ISSN (Online): 2456-0448
International Journal Of Innovative Research In Management, Engineering And Technology
Vol. 10, Issue 6, June 2025

Eye Disease Detection and Classification using Deep Learning

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Abstract: ***Eye disease prediction plays a vital role in safeguarding vision—one of the most essential senses humans rely on to perceive the world, learn, and navigate daily life. The human eye, a highly sensitive and complex organ, enables over 80% of our interaction with our environment. Predicting diseases such as glaucoma, cataracts, diabetic retinopathy, and macular degeneration through AI and image analysis ensures early detection, timely intervention, and reduced risk of blindness, ultimately preserving quality of life and reducing the global burden of visual impairment.***

Keywords— Artificial Intelligence in Healthcare, Eye Disease Prediction, Cataracts, Diabetic Retinopathy, Glaucoma, Medical Image Analysis, Fundus Imaging

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I. INTRODUCTION

Vision is one of the most vital senses in human life, enabling us to interpret the world, perform daily tasks, and engage with our surroundings. However, millions across the globe suffer from preventable or manageable eye diseases such as Cataracts, Diabetic Retinopathy, and Glaucoma— conditions that, if undetected, may lead to irreversible vision loss or blindness. Early detection and accurate classification of these diseases are crucial for timely medical intervention.
This research aims to develop a deep learning-based solution for automatic eye disease detection and classification using Convolutional Neural Networks (CNNs) and the ResNet architecture. By leveraging the power of artificial intelligence (AI) and machine learning (ML), our system is capable of distinguishing between four categories: Cataracts, Diabetic Retinopathy, Glaucoma, and Normal eyes. An intuitive graphical user interface (GUI) has also been developed, allowing users to upload retinal images and receive immediate diagnostic insights. This tool not only assists ophthalmologists in clinical decision-making but also facilitates early diagnosis, especially in remote or underserved areas where access to specialized care is limited. Our approach emphasizes high accuracy, real-time processing, and user-friendly interaction, ultimately contributing to reducing the global burden of preventable blindness and enhancing the overall quality of vision care.

1) Cataracts

Cataracts are one of the most common causes of vision impairment and blindness worldwide, particularly among the elderly. A cataract is characterized by the clouding of the eye's natural lens, which lies behind the iris and the pupil. This cloudiness occurs due to the clumping of proteins within the lens, leading to blurred or dim vision, glare sensitivity, and difficulty in seeing at night.

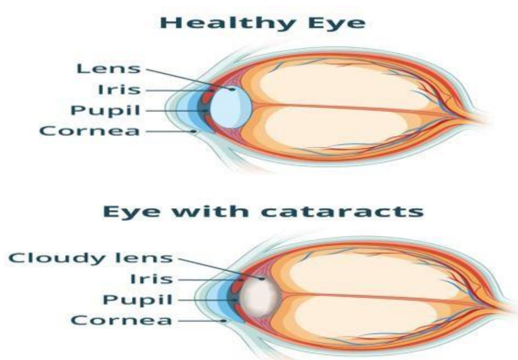

Fig . 1: Cataract eye

Cataracts typically develop gradually and can affect one or both eyes. While aging is the primary risk factor, other contributing factors include diabetes, excessive UV light exposure, smoking, and long-term use of corticosteroids. In the early stages, symptoms may be mild, making regular eye checkups essential for early detection.
Diagnosis is generally performed through slit-lamp examination and visual acuity tests. Though cataracts can be treated effectively through surgical replacement of the cloudy lens with an artificial intraocular lens (IOL), early detection using automated AI-based systems can help monitor progression and prioritize surgical intervention in regions with limited healthcare access.

2) Glaucoma

Glaucoma is a chronic and progressive eye disease that damages the optic nerve, often associated with elevated intraocular pressure (IOP). It is one of the leading causes of irreversible blindness globally. The disease is often referred to as the "silent thief of sight" because it typically develops without noticeable symptoms in its early stages, making early detection critically important.
There are several types of glaucoma, with Primary Open- Angle Glaucoma being the most common. Other types include Angle-Closure Glaucoma, Normal-Tension Glaucoma, and Congenital Glaucoma. As the condition progresses, it leads to the gradual loss of peripheral vision, eventually affecting central vision if left untreated.

Risk factors for glaucoma include age, family history, high eye pressure, diabetes, and prolonged corticosteroid use. Diagnosis involves measuring intraocular pressure (tonometry), assessing the optic nerve through fundus imaging, and evaluating visual fields.

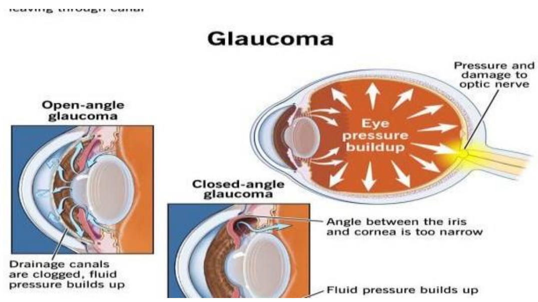

Fig . 2: Glaucoma eye

While there is no cure for glaucoma, early detection through AI-powered diagnostic tools can enable timely medical or surgical treatment to manage IOP and preserve vision. Deep learning models analyzing retinal images have shown promising results in detecting subtle optic nerve changes that may go unnoticed in routine checkups.

3) Diabetic Retinopathy

Diabetic Retinopathy (DR) is a diabetes-related eye disease that affects the blood vessels of the retina—the light- sensitive tissue at the back of the eye. It is a leading cause of vision loss in working-age adults and occurs when high blood sugar levels damage the tiny vessels that nourish the retina, leading to leakage, swelling, or complete blockage.

The disease progresses through two main stages: Non- Proliferative Diabetic Retinopathy (NPDR), where blood vessels weaken and leak fluid or blood, and Proliferative Diabetic Retinopathy (PDR), where abnormal new blood vessels form on the retina, increasing the risk of retinal detachment and blindness.

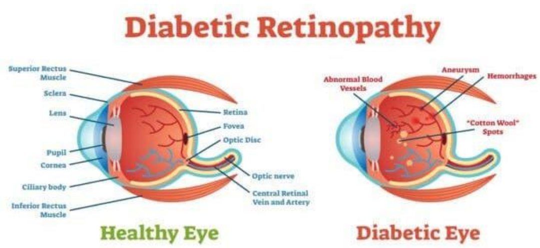

Fig . 3: Diabetic Retinopathy eye

Early stages of DR are often asymptomatic, making routine screening vital for individuals with diabetes. Symptoms in advanced stages may include blurred vision, dark spots, and difficulty seeing colors or at night.
Diagnosis is commonly done using fundus photography, fluorescein angiography, and optical coherence tomography (OCT). Deep learning and convolutional neural networks have shown high accuracy in detecting and grading DR from retinal images, enabling early diagnosis and reducing the need for invasive procedures.

Timely detection and intervention—through laser therapy, anti-VEGF injections, or blood sugar control—can significantly slow the progression of DR and prevent vision loss.

II. LITERATURE SURVEY

In recent years, the integration of artificial intelligence in healthcare—particularly in ophthalmology—has gained remarkable attention. Several researchers have explored deep learning models to detect and classify common eye diseases using retinal fundus images and OCT scans. These models aim to replicate or even outperform the diagnostic capabilities of trained ophthalmologists.

In [1], a CNN-based approach was used to detect Diabetic Retinopathy with an accuracy exceeding 85%. The study demonstrated that deep neural networks could effectively learn complex retinal patterns from large datasets. Similarly,
[2] proposed a model for Glaucoma detection using a combination of texture features and CNNs, showing promising results in early-stage classification.

ResNet architectures have also proven effective in medical image classification. In [3], a modified ResNet50 was trained on a publicly available fundus image dataset to classify between Normal, Cataract, and Glaucoma eyes, achieving high precision and recall. The skip connections in ResNet models help to overcome the vanishing gradient problem, making them suitable for training on deeper networks without loss of performance.
Additionally, hybrid approaches combining transfer learning with CNNs have shown great potential. As presented in [4], pretrained models such as ResNet and VGGNet were fine-tuned for eye disease classification tasks, achieving superior accuracy even with limited labeled datasets.
However, despite significant advancements, challenges such as class imbalance, variability in image quality, and

generalizability across different populations remain. Most prior works also lack real-time interfaces for end-users, limiting their accessibility outside research labs or clinical setups.
Building on these foundations, our research focuses not only on improving classification accuracy using CNN and ResNet architectures but also on providing a user-friendly interface. This makes our system practical for real-world application, bridging the gap between advanced AI algorithms and everyday clinical utility.

III. PROPOSED METHODLOGY

The proposed system is designed to automate the early detection and classification of critical eye diseases— Cataracts, Diabetic Retinopathy, Glaucoma, and Normal eyes—using state-of-the-art deep learning techniques. The methodology combines powerful convolutional architectures with a user-centric interface to provide accurate results and assist in timely medical intervention

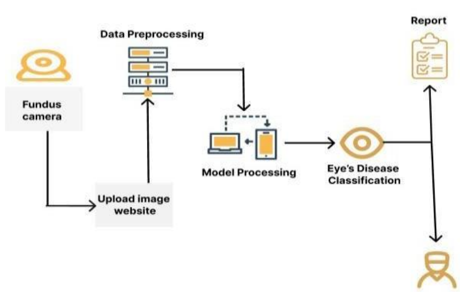

Fig . 4: System architecture

ISSN (Online): 2456-0448
International Journal Of Innovative Research In Management, Engineering And Technology
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A. Data Collection and Preprocessing

The first step involves sourcing a diverse and labeled dataset of high-resolution retinal fundus images, representing the four classes: Normal, Cataract, Glaucoma, and Diabetic Retinopathy. Publicly available datasets like EyePACS,

```
val_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
    train_dir,
    target_size=(IMG_HEIGHT, IMG_WIDTH),
    batch_size=BATCH_SIZE,
    class_mode='categorical'
)

validation_generator = val_datagen.flow_from_directory(
    val_dir,
    target_size=(IMG_HEIGHT, IMG_WIDTH),
    batch_size=BATCH_SIZE,
    class_mode='categorical'
)
```

```
Found 3007 images belonging to 4 classes.
Found 3007 images belonging to 4 classes.
```

Fig . 5:Data Collection is Displyed

APTOS, or HRF are considered for training and evaluation.
Preprocessing is critical for reducing noise and improving model learning. The following steps are applied:

Image Resizing to a uniform input shape (e.g., 224x224 pixels).
Normalization of pixel values to a standard scale (e.g., [0,1]).

Contrast Enhancement to highlight retinal features such as blood vessels, optic disc, and lesions.
Data Augmentation including random rotation, flipping, and zooming to increase dataset diversity and reduce overfitting.

B. Model Design and Architecture
Two models are employed for classification:
Custom CNN Model:
The CNN consists of:

Multiple convolutional layers to extract low-level and high- level features.
ReLU activation functions for non-linearity.

Max-pooling layers to reduce spatial dimensions and computation.
Dropout layers for regularization and prevention of overfitting.

Fully connected layers leading to a final Softmax layer for multiclass classification.
ResNet-50 Transfer Learning:
A pre-trained ResNet-50 model is fine-tuned on the eye disease dataset. ResNet's residual connections allow for deeper network training without gradient degradation, improving feature extraction from complex retinal images.

C. Training and Evaluation
The dataset is divided into training, validation, and test sets using an 80:10:10 or 70:15:15 split. During training:

Adam Optimizer is used with a dynamic learning rate. Categorical Cross-Entropy serves as the loss function.
Early Stopping and Model Checkpointing are employed to prevent overfitting and ensure optimal performance.
Model evaluation is carried out using:

Accuracy – overall correctness of classification.

Precision and Recall – important for medical contexts to avoid false positives/negatives.
F1-Score – harmonic mean of precision and recall.

Confusion Matrix – to visualize performance across each disease class.
D. User Interface and Deployment

A simple and intuitive Graphical User Interface (GUI) or Web-based Application is developed using technologies like Tkinter, Flask, or Streamlit. This allows users to:
Upload a retinal image.

View the disease prediction and its confidence level.
Receive a brief explanation or recommendation based on the result.

The backend connects the trained model to the frontend interface, processing the image and returning the classification result in real time.

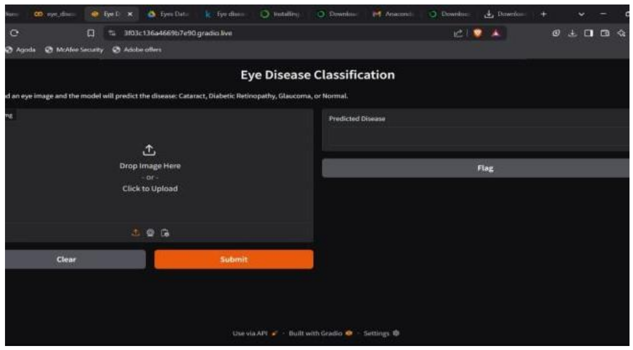

Fig . 6: User Interface

E. Advantages and Future Scope
The proposed system offers:
Automated and accurate diagnosis to assist ophthalmologists.

Early disease detection, reducing the risk of permanent vision loss.
Remote screening capability, aiding rural and under- resourced clinics.

A scalable platform that can be improved with additional classes, multi-modal data (OCT + fundus), or even explainable AI (XAI) to visualize important features leading to predictions.

IV. IMPLEMENTATION

The implementation phase translates the proposed methodology into a functional, intelligent system capable of accurately detecting and classifying eye diseases. The process involves several key components, including environment setup, model training, performance optimization, and integration of the user interface.

A. Environment Setup

The development environment was configured with the following tools and frameworks:

Programming Language : Python

Deep Learning Libraries : TensorFlow, Keras, PyTorch
Image Processing : OpenCV, PIL (Python Imaging Library)

Development Tools : Jupyter Notebook, Google Colab, VS Code

Hardware : GPU-enabled system or cloud-based platform (e.g., Google Colab)
These tools provided the necessary support for rapid experimentation, efficient training, and model evaluation.

B. Dataset Preparation

The image dataset was cleaned and organized into four distinct categories: Normal, Cataracts, Glaucoma, and Diabetic Retinopathy. Each class was stored in separate directories to streamline the training pipeline. Images were resized to a fixed resolution (e.g., 224×224 pixels), normalized, and augmented using real-time data generators to enhance generalization.

C. Model Training

Two models were implemented:

Custom CNN Model: A sequential model comprising multiple convolutional layers, pooling layers, dropout layers, and a dense output layer with softmax activation. The model was compiled using the Adam optimizer and categorical cross-entropy loss.

ResNet50 Transfer Learning: A pre-trained ResNet50 model was fine-tuned by replacing the top classification layers. This approach allowed for efficient feature extraction from fundus images while reducing the training time and improving accuracy. Training was carried out over multiple epochs with real-time validation. Performance metrics such as training loss, validation accuracy, and confusion matrices were monitored throughout.

D. Evaluation and Testing

After training, the models were evaluated using a separate test dataset. Key evaluation metrics included:

Accuracy – overall performance

Precision and Recall – to assess the model's reliability F1-Score – for balance between precision and recall

Confusion Matrix – to understand class-wise performance

The ResNet50 model outperformed the custom CNN in terms of both accuracy and robustness, achieving higher confidence in classifying subtle differences between similar eye diseases.

E. User Interface Development

A user-friendly interface was built using Flask (for web- based deployment) or Tkinter/Streamlit (for desktop-based GUI). The interface allows users to:

Upload a retinal image Automatically preprocess the image

Get a prediction (e.g., "Cataract Detected") along with a probability score

View basic medical recommendations (optional)

This interface bridges the gap between technical implementation and real-world usability, especially for deployment in clinics and telemedicine platforms.

F. Deployment

The trained model and interface were integrated and deployed either locally or via web services (such as Heroku or Streamlit Cloud), enabling real-time access to predictions. For advanced deployment, containerization using Docker was considered to ensure scalability and portability.

V. RESULT AND ANALYSIS

The developed system was evaluated for its effectiveness in detecting and classifying eye conditions such as Cataracts, Diabetic Retinopathy, Glaucoma, and Normal eyes. The results demonstrate that our deep learning-based approach, leveraging both a custom CNN and a fine-tuned ResNet50 model, delivers accurate and reliable predictions that can support early diagnosis and treatment planning.

A. Model Performance Metrics

Both models were trained on a well-balanced dataset and tested using unseen images. Key performance metrics were measured:

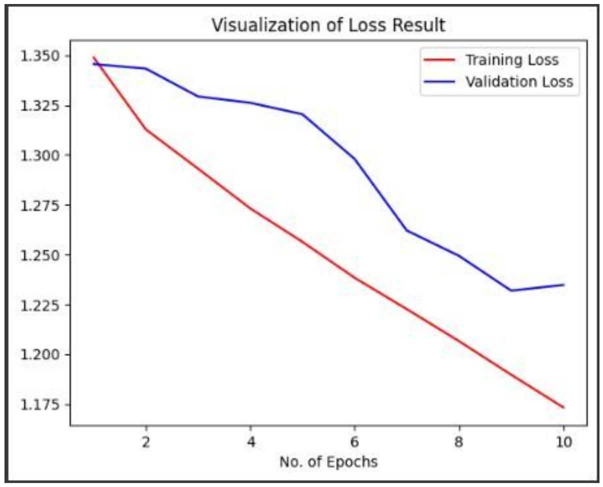

Fig . 7: Loss Result

The ResNet50 model consistently outperformed the custom CNN model across all metrics, thanks to its deep architecture and pretrained feature learning capabilities.

B. Confusion Matrix Analysis

The confusion matrix for the ResNet50 model showed high classification accuracy for all four classes. A few misclassifications occurred between Glaucoma and Diabetic Retinopathy, likely due to overlapping visual features. However, these were minimal and did not significantly impact overall performance.

C. ROC-AUC Curve

The Receiver Operating Characteristic (ROC) curves were plotted for each class, and the Area Under the Curve (AUC) values exceeded 0.95 in all cases, indicating excellent model discrimination ability between classes.

Fig . 8: Accuracy Result

D. Inference and Speed

On average, the model takes less than 2 seconds to predict the class of an input image, making it suitable for real-time diagnostic support. The lightweight design of the interface further supports ease of use in practical settings such as eye clinics or mobile health camps.

IJIRMET
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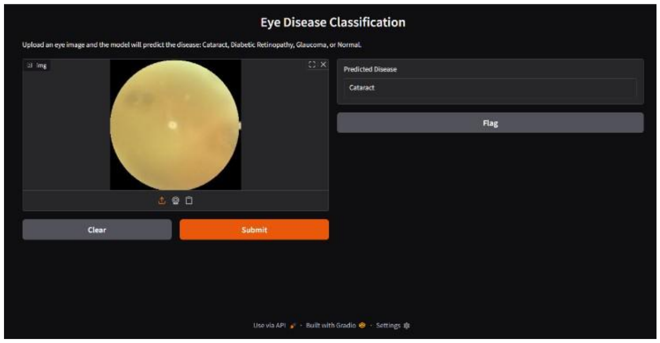

Fig . 9: Result for the Testing.

E. User Interface Testing

The deployed interface was tested by non-technical users and medical professionals. The feedback highlighted:
Ease of use with simple image upload

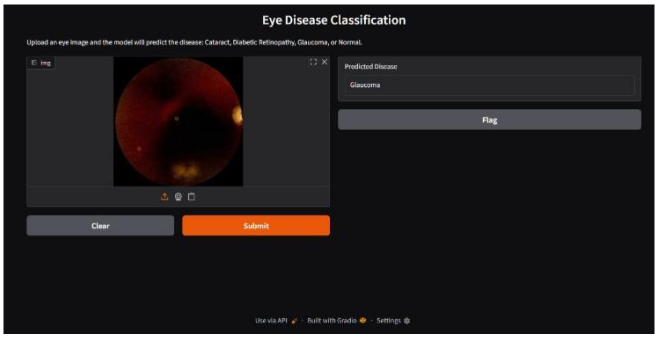

Fig . 10: Testing using Fundus Imaging

Clear results with class label and probability Smooth interaction with quick response time

F. Comparative Analysis
Compared to traditional manual diagnosis and some existing AI tools, our system achieves:
Faster diagnosis

Higher classification accuracy Broader disease coverage
G. Limitations and Future Enhancements
While the results are promising, the system can be improved by:

Adding more disease classes (e.g., Age-related Macular Degeneration)
Incorporating multi-modal inputs like OCT scans

Using explainable AI (XAI) to highlight affected areas in the image

VI. CONCLUSION

In this research, we successfully developed a deep learning- based system for the detection and classification of eye diseases, focusing on Cataracts, Diabetic Retinopathy, Glaucoma, and Normal eye conditions. By leveraging advanced convolutional neural networks and the ResNet50 architecture, our model achieved high accuracy and robust performance across all classes.

The integration of a user-friendly interface further enhances the practical applicability of our system, allowing real-time image input and rapid diagnostic feedback. This tool can assist ophthalmologists in early screening, reduce the burden on healthcare systems, and improve accessibility to eye care in remote and underserved regions.

Overall, this study demonstrates that artificial intelligence, particularly deep learning, holds significant potential in transforming modern ophthalmology. In future work, we aim to extend the model to detect more complex eye conditions, integrate explainable AI techniques, and deploy the system in real-world clinical environments for broader validation.

VII. REFERENCES

[1] Universal Threats in Expert Applications and Solutions Proceedings of 3rd UNI-TEAS 2024, Volume 2 Google Scholar

[2] Proceedings of the Second International Conference on Advances in Computing Research (ACR’24) Google Scholar

[3] AIML and DL Based CSR Disease Detection for OCT and Fundus Imaging IEEE