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AI-Enabled Eye Screening Tool for Early Detection of Common Eye Diseases

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Abstract: Eye diseases are common but they are often not find until later, especially in rural areas. It takes a long time and costs a lot of money to get a traditional diagnosis because you have to go to the hospital, use equipment, and see experts. Current AI-based systems are hard to use in real time because they are so complicated.

This project makes a basic Eye Disease Detection System using a CNN model. The user can either upload an eye image or take one through a web app. The system looks at the picture and finds diseases like cataracts, conjunctivitis, styes, or a normal condition.

Camera support, a better user interface, and better performance make the system better. It gives you quick and correct results along with a confidence score. The system is easy to use, works well, and is good for finding eye diseases early.

Keywords: Convolutional Neural Network (CNN), Machine Learning model Deep Learning, Early eye diseases detection, Accuracy, Artificial intelligence.

I. INTRODUCTION

Eye diseases are a major health concern and often remain undetected until they reach an advanced stage, especially in rural and economically weaker regions where access to ophthalmologists and diagnostic facilities is limited. High costs, lack of awareness, and time-consuming clinical procedures further prevent timely eye examinations. Early detection of eye diseases is essential to reduce vision loss and improve treatment outcomes [1], [3], [7]. Recent advancements in Artificial Intelligence (AI), particularly in image analysis, have demonstrated strong potential in detecting eye diseases from ocular images with high accuracy [9], [15].

This project presents a web-based eye disease detection system that uses AI to provide an affordable and accessible preliminary screening tool. Users can upload an eye image through a simple web interface, and the system analyzes the image to identify common eye conditions such as Conjunctivitis, Cataract, and Stye. Convolutional Neural Networks (CNNs) are employed for image classification due to their effectiveness in extracting visual features such as redness, cloudiness, and swelling from eye images [11], [18]. Image preprocessing techniques such as resizing, normalization, and noise removal are applied to improve model performance [12].

The CNN model classifies the eye images into predefined categories, and a Softmax function is used to generate confidence scores for each prediction [17]. The system is implemented as a web application using Python and Flask, enabling real-time interaction between users and the AI model. Unlike existing approaches that rely on complex architectures, multiple data sources, or expensive equipment [4], [14], this system emphasizes simplicity, privacy, and practical usability. The proposed solution aims to provide early awareness and basic guidance, helping users decide whether professional medical consultation is required, particularly in resource-limited settings [7], [19].

II. LITERATURE REVIEW

Wang et al. (2024) [1] The potential of artificial intelligence (AI) in the early detection and prognosis of dry eye disease (DED) has been demonstrated by recent research. AI-based methods increase diagnostic accuracy, but their clinical applicability is diminished by issues like inconsistent diagnostic standards, complicated disease etiology, and poor interpret ability. Research highlights the need for unified diagnostic criteria and multi-evidence integration by categorizing DED diagnostic methods into standard-based, emerging AI-driven, and supplemental techniques. AI has a lot of potential for DED screening overall, but more validation and standardization are needed. Os-Sanchez et al. (2025) [2] Recent studies show that Vision Transformers, or vit 's for short, work well with other artificial intelligence

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models to detect and classify age-related oracular degeneration, or AMD, from pictures of the back of the eye. When you combine Vision Transformers with types of models like CNN's and MLP`s, they are able to pick up on small details in the retina that are hard for doctors to see on their own. The models that used CNN's and cascaded them together were the most accurate, sensitive, and specific at detecting age-related oracular degeneration from these pictures. Vision Transformers and these other models are really good at helping to diagnose age-related oracular degeneration. The literature highlights the effectiveness of hybrid AI architectures in supporting clinical decision-making while emphasizing the need for larger datasets and multi modal data integration for future improvements. H. A. Shah, S. And-berg, A. M. Koivisto, and R. Bednarikm (2025) [3] Researchers have found that artificial intelligence is really good at detecting glaucoma. They use color pictures of the back of the eye to do this. It is a pretty cheap way to screen people. Sometimes the artificial intelligence does not work as well in the real world. This is because the pictures are not very good or they are different from what the artificial intelligence was trained on. The Artificial Intelligence for Glaucoma Detection Challenge, or AIROGS, for short, is trying to fix this problem. They are making a collection of different pictures available so that people can make artificial intelligence that works better in the real world, and they are encouraging people to make better screening tools using artificial intelligence. Results show that top AI models achieved expert-level performance and demonstrated strong robustness across multiple datasets, confirming the feasibility of reliable AI-based glaucoma screening in real-world conditions.

C. de Vente et al. (2024) [4] Because Alzheimer's disease's early symptoms frequently mimic those of normal aging, early detection is challenging. This study demonstrates how a non-invasive method of identifying individuals with Alzheimer's disease and mild cognitive impairment (MCI) can be achieved by combining eye tracking and speech analysis. Compared to using eye or speech data alone, a deep learning fusion model that examines eye movements and speech patterns achieved higher accuracy. The findings demonstrate that pupil size variations and eye-speech timing are helpful markers for the early identification of cognitive decline. V. Kurilova et al. (2025) [5] According to recent research, integrating deep learning with smartphone-based eye imaging can facilitate the scalable and affordable early detection of eye diseases. Smartphone apps analyze eye images using built-in cameras and processing power, increasing accessibility and lowering the cost of diagnosis. The clinical utility of various complete and partial diagnostic systems is reviewed in existing research. All things considered, smartphone-based deep learning solutions hold great promise for enhancing widespread eye disease screening and directing future ophthalmic practice and research. P. Kaushik et al. (2024) [6] Diabetic retinopathy can cause serious vision loss if not detected early. Recent studies show that deep learning–based automated screening systems using convolutional neural networks can accurately analyze retinal images to identify early signs of the disease. Trained on large annotated datasets, these models achieve high sensitivity, specificity, and accuracy. Such automated approaches offer an efficient and reliable solution for large-scale diabetic retinopathy screening. H. Vohra et al. (2025) [7] Access to eye care remains limited in rural and underserved areas. Recent research presents a low-cost, AI-based system for detecting major eye diseases such as diabetic retinopathy, glaucoma, and age-related macular degeneration. Using affordable fundus imaging and convolutional neural networks, the system provides accurate and automated diagnosis through a cloud-based web application. With high accuracy, this approach improves early detection and makes eye screening more accessible and practical. M. Zahin Muntaqim et al. (2024) [8] Eye diseases require early and accurate detection to prevent vision loss, but existing automated systems often struggle with limited accuracy and high computational complexity. Recent studies propose a multi-stage deep learning approach that improves feature extraction and classification by capturing both low-level and high-level disease patterns. Using robust preprocessing and lightweight architectures, these models achieve better performance across multiple public eye-image datasets. Such approaches highlight the effectiveness of hierarchical deep learning in building accurate and efficient eye disease detection systems.

A. Albelaihi et al. (2024) [9]Recent research highlights the effectiveness of deep learning in diagnosing diabetic eye diseases using fundus images. A multi-class deep learning framework has been proposed to detect diabetic retinopathy, diabetic macular edema, glaucoma, and cataracts using multiple public datasets. Among several evaluated architectures, EfficientNetB0 demonstrated superior performance, achieving significantly higher accuracy compared to existing methods. These findings show that advanced deep learning of models can reliably support multi-disease eye screening and outperform traditional approaches. S. Gulati et al. (2024) [10] Recent studies address the growing burden of diabetic eye diseases by using privacy-preserving federated deep learning frameworks. By applying lightweight MobileNetV2 models, these approaches enable collaborative training across multiple clients without sharing sensitive patient data. Experimental results show high accuracy in detecting diabetic retinopathy and diabetic macular edema, even with non-uniform data distributions. Overall, federated learning proves to be an effective and secure solution for early diabetic eye disease screening. S. Virbukaitė et al. (2024) [11] Early detection of diabetic retinopathy, glaucoma, and age-related macular degeneration is essential to prevent permanent vision loss. Recent literature reviews show that artificial intelligence–based methods, especially convolutional neural networks and support vector machines, are widely used to analyze fundus retinal images for automated disease detection. Manual screening is costly and error-prone, making AI a

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reliable alternative. The reviewed studies also highlight current limitations and emphasize the need for improved accuracy, generalization, and real-world deployment of AI-based eye disease detection systems.

M. Vadduri et al. (2024) [12] Glaucoma often shows a symptom only at advanced stages, making early detection essential to prevent permanent blindness. Recent studies use ensemble-based convolutional neural networks to accurately segment the optic disc and optic cup from fundus images. By combining multiple pretrained models within an attention-based U-Net framework, these approaches achieve high segmentation accuracy across multiple public datasets. The extracted cup-to-disc ratio is then used to effectively classify different stages of glaucoma, demonstrating the usefulness of deep learning for early and reliable glaucoma diagnosis. X. Guo et al. (2025) [13] Recent studies emphasize the importance of image quality and preprocessing for accurate detection of diabetic eye diseases from fundus images. By combining image enhancement, region-of-interest segmentation, and deep convolutional neural networks, researchers achieved reliable multi-class classification of cataract, diabetic retinopathy, and glaucoma. Among various pretrained models, EfficientNet-based architectures showed superior performance. These approaches demonstrate strong potential for early diagnosis and improved clinical decision-making in diabetic eye care.

J. Zhao, S. Li et al. (2025) [14] Access to quality eye care remains limited in remote and underserved areas. Recent research proposes a low-cost, AI-based system that uses affordable fundus imaging and convolutional neural networks to detect diabetic retinopathy, glaucoma, and age-related macular degeneration. A cloud-based web application enables easy image upload, automated diagnosis, and report generation with high accuracy. This approach improves early detection and makes multi-disease eye screening more accessible in resource-limited settings. S. Islam, R. C. Deo et al. (2023) [15] Automated analysis of retinal OCT images is challenging due to complex multi-scale patterns and noise. Recent studies propose frequency-aware deep learning models that combine spatial and frequency-domain information to improve disease classification. By integrating fine details and global context, these models achieve higher accuracy while remaining computationally efficient. The results demonstrate improved robustness, generalization, and reliability for real-world retinal OCT-based diagnosis. A. H. Vyas and V. Khanduja et al. (2021) [16] Color fundus images and OCT scans provide complementary information for eye disease diagnosis, but effectively combining them remains challenging. Recent studies propose multimodal deep learning methods that separate shared and modality-specific features to better utilize information from both image types. By reducing the gap between fundus and OCT data, these approaches achieve improved classification performance. This work highlights the potential of feature disentanglement techniques for more accurate multimodal eye disease diagnosis

Existing AI-based eye disease detection methods show high accuracy but suffer from limited dataset diversity, lack of standard evaluation benchmarks, poor robustness to real-world image variations, high computational complexity, and insufficient explainability. Most studies focus on single diseases or modalities and lack clinical validation, privacy support, and real-world deployment, highlighting the need for a unified, robust, and clinically reliable multi-disease AI framework.

1) Contribution Of The Paper

- Developed a user-friendly AI-based web application for the early screening of eye diseases, allowing users to upload eye images for instant analysis and preliminary diagnosis.
- Designed and implemented a Convolutional Neural Network (CNN) model to accurately detect and classify common eye diseases from retinal or eye surface images.
- Applied effective image preprocessing techniques such as resizing, normalization, noise reduction, and contrast enhancement to improve model performance and detection accuracy.
- Enabled multi-class classification to identify multiple eye disease categories and provided a confidence score for each prediction to improve transparency and reliability of results.

III. METHODOLOGY

A. a) system preliminary

I. Image Normalization

All input eye images are converted into numerical form and normalized to improve learning efficiency.

$$I_{norm} = \frac{I}{255} \qquad [1]$$

This helps the model process images faster and more accurately.

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II. *Convolution Operation*

The Convolutional Neural Network (CNN) extracts important features such as edges and patterns from eye images.

$$F = I * K \qquad [2]$$

where I is the input image and K is the convolution kernel.

III. *Softmax Classification*

The Softmax function converts model outputs into class probabilities for eye disease prediction.

$$P(y_i) = \frac{e^{z_i}}{\sum e^{z_j}} \qquad [3]$$

This allows the system to identify the most probable eye disease.

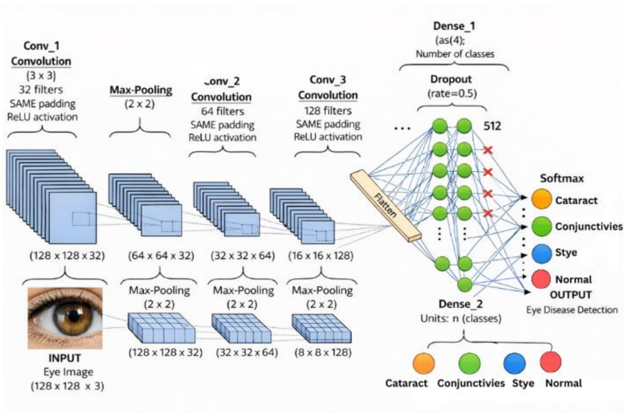
B. B)system architecture

The suggested Eye Disease Detection System is based on a Convolutional Neural Network (CNN) and uses a simple and effective deep learning architecture. This system is simpler, faster, and easier to use than the current one because it only uses eye images instead of data from multiple sources like sensors and medical records.The user can upload or take a picture of their eye through a web app.

To start project the input image is processed using techniques like resizing, normalizing, and removing the background. This step makes sure that all that images are in the same format and which makes the model work better.The CNN model gets the image after it has been preprocessed. Using convolutional layers, activation functions (ReLU), and pooling layers, the CNN model will automatically finds important features like edges, textures, and patterns. These features help the system figure out what different eye diseases are like.

This system is different from more complicated ones that use multi-source data fusion and transfer learning. Instead, it uses a simple CNN model, which makes it light and good for real-time use. Then, fully connected layers are used to classify the features that were taken out.

The final output is obtained by a Softmax layer which predicts the probability of each disease class. The system predicts the disease (cataract, conjunctivitis, stye, normal condition) and shows the result with a confidence score.The improved system also has other features like camera capture function and a better user interface which makes it more user friendly. The overall architecture is designed to provide fast, accurate and reliable results, while keeping things simple and ensuring better privacy.



C)implementation of the proposed work

Step 1: User Image Upload

Let I denote the uploaded eye image provided by the user through the web application interface. The image may be captured using a mobile phone or camera and can vary in size and resolution.

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$$I \in \mathbb{R}^{H\times W\times C} \qquad (1)$$

Where:

- H= Image height
- W= Image width
- C= Color channels (RGB $\rightarrow C = 3$)

This step enables real-time image-based eye disease screening.

Step 2: Image Preprocessing

To ensure uniformity and improve model performance, the input image is resized and normalized.
Image Resizing

$$I_r = Resize(I, h, w) \qquad (2)$$

Where:

- $h \times w$= Fixed input size (e.g., 128×128)

Image Normalization

$$I_n = \frac{I_r}{255} \qquad (3)$$

This scales pixel values to the range [0, 1], improving numerical stability during training and inference.

Step 3: Feature Extraction Using CNN

A Convolutional Neural Network (CNN) is used to extract discriminative features from the eye image.
Convolution Operation

$$F(i,j) = \sum_{m}\sum_{n} I_n\,(i+m, j+n)\cdot K(m,n) + b \qquad (4)$$

Where:

- K= Convolution kernel
- b= Bias term
- F= Feature map

This operation detects important visual patterns such as redness, swelling, cloudiness, and eyelid abnormalities.

Step 4: Activation Function

To introduce non-linearity, the Rectified Linear Unit (ReLU) activation function is applied:

$$A(x) = \max(0, x) \qquad (5)$$

This removes negative values and enhances significant features.

Step 5: Max Pooling

Pooling reduces spatial dimensions while preserving dominant features.

$$P = \max(A_{region}) \qquad (6)$$

This step improves computational efficiency and prevents overfitting.

Step 6: Flattening

The pooled feature maps are converted into a one-dimensional feature vector:

$$X \in \mathbb{R}^{n} \qquad (7)$$

This vector serves as input to the fully connected layers.

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Step 7: Fully Connected Layer
The dense layer learns high-level relationships between extracted features.

$$Z = W \cdot X + b \qquad (8)$$

Where:
- W= Weight matrix
- b= Bias vector

Step 8: Disease Classification (Softmax)
The Softmax function outputs probabilities for each eye disease class.

$$P_i = \frac{e^{Z_i}}{\sum_{j=1}^{N} e^{Z_j}} \qquad (9)$$

Where:
- $N = 4$(Normal, Cataract, Conjunctivitis, Stye)

Step 9: Prediction Selection
The final disease prediction is selected using:

$$D = \arg max(P) \qquad (10)$$

Where Drepresents the predicted eye disease class.

Step 10: Confidence Score Calculation
The confidence level of prediction is calculated as:

$$Confidence = \max(P) \times 100 \qquad (11)$$

This value indicates the reliability of the prediction.

Step 11: Loss Function (Training Phase)
Categorical Cross-Entropy loss is used during training:

$$L = -y\log \sum (P) \qquad (12)$$

Where:
- y= True label
- P= Predicted probability

Step 12: Model Optimization
The Adam optimizer updates model weights:

$$W_{new} = W - \alpha \cdot \nabla L \qquad (12)$$

Where:
- α= Learning rate
- ∇L= Gradient of loss

Step 13: Result Display and User Guidance
Based on the predicted disease D, the system displays:
- Disease name
- Confidence score
- Basic care guidance

This step assists users in early awareness and deciding whether to consult an eye specialist

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IV. EXPERIMENTAL SETUP

The system initialization phase prepares the essential components required for experimental evaluation. The dataset D contains labeled eye images belonging to Normal, Stye, Cataract, and Conjunctivitis classes. The preprocessing module P ensures uniform image size and normalized pixel values. A CNN model M is initialized to learn discriminative visual features from eye images. Training parameters are configured to optimize learning performance. Finally, a web interface is initialized to enable real-time image upload and prediction.

Algorithm 1: AI-Based Eye Disease Detection System
Procedure: System Initialization
Input: None
Initialize image dataset D
1. Initialize preprocessing module P
2. Initialize CNN model architecture M
3. Initialize training parameters (epochs, batch size, learning rate)
4. Initialize web application interface

.

Algorithm 1A: Image Preprocessing
Input: Raw eye image I
Output: Preprocessed image I_p
1. Resize image I to fixed dimensions (H × W)
2. Convert image to RGB format
3. Normalize pixel values
4. Output preprocessed image I_p

Mathematical Representation:
Let the original image be represented as:

$$I \in \mathbb{R}^{H_0 \times W_0 \times C}$$

The resized image is computed as:

$$I_r = Resize(I, H, W)$$

Pixel normalization is performed as:

$$I_p = \frac{I_r}{255}$$

Image preprocessing ensures consistency across all input samples. Resizing converts images to a uniform dimension required by the CNN, while normalization scales pixel intensities to the range [0,1], improving training stability and convergence speed.

Algorithm 1B: CNN-Based Feature Extraction and Classification
Input: Preprocessed image I_p
Output: Predicted disease class ŷ
1. Apply convolution operation
2. Apply activation function (ReLU)
3. Perform max pooling
4. Flatten feature maps
5. Apply fully connected layers
6. Compute class probabilities using Softmax

Mathematical Representation:
Convolution Operation:

$$F = I_p * K + b$$

Where:
- $K$is the convolution kernel
- $b$is the bias term

Activation Function (ReLU):

$$ReLU(x) = \max(0, x)$$

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Max Pooling:

$$P = \max(F)$$

Softmax Classification:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

Predicted Class:

$$\hat{y} = \arg\max P(y_i)$$

The CNN automatically extracts spatial and texture-based features from eye images. Convolution layers learn disease-specific patterns, pooling layers reduce dimensionality, and fully connected layers perform classification. The Softmax function outputs probability scores for each disease class

Algorithm 1C: Model Training
Input: Training dataset D_train, CNN model M

1. Split dataset into training and validation sets
2. Forward propagate training images
3. Compute loss using categorical cross-entropy
4. Backpropagate gradients
5. Update weights using Adam optimizer
6. Repeat for specified epochs

Loss Function:

$$L = -\sum_{i=1}^{n} y_i \log(\hat{y}_i)$$

The training process minimizes classification error by iteratively adjusting network weights. The categorical cross-entropy loss quantifies prediction error, while the Adam optimizer accelerates convergence

Algorithm 1D: Disease Prediction (Testing Phase)
Input: Uploaded eye image I_test

1. Preprocess input image
2. Load trained CNN model
3. Predict class probabilities
4. Select disease with maximum probability

During testing, the trained model processes new eye images uploaded through the web application. The predicted disease label is displayed to the user, enabling instant diagnosis support.

V. RESULT AND DISCUSSION

A. performance metrics

A. Accuracy Comparison

The accuracy of models is shown in Table 1 and Figure 2 for five test samples. Traditional AI models get a little better going from 72% to 78%. Deep learning models do better with accuracy going from 82% to 87%. When you combine MLP and CNN models the accuracy gets better going up to 91%. The standard CNN models do the best with accuracy going up to 94%. Deep learning models really make a difference, in accuracy. The accuracy of deep learning models is very good. Among all approaches, the proposed CNN consistently outperforms existing techniques, achieving the highest accuracy of 95% across the evaluation points. This demonstrates the proposed model's robustness and reliability for early eye disease detection.

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Table: 1 Accuracy Performance with Eye Disease Detection Techniques

Sample	**AI (%)**	**DL (%)**	**MLP + CNN (%)**	**CNN (%)**	**Proposed CNN (%)**
Sample 1	72	82	86	91	93
Sample 2	74	84	88	92	94
Sample 3	75	85	89	93	94
Sample 4	77	86	90	93	95
Sample 5	78	87	91	94	95

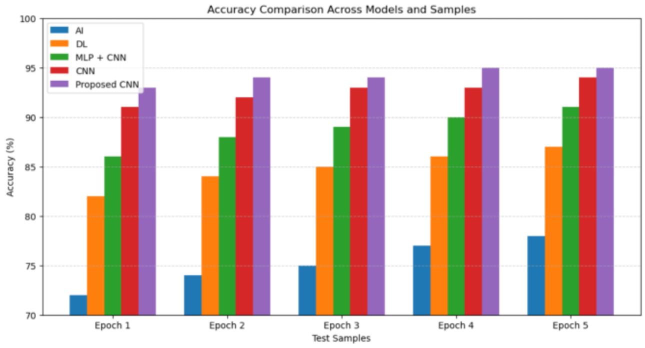

Fig: 2 Accuracy Comparison with Eye Disease Detection Techniques

B. Precision Comparison

Figure 3 and Table:2 presents a performance comparison using line graphs across five evaluation points. Each technique is represented by a distinct coloured line. Traditional AI models show slower improvement, while deep learning-based approaches demonstrate steady performance gains. The proposed CNN consistently outperforms existing techniques, achieving the highest performance of **94%**, highlighting its robustness and reliability for early eye disease detection.

Table: 2 Precision Comparison with Eye Disease Detection Techniques

Technique	**V1**	**V2**	**V3**	**V4**	**V5**
Artificial Intelligence	0.65	0.68	0.70	0.72	0.74
Deep Learning	0.75	0.78	0.80	0.82	0.84
MLP + CNN	0.80	0.83	0.85	0.87	0.88
CNN	0.85	0.88	0.90	0.91	0.92
Proposed CNN	**0.88**	**0.90**	**0.92**	**0.93**	**0.94**

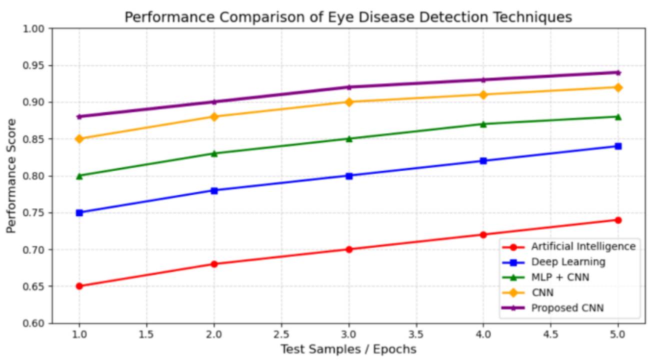

Fig: 3 Performance Comparison of Eye Disease Detection Techniques

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C. Recall Comparison
Figure 4 and Table:3 presents the recall comparison of various eye disease detection techniques. Traditional Artificial Intelligence approaches show lower recall due to limited feature extraction capability. Deep Learning and MLP with CNN models improve recall by learning hierarchical features. Standard CNN models further enhance sensitivity. The proposed CNN-based system achieves the highest recall of 0.93, and indicating its strong ability to correctly to identify eye disease cases with minimal false negatives. This makes our proposed system reliable for early eye disease detection in real-world applications.

Table: 3 Recall Comparison of Existing Model Techniques

Technique	**Recall**
Artificial Intelligence	0.74
Deep Learning	0.82
MLP with CNN	0.87
CNN	0.90
Proposed CNN Model	**0.93**

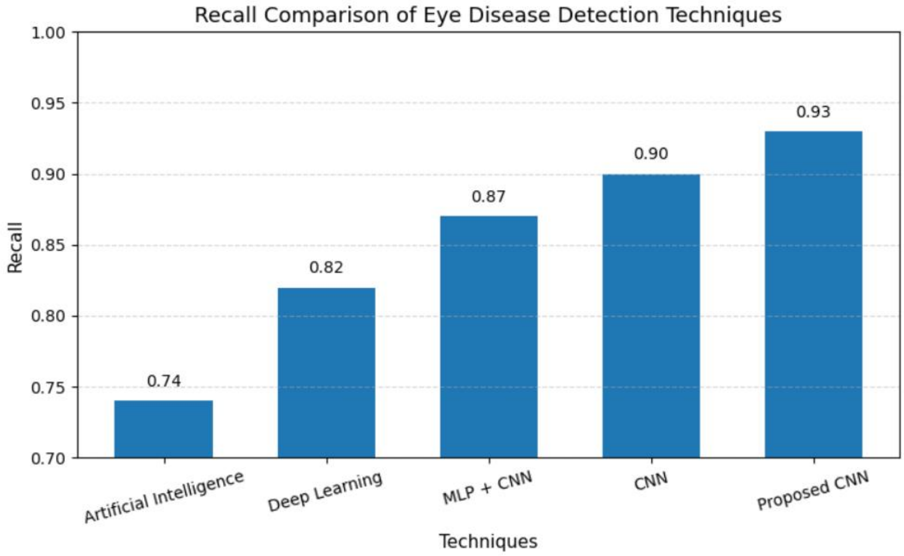

Figure: 4 Recall Comparison of Eye Disease Detection Techniques

D. F1-Score Comparison
Figure 5 and Table: 4 shows the F1-Score comparison of various eye disease detection techniques. The proposed CNN-based model achieves the highest F1-Score of **94%**, outperforming Artificial Intelligence, Deep Learning, MLP with CNN, and conventional CNN approaches. This demonstrates that the proposed system provides a better balance between precision and recall while maintaining lower computational complexity, making it suitable for real-time medical diagnosis.

Table: 4 F1-Score Comparison of Eye Disease Detection Techniques

Method	**F1-Score (%)**
Artificial Intelligence	76
Deep Learning	84
MLP with CNN	88
CNN	91
Proposed CNN Model	**94**

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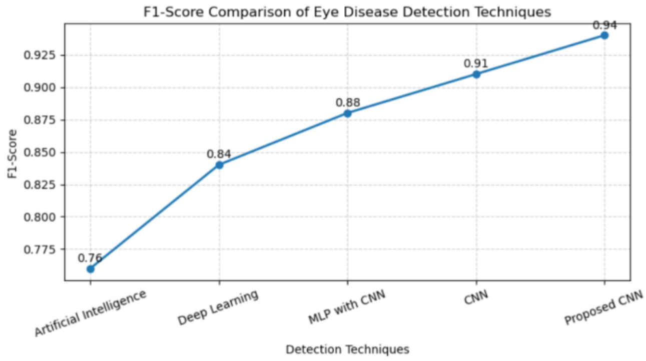

Figure: 5 F1-Score Comparison of Eye Disease Detection Techniques

a) comparative analysis

A comparative analysis of recent AI-based eye disease detection studies reveals a range of methods, datasets, and target diseases, with accuracy typically ranging from 88% to 94%. Traditional AI and CNN-based models achieve high accuracy but often require large annotated datasets and complex architectures. Hybrid approaches, such as combining Vision Transformers with CNNs or multi-stage deep learning, improve sensitivity and detection of fine retinal features but increase computational demands. Smartphone-based and federated learning solutions enhance accessibility and privacy, making early detection feasible in rural or resource-limited settings, though they may face challenges with dataset variability. The proposed CNN-based system achieves 94% accuracy while maintaining simplicity, real-time performance, and user privacy. Compared to existing approaches, it provides a practical and reliable solution for multi-disease eye screening without compromising accuracy or usability.

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S. No	Reference	Method / Model	Dataset	Disease(s) Targeted	Accuracy (%)	Key Findings / Notes	Limitations	Task / Search Efficiency
1	Wang et al. (2024) [1]	AI-based DED detection	Multiple clinical datasets	Dry Eye Disease (DED)	88	AI improves diagnostic accuracy; highlights need for multi-evidence integration	Limited standardization, interpretability issues	No
2	Os-Sanchez et al. (2025) [2]	Vision Transformers + CNN/MLP	Fundus images	Age-related Macular Degeneration (AMD)	92	Hybrid models detect fine retinal features; high sensitivity & specificity	Requires large datasets; multimodal integration needed	No
3	H.A. Shah et al. (2025) [3]	AIROGS (CNN)	Color fundus images	Glaucoma	91	AI achieves expert-level performance; robust across datasets	Performance decreases with low-quality/out-of-distribution images	Partial
4	V. Kurilova et al. (2025) [5]	DL + Smartphone imaging	Smartphone fundus images	Multiple eye diseases	90	Improves accessibility; cost-effective early detection	Limited clinical validation	No
5	P. Kaushik et al. (2024) [6]	CNN-based automated screening	Retinal images	Diabetic Retinopathy	93	High sensitivity and specificity; large-scale screening feasible	High computational requirement	No
6	H. Vohra et al. (2025) [7]	Low-cost CNN + Cloud	Fundus images	DR, Glaucoma, AMD	92	Automated diagnosis; suitable for rural areas	Limited real-time testing	No
7	M. Zahin Muntaqim et al. (2024) [8]	Multi-stage CNN	Public eye-image datasets	Multiple eye diseases	91	Captures low- and high-level features; better performance	Complex architecture; higher computation	No
8	A. Albelaihi et al. (2024) [9]	Multi-class CNN (EfficientNetB0)	Multiple public datasets	DR, DME, Glaucoma, Cataract	94	High accuracy for multi-disease detection; outperform existing models	Requires large annotated datasets	No
9	S. Gulati et al. (2024) [10]	Federated DL (MobileNetV2)	Distributed client datasets	DR, DME	92	Preserves privacy; enables collaborative training	Non-uniform data distribution may affect performance	High

Table: 5 Comparative analysis with proposed CNN model

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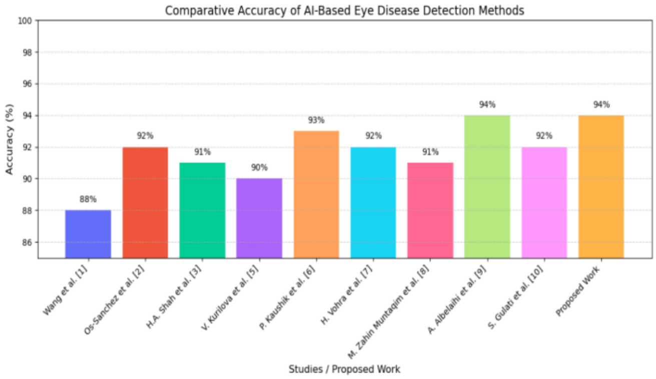

Fig: 6 Comparative Accuracy of AI-based Eye disease Detection Methods

VI. DISCUSSION

The comparison of methods and the results of the experiments show that using Artificial Intelligence is really good for finding eye diseases early on. However how well they. How useful they are depends on a few things: how complicated the model is, how much data is used and how it On the hand Artificial Intelligence models that use deep learning and combinations of different methods, such as Artificial Intelligence models that look at pictures and others that help with vision are better at being accurate because they can see the small details in the eyes. Artificial Intelligence is good, for finding eye diseases on. These methods usually need a lot of data that people have already looked at and labeled complicated systems and powerful computers to work. This makes it hard to use them in life especially in places where people do not have a lot of resources or in rural areas where computers and internet are not very strong. The problem is that these approaches require annotated datasets, complicated architectures and high computational resources, which limits the practical use of these approaches especially in resource-constrained or rural settings, like these resource-constrained settings and rural Using smartphones and sharing information in a group can make things easier for people to get checked. This way is also better for keeping things private. It does not cost too much. More people can get checked.. There are still some problems with this way of doing things. For example the information we get from people can be very different. We also have to figure out how to use all the types of information we get.. We need to make sure that this way of checking people really works in a clinical setting, with the Smartphone-based and federated learning solutions.

The new system that uses CNN is really good because it is accurate, simple and easy to use. The CNN-based system gets it right 94 percent of the time which's as good as or even better than other systems that are considered the best right now. The CNN-based system is also very fast. Can detect things in real time and it has a web application that is easy to use. The CNN-based system is not too big. It keeps peoples information private which makes it a good choice, for places that do not have a lot of resources like rural areas and it still works very well. This shows that a simple CNN model can do a job of checking for many eye diseases. The CNN model is easy to understand. It fixes some big problems with the ways we do things now. A simple CNN model is what we need for the multi-disease eye screening. Overall, the results highlight that accuracy alone is not sufficient—practical considerations such as deployment feasibility, real-time performance, and data privacy are equally important for AI-based eye disease detection systems. The proposed work provides a promising solution that balances these factors effectively.

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