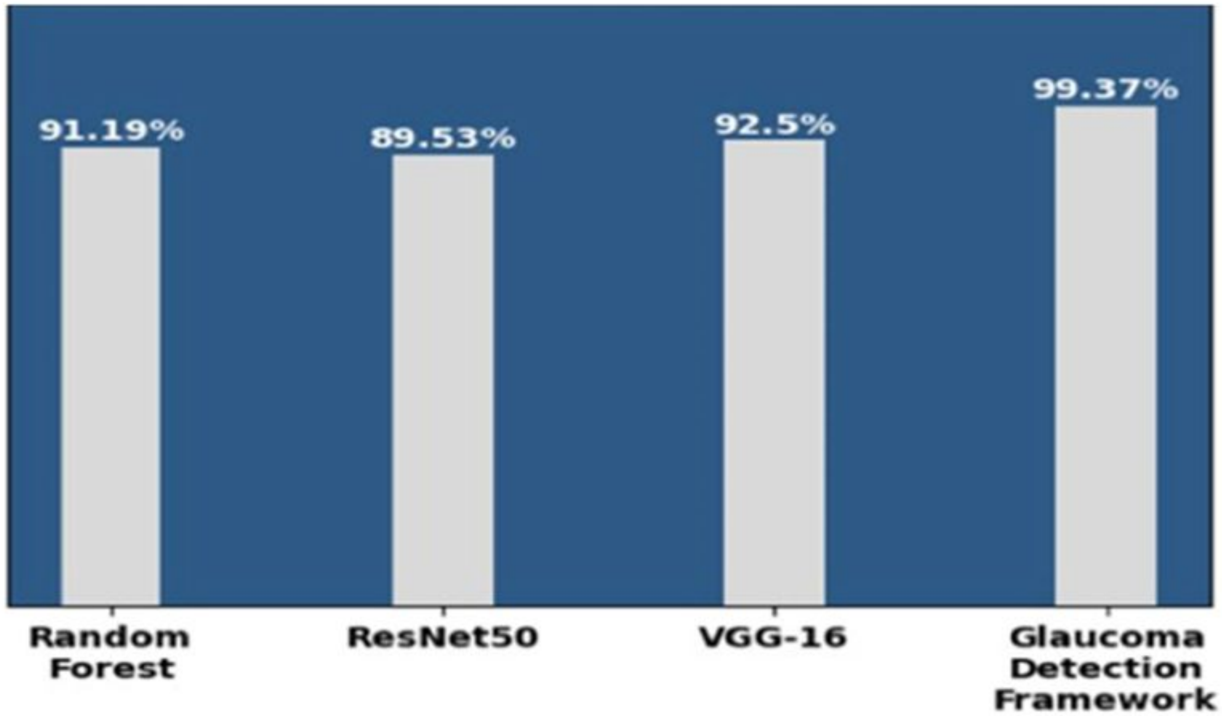


Fig 2- Model and Precision

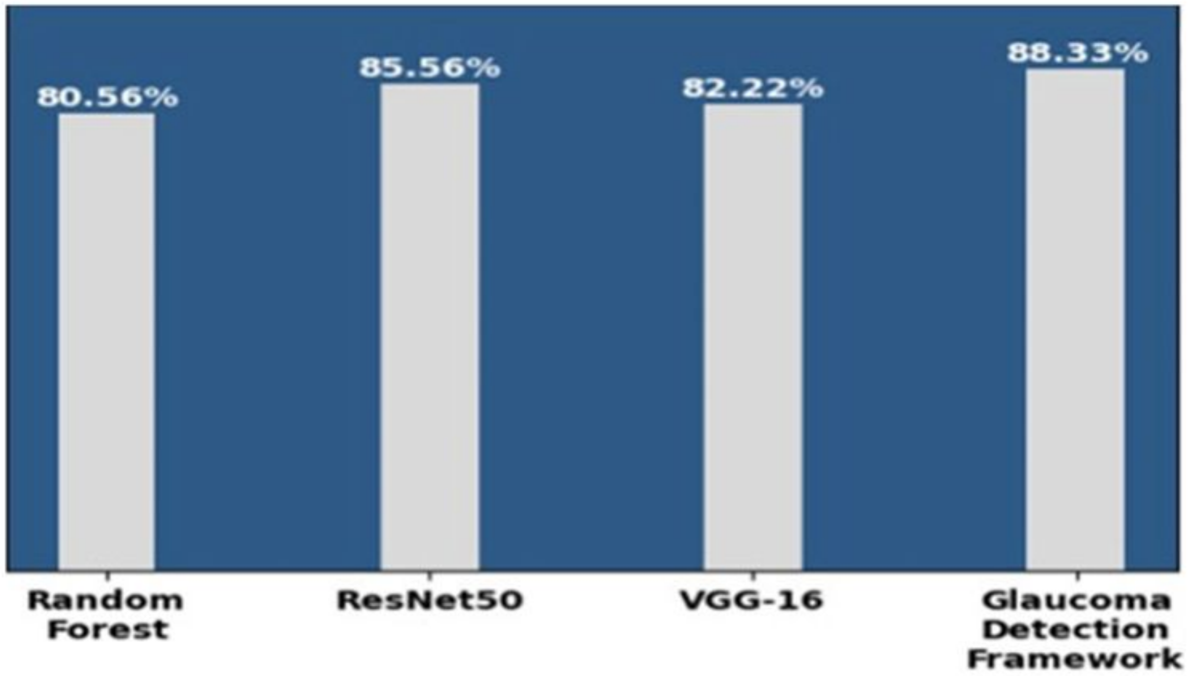


Fig 3- Model and Recall

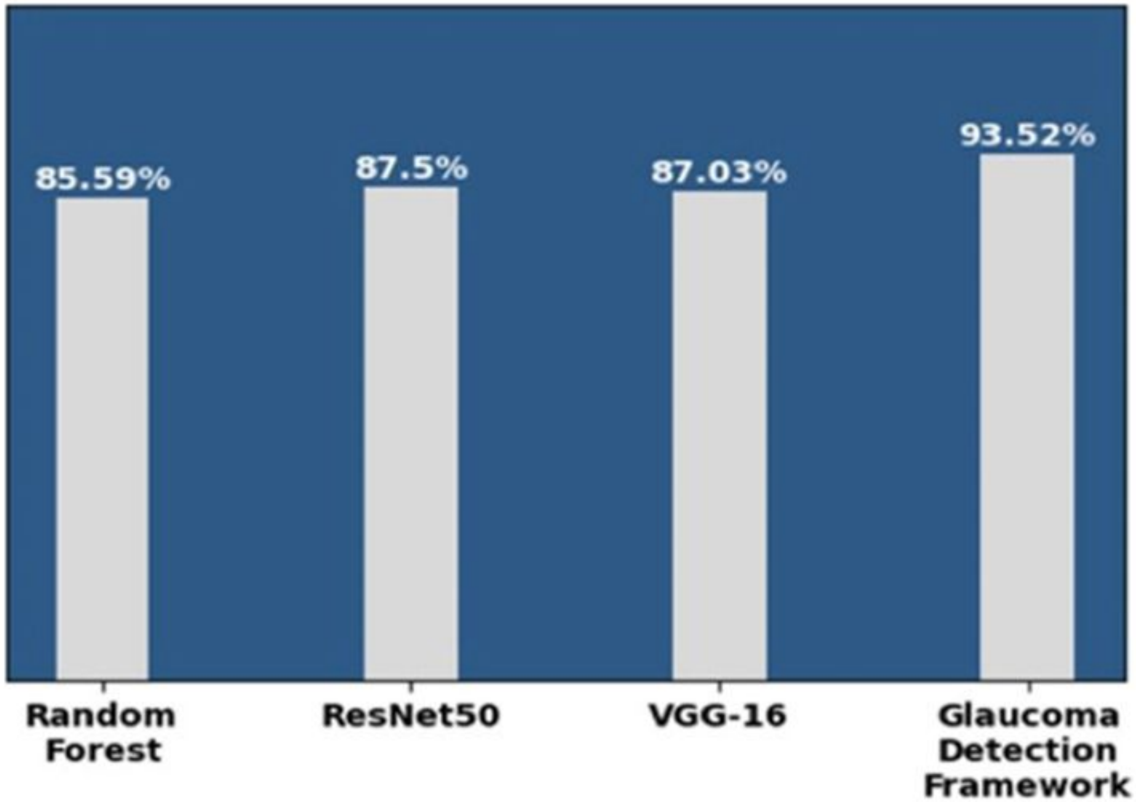


Fig 4- Model and F1 Score

Fundus-DeepNet: Multi-label deep learning classification system for enhanced detection of multiple ocular diseases through data fusion of fundus images

Authors: Shumoos Al-Fahdawia, Alaa S. Al-Waisyb, Diyar Qader Zeebareec, Rami Qahwajid, Hayder Natiqe, Mazin Abed Mohammed, Jan Nedomag, Radek Martinekh, Muhammet Deveci

- Objective: Develop an automated deep learning system (Fundus-DeepNet) to detect multiple ocular diseases using fundus image data fusion.
- Disease Categories: Diabetic retinopathy, glaucoma, cataract, AMD, myopia, hypertension and other abnormalities

- Methodology:
  - Dataset: OIA-ODIR dataset (10,000 fundus images, 8 disease categories)
  - Preprocessing: Cropping, resizing, contrast enhancement, noise removal, data augmentation
  - Architecture:
    - HRNet for feature extraction
    - Attention & SENet blocks for feature refinement
    - DRBM classifier with Softmax for multi-label classification

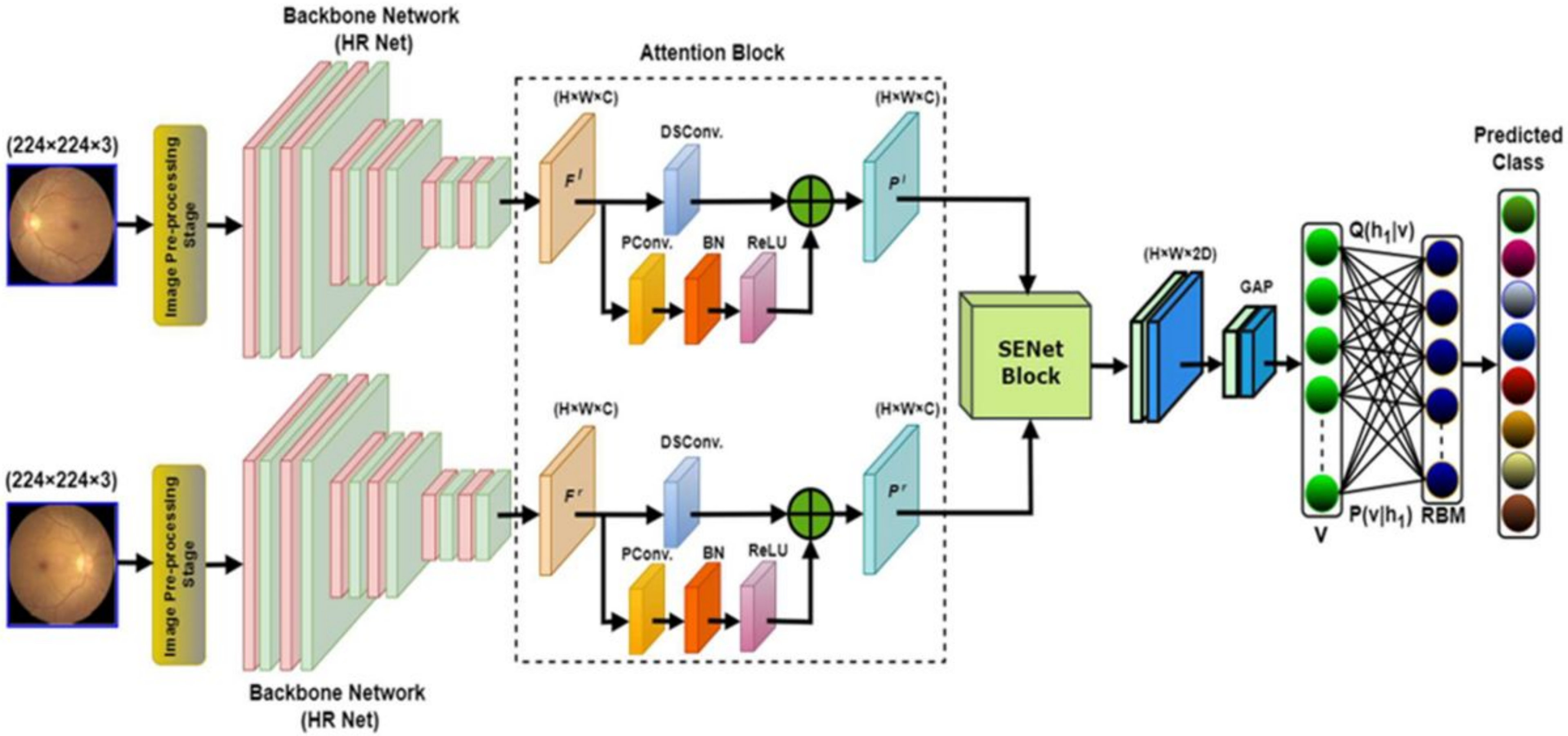


Fig- Diagram illustrating the architecture of Fundus-DeepNet Model

Comparative analysis of proposed model with other existing models on OIA-ODIR dataset

Table1- Comparative analysis on off-site test set

Methods	F1	KS	AUC	Final
VGG16 + SGD	85.57	43.35	84.93	71.28
Inception-v4	87.93	50.63	86.91	75.16
VGG16	87.30	44.94	86.81	73.02
BFENet	89.2	53.5	91.2	77.97
ResNet-101	88.6	52	90.3	76.97
Fundus-DeepNet	**88.56**	**88.92**	**99.76**	**92.41**

Table2- Comparative analysis on on-site test set

Methods	F1	KS	AUC	Final
VGG16 + SGD	84.9	42	83.4	70.1
Inception-v4	86.68	45.05	83.63	71.78
VGG16	87.18	43.97	87.05	72.73
BFENet	88.6	51.3	90.3	76.73
ResNet-101	87.7	50	89.7	75.8
Fundus-DeepNet	**89.13**	**88.98**	**99.85**	**92.66**

Conclusion & Future Work

- Conclusion:
  - Fundus-DeepNet demonstrates superior performance in detecting multiple ocular diseases.
  - The system enhances diagnostic accuracy and efficiency through feature fusion.
  - The model integrates information from both left and right eye fundus images. This fusion enhances disease detection accuracy.
- Future Work:
  - Exploring Vision Transformers (ViTs) and hybrid CNN-ViT models to improve feature extraction and attention mechanisms.
  - Investigating more sophisticated attention mechanisms such as Swin Transformers or SE-Network improvements for better feature weighting.

Age-Related Macular Degeneration (AMD)

- Progressive eye disease affecting the macula, leading to central vision loss.
- **Types:**
  - **Dry AMD (90%)**: Drusen accumulation, slow progression.
  - **Wet AMD**: Abnormal blood vessel growth, rapid vision loss.
- **Symptoms**: Blurred/distorted vision, dark spots, wavy lines.
- **Risk Factors**: Age (>50), smoking, genetics, obesity, hypertension.
- **Diagnosis**: Eye exam, imaging (drusen, retinal thinning).
- **Treatment**:
  - **Dry**: Antioxidants, lifestyle changes.
  - **Wet**: Anti-VEGF injections, laser therapy.
- **Impact**: Leading cause of vision loss in elderly, affects 200M+ globally.
- **Key Message**: Early detection and management are critical to preserving vision.

Automated Grading of Age-Related Macular Degeneration From Color Fundus Images Using Deep Convolutional Neural Networks

Philippe M. Burlina, PhD; Neil Joshi, BS; Michael Pekala, MS; et al
JAMA Ophthalmol.

- **Disease Description**: Age-related macular degeneration (AMD) is a leading cause of vision loss, with intermediate stages often going undetected. Early identification can prevent progression to advanced stages.

Model:

- Deep Convolutional Neural Network **(CNN).**
- A deep learning model designed for image classification and feature extraction.

Dataset:

- National Institutes of Health AREDS dataset (130,000+ fundus images from 4,613 patients).
- A large, diverse dataset ensuring robust model training and better generalization.

Features:

- Color fundus photographs were graded into four severity levels (no AMD, early, intermediate, advanced).
- Helps the model learn distinct patterns in retinal images for accurate classification.

Betterment:

Compared with human expert grading; the model achieved substantial agreement (kappa coefficient: 0.76–0.83).

Suggested Improvements

Use of hybrid models combining CNNs with transformers for better feature extraction

Multi-modal data integration (OCT + fundus images) for enhanced accuracy.

- **Results:**
    - **Accuracy**: 88.4%–91.6%.
    - **AUC**: 0.94–0.96.

- **Reference**: NIH AREDS dataset; publicly available.

Automatic detection of 39 fundus diseases and conditions in retinal photographs using deep neural networks

- Cen, LP., Ji, J., Lin, JW. *et al.*
- *Nat Commun* 12, 4828 (2021).

System : Developed a system capable of identifying up to 39 retinal conditions using fundus images from diverse sources.

Automatic Detection of 39 Fundus Diseases Using Deep Learning

- Model Details:
  - Model: Two-step CNN strategy for multi-label classification.
  - Dataset: Large-scale dataset with over 249,620 fundus images from multiethnic sources.
  - Features:
    - Data augmentation techniques applied to improve performance on imbalanced classes.
    - Multi-label classification enabled simultaneous detection of multiple diseases per image.

- **Betterment**:
  - Compared with standalone CNNs, the two-step approach improved sensitivity and specificity but had moderate F1 scores (~92%).
  - Suggested Improvements:
    - Hybrid models combining CNNs with transformers for better generalization and feature extraction.
    - Increasing dataset diversity to improve real-world applicability.
- **Results**:
  - Sensitivity: ~97.8%.
  - Specificity: ~99.6%.
  - F1 Score: ~92%.

- Reference: Dataset is publicly accessible.

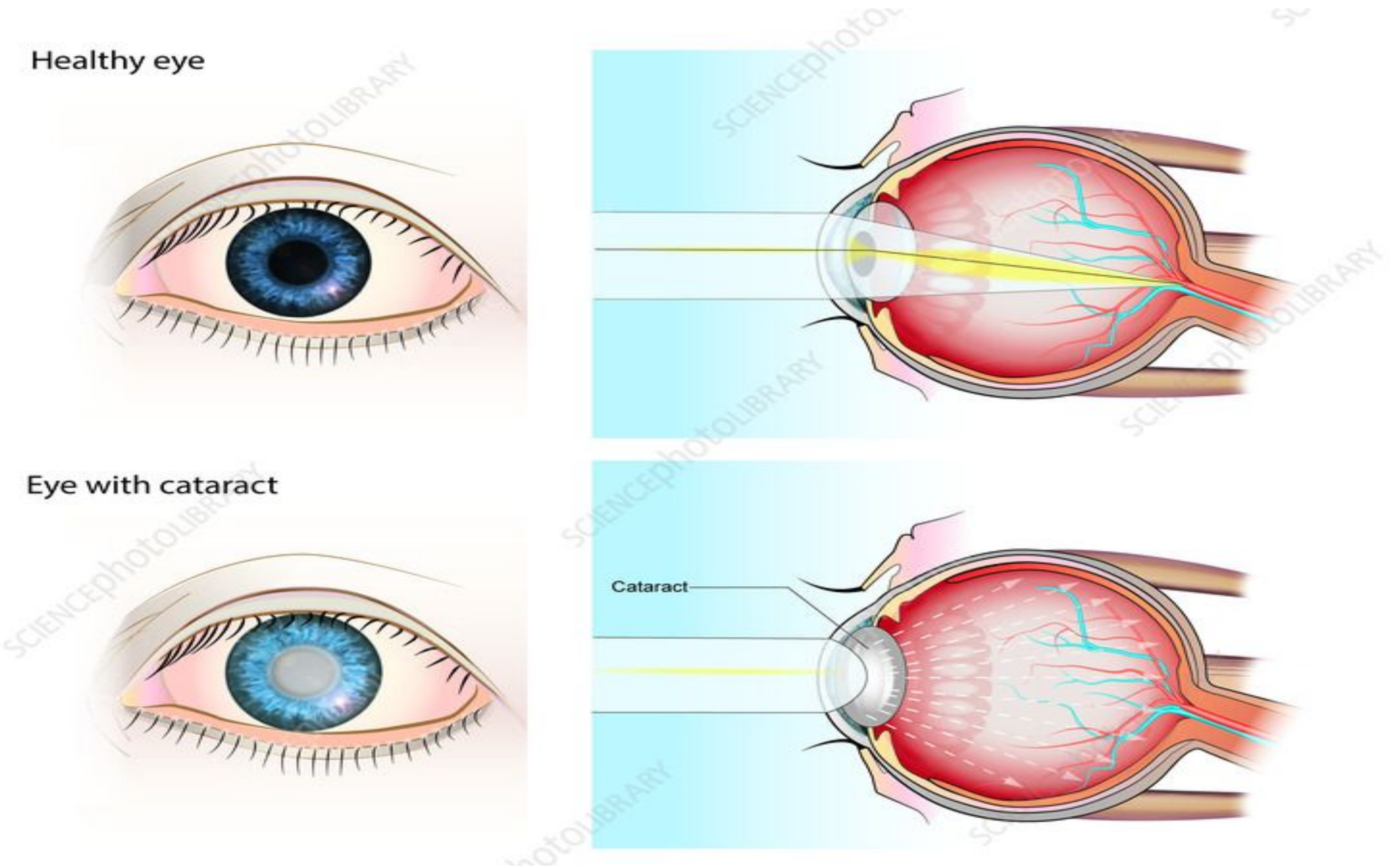
Summary Table

Paper Title	Disease(s)	Model Used	Dataset	Accuracy (%)	Key Limitations / Future Work
Automated Grading of AMD From Fundus Images	AMD	CNN	NIH AREDS	~88–91	Limited generalization; hybrid models suggested
A Deep Learning Framework for Multi-Retinal Diseases	DR, MH, ODC	EyeDeep-Net, ResNet152	RFMiD	~82–89	Multi-label classification suggested
Automatic Detection of 39 Fundus Diseases	Multiple Diseases	Two-step CNN	Large-scale Fundus Images	~92 (F1)	Hybrid models; better dataset diversity needed

- Eye-Vision Net: Cataract Detection and Classification in Retinal and Slit Lamp Images using Deep Network
Authors: Binju Saju1, Rajesh R2.
Journal: *IJACSA* (June 17, 2022)

Cataract Disease

- **What is Cataract?**
  - A cataract is a clouding of the eye's natural lens, leading to blurred vision.
  - It is one of the primary causes of vision impairment and blindness worldwide.
- **Causes and Risk Factors:**
  - Aging is the most common cause.
  - Other factors include diabetes, prolonged UV exposure, smoking, and genetic predisposition.
- **Symptoms of Cataracts:**
  - Blurry vision, difficulty seeing at night, glare sensitivity, faded colors, and double vision in one eye.
- **Diagnosis and Treatment:**
  - Diagnosed using slit lamp examinations, retinal imaging, and visual acuity tests.
  - Treatment includes stronger eyeglasses in early stages, and surgery in advanced stages.


Healthy eye
Eye with cataract
Cataract

Architecture Presented in the paper

- **Phase 1: Cataract Detection**
  - Deep OCRN_IAO model combines Convolutional Recurrent Network (CRNN) with Improved Aquila Optimization (IAO).
  - Feature extraction using Pyramidal HOG, Haar Wavelet Transform, and GLCM.
  - Feature selection using Relief Neighbourhood Component Analysis (RNCA).

- **Phase 2: Cataract Classification**
  - Uses Dense CNN for cataract type classification.
  - Uses BE_ResNet101 for cataract grade classification (Mild, Moderate, Severe).
  - Batch balancing technique improves classification accuracy.

Dataset Used

- **Datasets:** DRIMDB (Diabetic Retinopathy Images Database) & Real-time Slit Lamp Images.
- DRIMDB contains 216 retinal images for analysis.
- Slit lamp images include five types of cataracts: Cortical, Hyper Mature, Mature, Nuclear, and Posterior.
- Image preprocessing steps: resizing, color conversion, illumination removal, and enhancement.

Performance Comparison

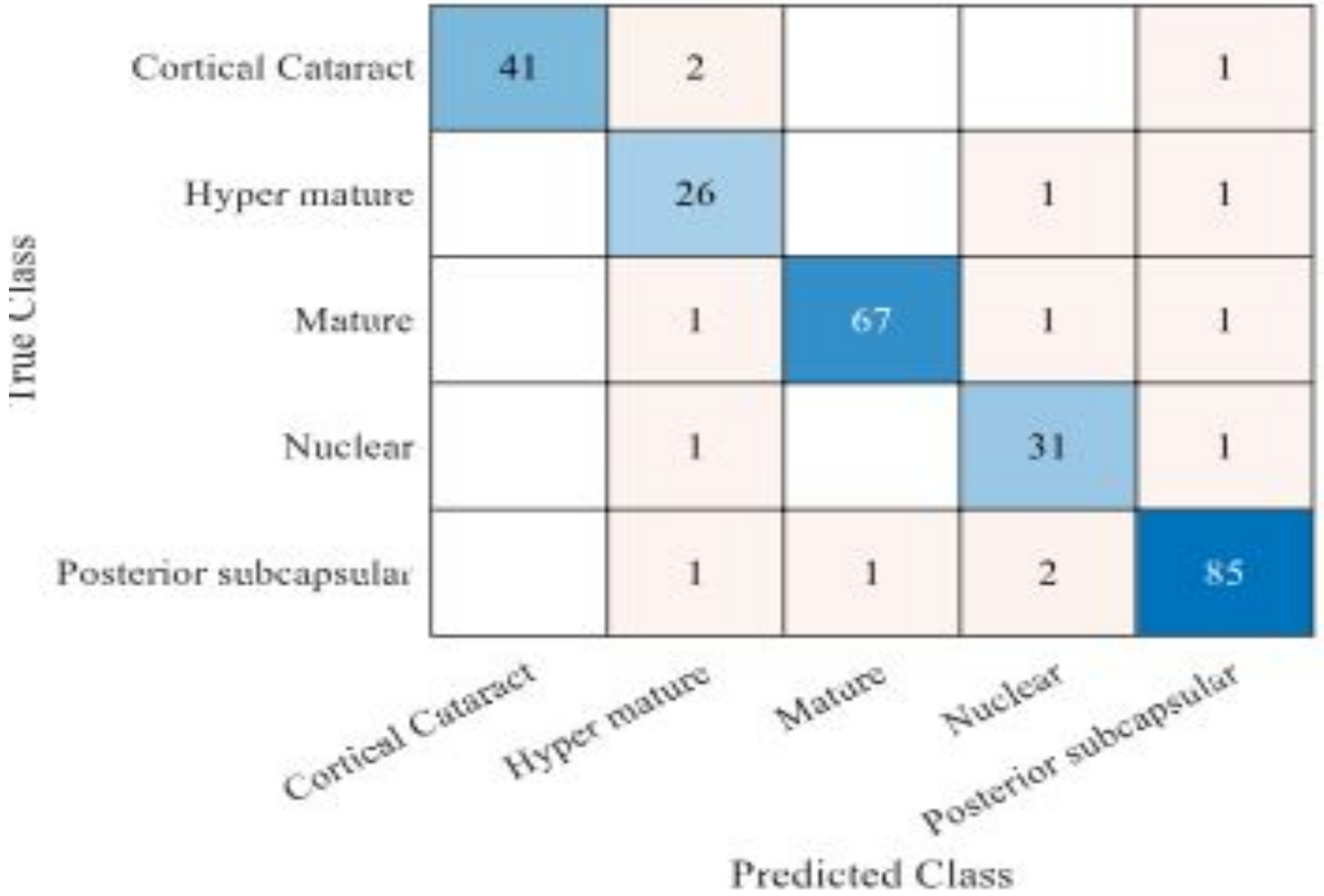


Fig. 6. Confusion matrix of proposed Dense CNN+BE_ResNet101 classification model

Performance Analysis in Phase I using Retinal and Slit Lamp Images

Datasets	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1 Score (%)	Youden Index (%)	Kappa (%)
DRIMDB Retinal Images	92.36	94.58	96.57	91.06	91.47	89.65	89.32
Slit Lamp Images	94.67	96.68	98.29	93.03	93.81	91.23	90.28

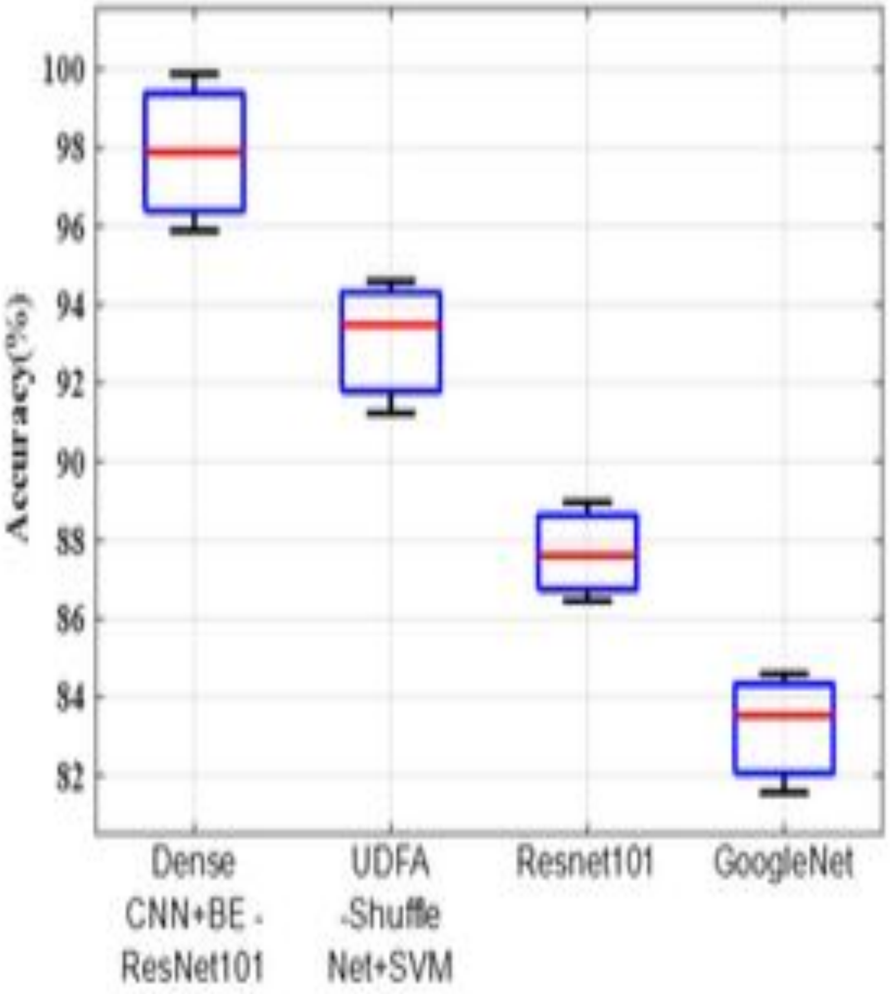


Fig. 8. Accuracy performance comparison

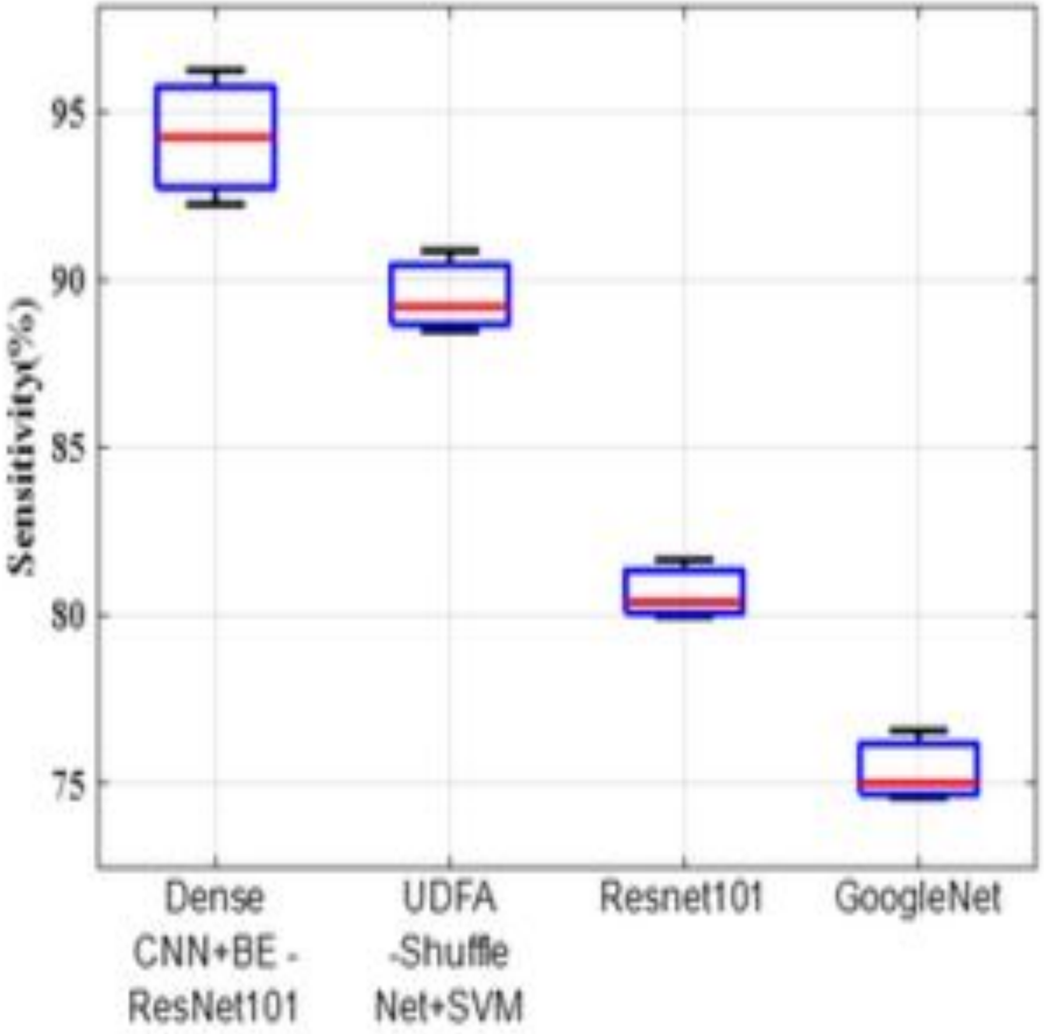


Fig. 9. Sensitivity performance comparison

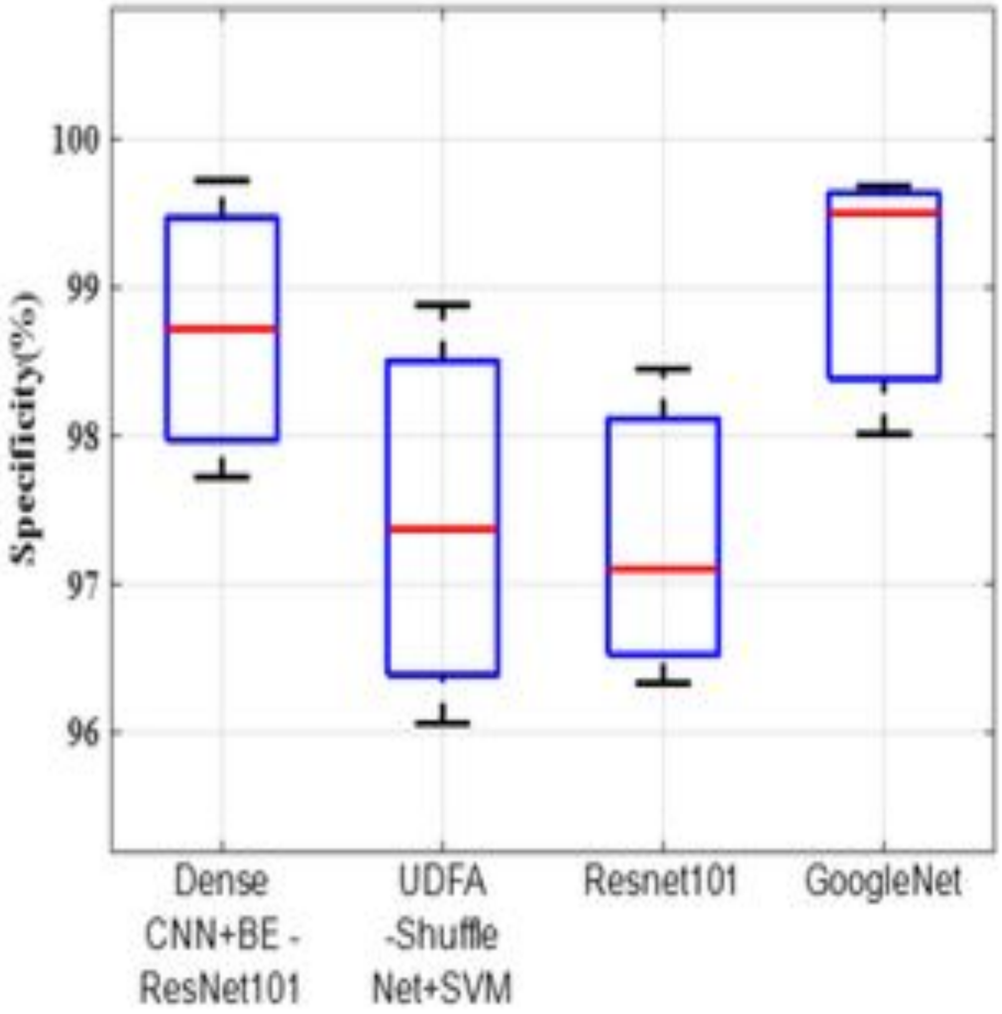


Fig. 10. Specificity performance comparison

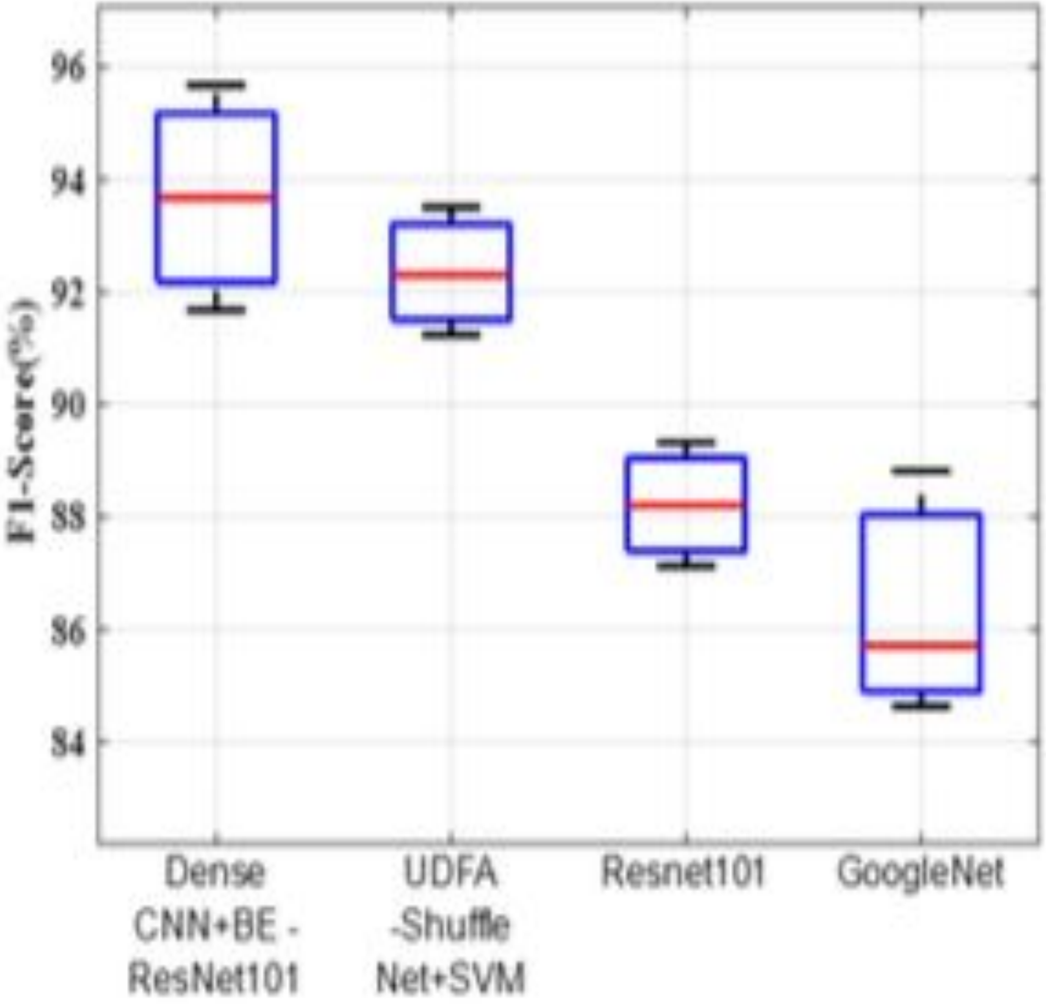


Fig. 11. F1 score performance comparison

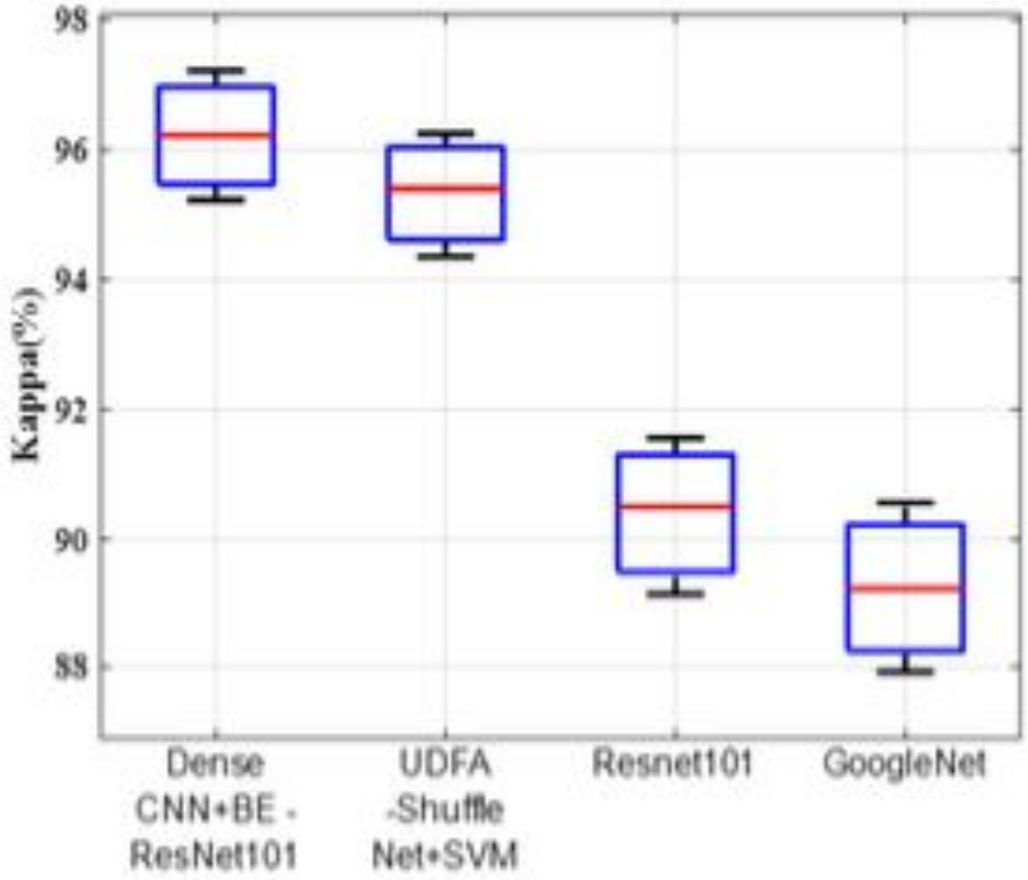


Fig. 12. Kappa performance comparison

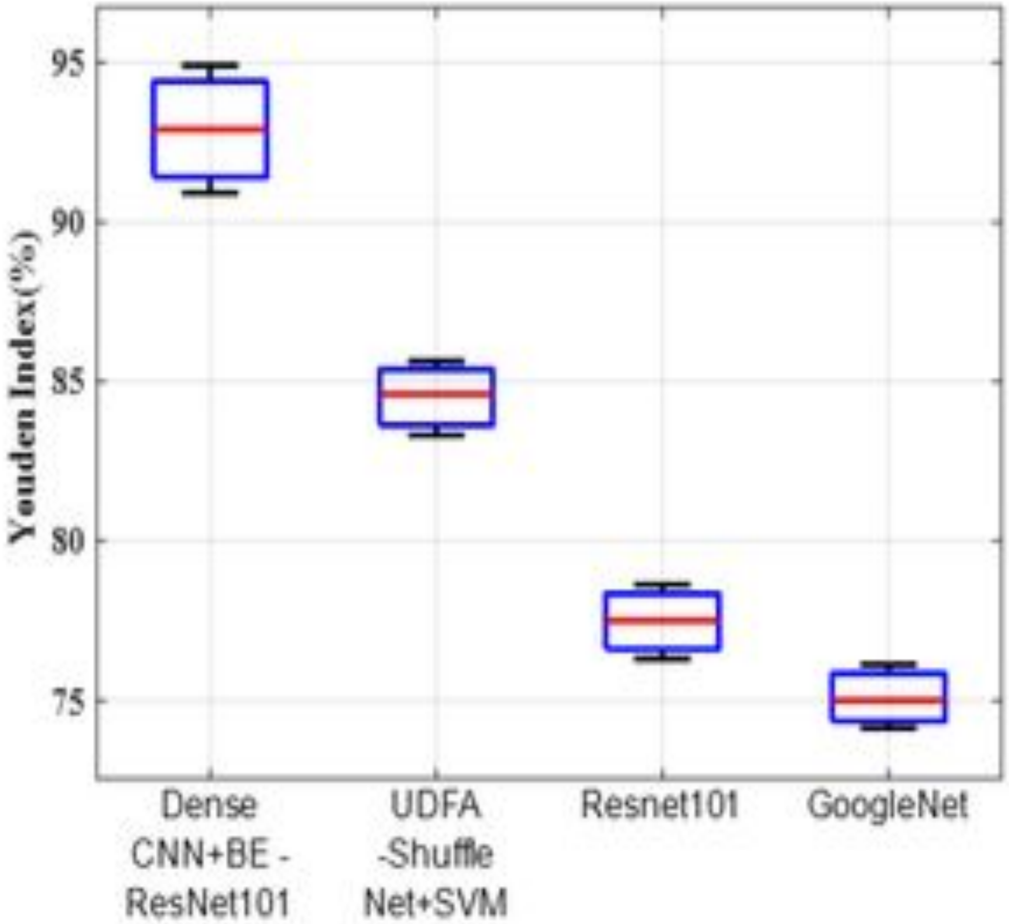


Fig. 13. Performance comparison in terms of Youden index

OverView

Lamp Images using Deep Network

- Cataracts are a leading cause of blindness. Early detection is crucial for risk management and prevention.
- Existing methods have limitations like high detection errors and computational complexity.
- The study introduces a Deep Optimized Convolutional Recurrent Network (Deep OCRN_IAO) for cataract detection.
- Slit lamp images perform better than retinal images for classification.
- Uses Batch Equivalence ResNet-101 (BE_ResNet101) for cataract type and grade classification.
- Achieves high accuracy, specificity, and sensitivity in cataract detection.

Enhancing Performance of proposed model

Potential Improvements:

- **Data Augmentation:** Using synthetic slit lamp images and increasing dataset size.
- **Hybrid Models:** Combining CNNs with transformers for improved feature extraction.
- **Attention Mechanisms:** Implementing self-attention layers for better localization of cataract regions.
- **Multi-Modal Learning:** Integrating additional medical imaging techniques like Optical Coherence Tomography (OCT).
- **Fine-Tuning on Larger Datasets:** Pretraining on large-scale medical image datasets to generalize better.

Deep Learning-Based Eye Disease Recognition Using Transfer Learning and Improved D-S Evidence Theory

Paper Idea:

- Eye diseases often develop silently, leading to vision impairment or blindness if undetected.
- Deep learning techniques, particularly Convolutional Neural Networks (CNNs), offer automated and efficient eye disease recognition.
- The study improves upon existing models by leveraging **transfer learning** and **Dempster-Shafer (D-S) evidence theory**.
- A novel **Improved D-S Evidence Theory (ID-SET)** is proposed to enhance decision fusion and reduce conflicts in classification.
- The model achieves **92.37% accuracy**, surpassing previous methods.

- **Dataset:** ODIR-5K fundus image dataset (7 eye disease classes: Normal, Diabetic Retinopathy, Glaucoma, Cataract, AMD, Hypertension, Myopia).
- **Model Components:**
  - **ResNet50 & ResNet101**: Used as subnetworks for transfer learning and feature extraction.
  - **Probability Assignment Functions (m1, m2)**: Generated from ResNet models.
  - **ID-SET Fusion Module**: Combines outputs from both networks using an improved D-S evidence theory for better decision making.
  - **Final Classifier**: Determines the most probable eye disease based on fused results.
- **Advantages:**
  - Reduces bias and decision conflicts.
  - Enhances learning efficiency with transfer learning.
  - Outperforms standalone deep learning models in precision and recall.

Detecting Hypertensive Ratinopathy

Paper 1: "Computer-Aided Detection of Hypertensive Retinopathy Using Depth-Wise Separable CNN" (2022)

Method:

- The paper introduces a **CAD-HR system** to detect hypertensive retinopathy by using a **Depth-Wise Separable Convolutional Neural Network (DSCNN)** with a **Linear Support Vector Machine (LSVM)** classifier.
- **Key Contributions**:
    1. **Depth-Wise Separable Convolution**: A lightweight CNN architecture that reduces computational load while extracting relevant features from retinal images.
    2. **Data Augmentation**: This is used to enhance the dataset, including 9500 images from publicly available datasets (DRIVE, DiaRetDB0, and Imam-HR).
    3. **Performance**: The model achieved:
        - Sensitivity: 94%
        - Specificity: 96%
        - Accuracy: 95%
        - AUC: 0.96
    4. **Classifier**: Uses **LSVM** for binary classification (HR vs. non-HR).

Strengths and Weaknesses:

- **Strengths**:
    - Lightweight model with fewer parameters compared to traditional CNNs.
    - High performance with significant sensitivity and specificity.
- **Weaknesses**:
    - The model only classifies HR vs. non-HR, not distinguishing different severity levels of hypertensive retinopathy.
    - Performance might degrade when using larger datasets or more complex HR stages.

Paper 2: "A Foundation Model for Generalizable Disease Detection from Retinal Images" (2023)

Method:

- This study introduces **RETFound**, a self-supervised learning (SSL) foundation model for retinal disease detection.
- **Key Contributions**:
  1. **Self-Supervised Learning (SSL)**: The model is pre-trained on unlabelled retinal images using SSL techniques, such as **masked autoencoders**.
  2. **Large Dataset Training**: It is trained on **1.6 million unlabelled images** and fine-tuned for specific disease detection tasks, including hypertensive retinopathy, diabetic retinopathy, and systemic disease prediction.
  3. **Generalizability**: The model adapts to various tasks with fewer labeled data and generalizes well to unseen data.
  4. **Performance**:
     - In ocular disease diagnosis, it outperformed other models (e.g., SL-ImageNet).
     - Achieved high AUC scores (e.g., AUC of 0.94).

Strengths and Weaknesses:

- **Strengths**:
  - **Self-supervised learning** reduces the need for large labeled datasets, making it scalable to diverse clinical applications.
  - Can be adapted to multiple disease detection tasks using the same foundation model.
- **Weaknesses**:
  - The model's generalizability is based on a vast amount of unlabelled data, which might not always be available for specific diseases like HR.
  - It might require more computational resources during pre-training on such large datasets.

Proposed Approach: Hybrid Model with Attention Mechanism and Multi-Stage SVM

Improvements:

1. **Hybrid Architecture**: Combine **Depth-Wise Separable CNN** (from Paper 1) with **Self-Supervised Learning (SSL)** (like Paper 2), using **attention mechanisms** to focus on specific HR features like hemorrhages and cotton wool spots.

    ○ **Why SSL**: This will allow the model to learn better representations from unlabelled data, improving generalization across diverse datasets.
    ○ **Attention Mechanism**: This will help the model focus on critical areas like micro-aneurysms and hemorrhages, improving detection, especially in early stages of HR.

2. **Multi-Class SVM**: Instead of just HR vs. non-HR, use a **multi-class SVM** to classify the severity of hypertensive retinopathy (mild, moderate, severe).

    ○ **Why Multi-Class SVM**: It would provide more clinical insight into the severity of HR, helping doctors assess the stage of the disease and plan treatment.

3. **Handling Class Imbalance**: Implement **oversampling** for minority classes and use **weighted loss functions** to handle the imbalance in retinal disease datasets.

    ○ **Why Oversampling and Weighted Loss**: It will improve model performance in detecting less common diseases, as discussed in Paper 2.

Advantages:

- **Efficiency**: The use of **DSCNN** ensures the model is computationally efficient and scalable for real-time applications.
- **Generalization**: **SSL** and **attention mechanisms** will improve the model's ability to generalize across different datasets and identify subtle features in HR.
- **Improved Clinical Insight**: Multi-class classification will provide a more detailed prognosis of HR severity, which is essential for clinical decision-making.

What is Pathological Myopia?

Pathological Myopia (PM) is a severe form of myopia that leads to irreversible vision loss due to excessive elongation of the eyeball.

Prevalence of **Pathological Myopia** in India

rapidly increasing worldwide, especially in Asian countries

.10-15% of myopic individuals in India may develop pathological myopia.

With the rising use of digital screens and changing lifestyle habits, cases of high and pathological myopia are expected to increase in India.

The paper titled **"Pathological Myopia Classification with Simultaneous Lesion Segmentation Using Deep Learning**", published in 2021, explores a deep learning approach for detecting Pathological Myopia. This study proposes a multi-task model using CNNs (Convolutional Neural Networks) for both classification and segmentation.

The model **outperforms** feature-extraction methods.

Summary of What the Paper Did

Used Deep Learning (CNNs) to Detect Pathological Myopia

- Designed a **multi-task model** that performs **classification + segmentation** simultaneously.
- Used **ResNet-18** for **feature extraction** and **UNet++** for **lesion segmentation**.

Trained on Retinal Fundus Images

- Used the **Pathological Myopia (PALM) dataset** (1,200 images).
- Also validated on the **ODIR dataset** (3,350 images).

Compared with Other Models

- **Outperformed traditional handcrafted feature-extraction methods**.
- **Beat standard U-Net in segmentation accuracy**.

Improved Pathological Myopia Classification

- **Achieved AUC = 0.9867, outperforming classification-only CNN models (AUC = 0.858).**

Fovea Localization with Segmentation Instead of Regression

- Previous models used coordinate regression, but this paper used image segmentation for better accuracy (58.3 pixels vs. 229.4 pixels)**.**

Better Lesion Segmentation Accuracy

Task	Metric	Proposed Model	Other Models
PM Classification	AUC	0.9867	0.858 (classification-only model)
Fovea Localization	Euclidean Distance	58.3 pixels	229.4 pixels (Regression model)
Optic Disc Segmentation	Dice Score	0.9303	0.91 – 0.95 (Other PALM participants)
Atrophy Segmentation	Dice Score	0.8001	0.77 – 0.82 (Other PALM participants)
Retinal Detachment Segmentation	Dice Score	0.8073	0.7449 (Other models)

What improvements we will be doing

1. Use a Larger Dataset Instead of PALM

ODIR-5K (5,000+ retinal images for multiple diseases).
REFUGE Dataset (glaucoma & optic disc segmentation).

2. Replace ResNet-18 with a More Powerful CNN Model

ResNet-18 is **lightweight**, but newer models offer **better feature extraction**.
EfficientNet-B4 ,**DenseNet-121**,**ConvNeXt**

3.Replace U-Net++ with Attention U-Net for Better Segmentation

4. Improve Loss Functions for Segmentation

Dice Loss struggles with **small lesions & imbalanced data**.
Tversky Loss – Improves small lesion segmentation.

5. Apply CLAHE (Contrast-Limited Adaptive Histogram Equalization) Before Training

Enhances **retinal structures** for **better feature recognition**.

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Multi-Task Knowledge Distillation for Eye Disease Prediction

1. **Shared ResNet-50 Backbone (Encoder):**
   - Pretrained on ImageNet, fine-tuned on fundus images.Extracts image features used across all tasks (T1, T2, T3).
2. **Multi-Task Learning (MTL) Setup:**
   Shared encoder + three task-specific heads:
   - **T1:** Coarse disease classification (5 classes: DR, AMD, Glaucoma, Melanoma, Normal)
   - **T2:** Fine-grained disease classification (320 sub-classes)
   - **T3:** Diagnosis captioning (sequence generation)
3. **Task-specific Heads:**
   T1 & T2: Fully Connected + Softmax layers.
   T3: CNN features → Dense projection → **LSTM Decoder** to generate textual diagnosis. (Uses Teacher Forcing during training)
4. **Multi-Teacher Knowledge Distillation (KD):**
   7 teacher models (trained on different task combinations) distill knowledge to the MTL student via **KL-Divergence loss** on soft predictions.
5. **Semi-supervised Learning with Unlabeled Data:**

   KD also applied on **unlabeled fundus images** to enhance generalization with limited labeled data

Proposed Approach: Combined Model for Retinal Disease Detection

- Develop a **single unified model** to detect all 6 retinal diseases from fundus images.

- Use H**ybrid CNN-ViT architectur**e for enhanced feature extraction.

  Replace ResNet-50 with Vision Transformer (ViT) for better global context understanding.

- **Apply Knowledge Distillation (KD)**:

  Train the combined model to replicate outputs of six individual disease-specific models.

- Enable **multi-label classification** to detect multiple diseases in a single image.

- Fine-tune on large-scale medical datasets to boost model accuracy.

Why Our Approach Works?

- **Each disease-specific model already works well individually**
  → This proves that our base models are strong and reliable, making them ideal teachers for the combined model.

- **Combined model reduces cost and deployment complexity**
  Instead of maintaining six separate models, one model can handle everything — saving time, storage, and resources.

- K**nowledge Distillation helps transfer the best of all models**
  The combined model learns how each expert model makes decisions, improving its own performance.

- **Multi-label prediction reflects real-life scenarios**
  → Since a patient can have multiple eye diseases at once, our model can detect all of them in one go.

- **Proven architectures like CNN + Transformer improve results**
  → Using CNNs for local patterns and Transformers for global context boosts accuracy and feature learning.

:

Progress Till Now

Work Done	Description
Studied 6 Eye Diseases	Understood symptoms, causes, and affected eye parts for DR, Glaucoma, Cataract, AMD, Hypertensive Retinopathy, and Pathological Myopia.
Combined Disease Understanding	Identified how all diseases can be detected together using a unified model.
Literature Review	Reviewed multiple research papers on both individual and multi-disease detection models.
Analysed Existing Architectures	Explored CNNs, Vision Transformers, hybrid models, and Knowledge Distillation techniques.
Identified Model Improvement Ideas	Highlighted gaps in current solutions and proposed ways to enhance performance

Final Deliverables

Deliverable	Description
Combined Multi-Disease Detection Model	A single model that detects all six eye diseases using fundus images.
Model Architecture Improvement	Modify and enhance the model using CNN + ViT, attention layers, etc., to improve accuracy.
Performance Evaluation Report	Compare results before and after improvement using accuracy, precision, recall, etc.
Knowledge Distillation	Use outputs from individual models to guide the combined model for better performance.
Web-Based Demo Interface (Optional)	Simple interface to upload images and view disease predictions.

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