Deep Learning -Based System for Early Detection of Ocular Diseases

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***Abstract*— The Ocular Disease Detection project aims to automate the diagnosis of various eye diseases from fundus images using deep learning techniques. The project leverages the dataset, which includes fundus images of patients diagnosed with conditions such as Diabetic Retinopathy, Glaucoma, Cataract, and others. The project utilizes ResNet50 architecture for classification. The system is trained to classify the images based on the presence of diseases, improving its accuracy over multiple epochs. Evaluation parameters like training accuracy, training loss, validation accuracy, and validation loss are used to assess the model's performance. By the end of the project, the trained model can predict ocular diseases from fundus images, providing an automated solution for faster and more reliable diagnoses.**

Keywords - Automated diagnosis, Convolutional Neural networks (CNN), Eye health monitoring, Neural network classification, Ophthalmology AI, Retinal image processing, Image-based disease detection, Vision diagnosis system.

I. INTRODUCTION

Ocular diseases such as glaucoma, diabetic retinopathy, cataracts, and age-related macular degeneration are leading causes of visual impairment and blindness worldwide. Early diagnosis and timely treatment are crucial in preventing severe vision loss. However, traditional diagnostic procedures often require specialized equipment and expert ophthalmologists, making timely access to care difficult, especially in rural or under-resourced areas. recent advancements in artificial intelligence, particularly in deep learning, have opened new possibilities in the field of medical image analysis. Deep learning models, especially convolutional neural networks (CNNs), have demonstrated remarkable success in identifying complex patterns within medical images, including retinal scans and fundus photographs. By leveraging large datasets of labelled ocular images, these models can be trained to automatically detect and classify various eye conditions with high accuracy. This project aims to develop a deep learning-based system for the automated detection of ocular diseases. The goal is to support ophthalmologists in early screening, reduce diagnostic errors, and enhance the efficiency of eye care services. Integrating such AI tools into healthcare systems can help bridge the gap between patient needs and specialist availability, ultimately contributing to the early detection and better management of eye diseases.

II. LITERATURE REVIEW

Ocular diseases remain a major public health concern worldwide, contributing significantly to vision impairment and blindness. Numerous studies have explored their prevalence, diagnosis, and the integration of advanced technologies like deep learning for early detection. Elloumi et al. [1] emphasized the use of deep learning algorithms in analyzing fundus images for ocular disease detection. Their work highlights various neural network architectures and evaluates their performance in diagnosing conditions such as diabetic retinopathy and glaucoma. The study demonstrates that deep learning not only improves diagnostic accuracy but also supports real-time image processing in clinical settings. Northwest Hills Eye Care [2] provides an overview of common ocular conditions including glaucoma, cataracts, and macular degeneration. Their insights help in understanding the symptoms, risk factors, and the importance of early intervention in preserving vision. WebMD also presents detailed information about common eye problems, stressing the significance of early diagnosis and regular eye checkups [3]. This foundational knowledge helps in identifying which diseases are most suitable for AI-based detection. Several epidemiological studies contribute to the understanding of ocular disease distribution across different regions. Adio et al. [4] conducted a survey in a Nigerian hospital, highlighting pediatric eye conditions and the need for better diagnostic tools in developing countries. Similarly, studies from Vietnam [5], Sri Lanka [6], and Iran [7] by various researchers provide statistical data on visual impairments, identifying uncorrected refractive errors and cataracts as major causes of blindness. The World Health Organization (WHO) has also reported on the global burden of vision loss, indicating that many cases are preventable or treatable with early intervention. Their reports serve as a call to action for adopting technology-driven healthcare solutions [8] The Global Burden of Disease (GBD) Study [9] analyzed trends in blindness and visual impairment over three decades. The study underlines how socio-economic factors and access to medical care influence ocular health outcomes. This reinforces the need for scalable and automated diagnostic solutions like deep learning. Bourne et al. [10] further support these findings with data from Bangladesh, showing a high prevalence of uncorrected refractive errors in adults. Their research highlights the gap in access to basic eye care services, which automated detection systems could help bridge. Together, these studies underscore the urgent need for intelligent, accessible, and accurate diagnostic tools. Deep learning models have shown promising results in filling this gap by enabling early detection, supporting clinical decision-making, and ultimately reducing the global burden of preventable blindness.

III. METHODOLOGY

A) SYSTEM ARCHITECTURE

We propose a deep learning-based automated system for ocular disease detection. Using CNNs, transfer learning, and medical image datasets, we aim to enhance accuracy and efficiency in diagnosis. the dataset was balanced by using the same amount of data for each class in this paper, and the classes were trained using the pretrained Res Net 50 architecture. We began by loading the dataset and corresponding images into the model, using the same number of images for both classes. The transfer learning method was used in this work for the VGG-19 model. The accuracy of the individual classes improved after we properly balanced the dataset. The work attempted to identify the correct class after training.

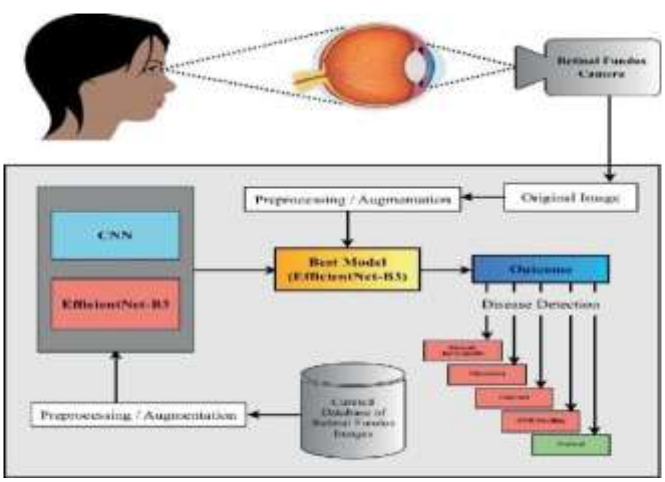

Fig 1: System architecture

Dataset:

ODIR (Ocular Disease Intelligent Recognition) is the dataset [42] used in this study. This dataset is one of the most comprehensive resources available to the public on Kaggle for detecting eye diseases. The fundus images in this dataset are divided into eight categories of ocular disease classification. These categories include seven disease classes, that is, normal (N), myopia (M), hypertension (H), diabetes (D), cataract (C), glaucoma (G), age-related macular degeneration (A), and other abnormalities/diseases (O). This dataset contains 5000 colour fundus photographs, which are divided into training and testing subsets. A little more than 3500 cases are used for training and the rest for testing. For this work, all images were resized to 224 × 224. Detailed information regarding image distributions for the ODIR.

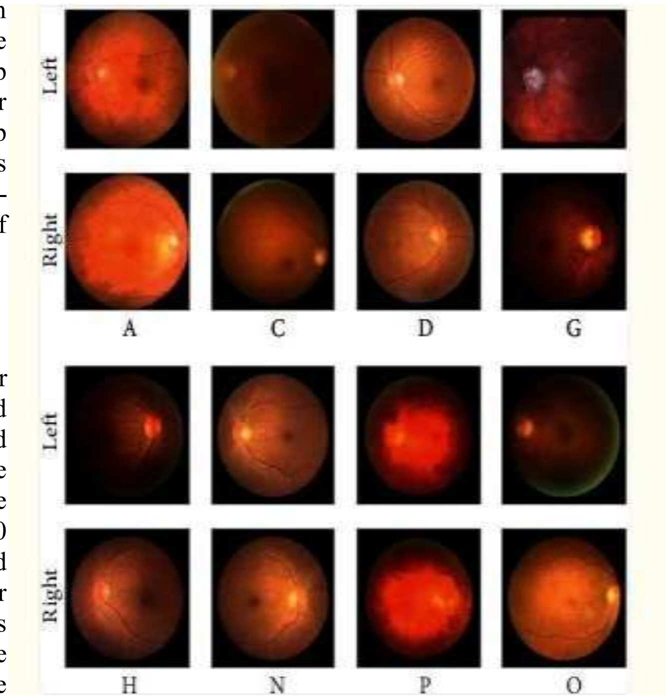

Fig 2: eye Dataset

Convolutional Neural Network:

The convolutional neural network shows exceptional performance in image classification [43] and object recognition [44] applications. CNNs (convolutional neural networks) are one of the machine-learning methods for developing Multilayer Perceptron (MLPs) designed to process two-dimensional data. CNNs are deep neural networks because they have multiple ways of combining image data in a network, which makes them a type of deep neural network. In CNNs, convolution is used as the basis for the algorithm. The CNN algorithm has multiple layers: convolution operations, activation layers, pooling layers, and flattening layers.

$$\text{Convolution Operation,}$$
$$C(i,j) = (I*K)(i,j) = \sum m \sum n \times I(m,n) K(i-m, j-n),$$
$$\text{Activation Layer, Sigmoid } S(x) = \frac{1}{1+e^{-x}}.$$

Transfer Model:

The transfer learning [19] technique refers to the use of a model created for one task as the basis for a model for another task. Deep learning models can be developed and implemented more effectively using transfer learning. Due to deep learning's increasing importance in tackling a wide variety of issues in fields such as computer vision (CV), we should expect to see more components of transfer learning. Transfer learning is only effective when the first model's characteristics learned on its first task are generalized and transferable to the second task. In this work, we used the pretrained Res Net model.

Deep neural networks have aided in a number of breakthroughs in image classification. Many other visual recognition tasks have benefited from these advanced models as well. Therefore, as time passes, we tend to deepen and solve more challenging tasks and improve our accuracy. As we progress deeper into neural networks, however, training gets harder and accuracy degrades as well. By implementing ResNet50, these issues are being addressed. ResNet50 is a CNN-based model that uses 3 × 3 filters with a single stride and always employs the same padding and max pooling layers of 2 × 2 filters with a stride of 2, instead of having a huge number of hyperparameters.

In the architecture, the convolution and max pooling layers are organized in a similar manner. There are two FC layers in the model. There are more than 138 million trainable parameters in this ResNet50network, which is a large network. After the classification layer, which included a densely connected classifier and a dropout layer, a series of convolutional layers were applied (conv1, conv2, conv3, conv4, and conv5). Each neuron in a dense layer is connected to all the neurons in the preceding layer. Compared with a convolutional layer, a densely connected layer learns from the previous layer's features. How the densely connected layer is activated must be specified.

B) IMPLEMENTATION

The model is configured to use the Adam optimizer and a binary cross-entropy loss function. Additionally, the sigmoid activation function is used. All experiments were carried out on Google Collab. After we had selected those parameters, we ran the model through 20 iterations on the training data. Finally, we evaluated the model on the test set.

Pre-processing

Reduce noise and enhance image contrast for clarity

Training

Tune hyperparameters; use loss functions like categorical cross-entropy. Optimal with Adam or SGD optimizers.

Evaluation

Assess using accuracy, precision, recall, F1-score, AUC-ROC metrics.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

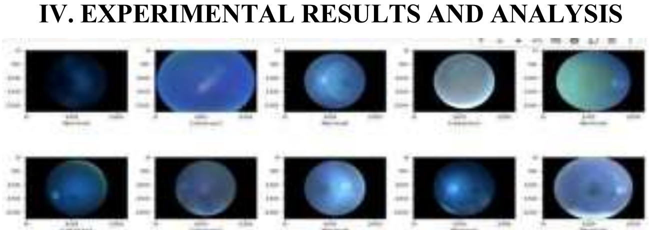

Fig 3: Vgg16 model for detecting images

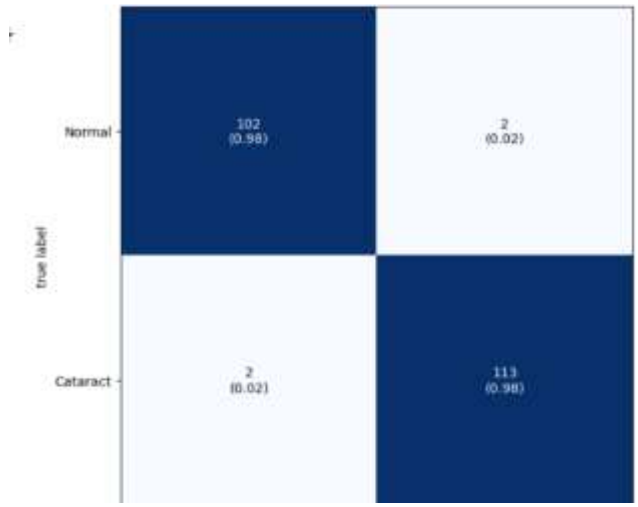

Fig 4: Classification model

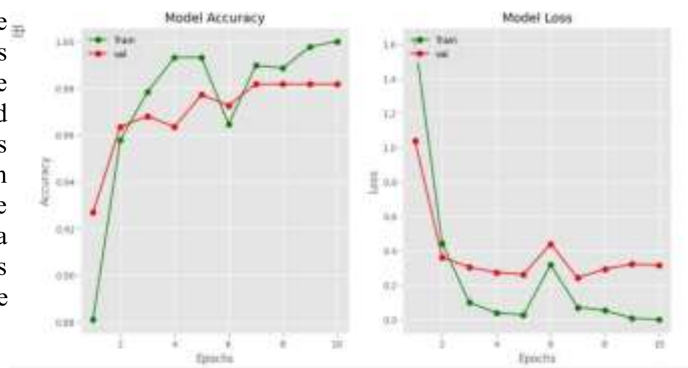

Fig 5: Model Accuracy and Loss

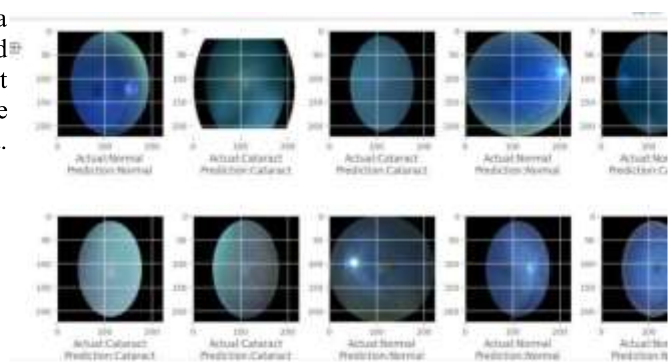

Fig 6: ResNet model for detecting images

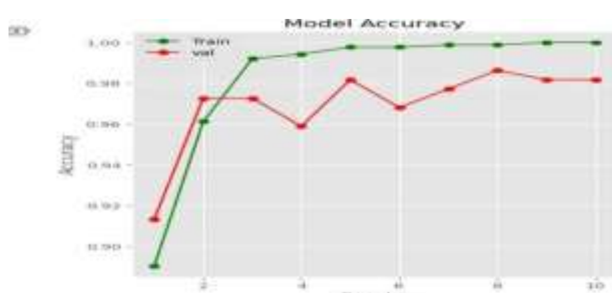

Fig 7: Model Accuracy

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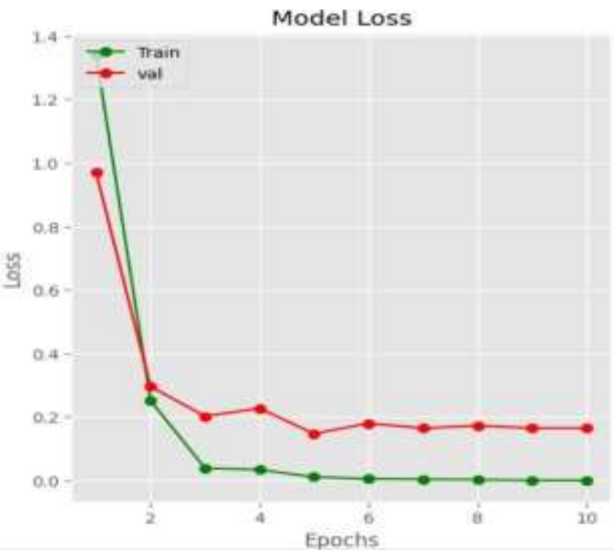

Fig 8: Model Loss

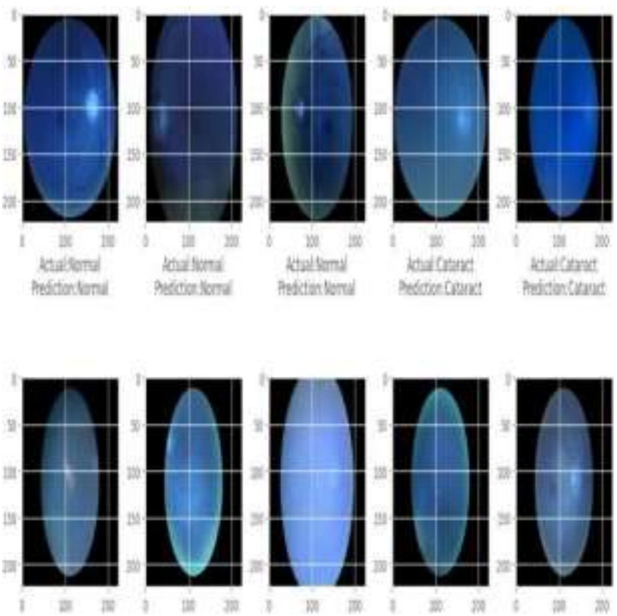

Fig 9:Vision Transformer model for detecting iamges

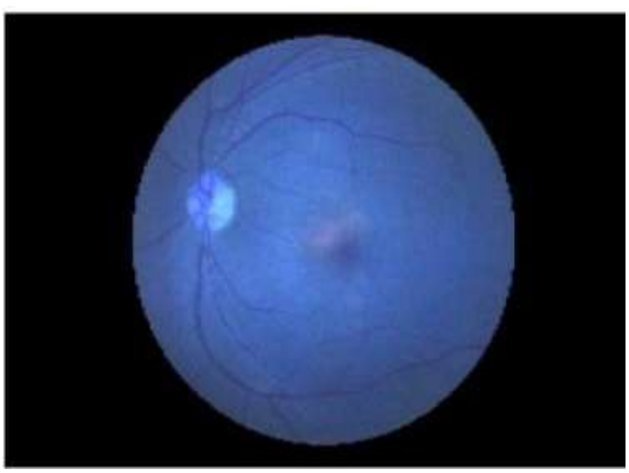
Fig 10: Eye Retinal Fundas Image

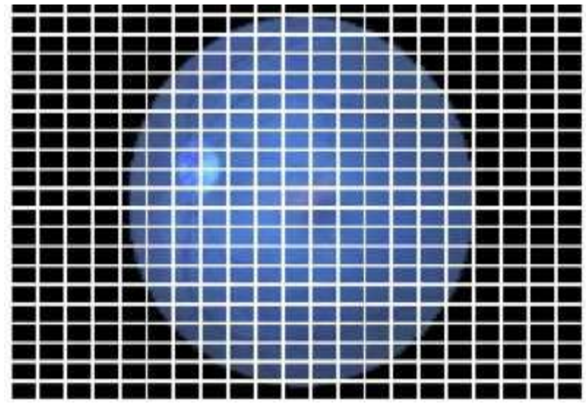
Fig 11: Eye Retinal Grid Image

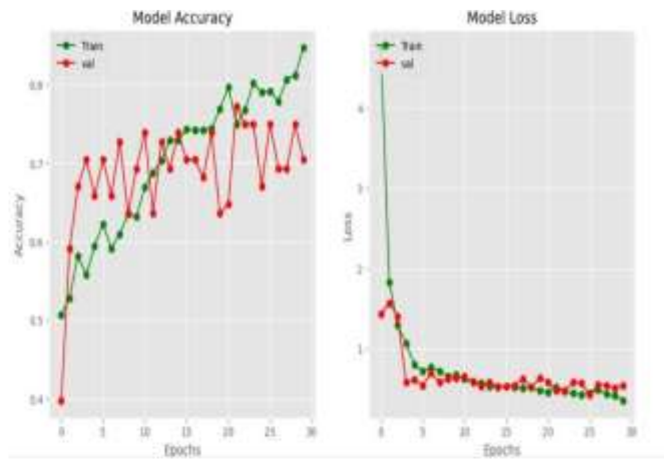

Fig 12:Model Accuracy and Loss

	Model	Training_Accuracy	Training_Loss	Validation_Accuracy	Validation_Loss
0	VGG19	1.000000	0.000231	0.981735	0.241133
1	ResNet50	1.000000	0.000033	0.986301	0.146919
2	Vision Transformer	0.847522	0.355424	0.772727	0.421047

Fig 13: Comparision Table

Fig 14: Final Output of Normal and Diabetic Retina

V. CONCLUSION

The future of ocular disease detection with deep learning is robust, aiming to revolutionize early detection, improve accessibility, and personalize care. With ongoing innovations, it holds the potential to significantly reduce preventable blindness globally.

VI. FUTURE SCOPE:

The future scope of ocular disease detection using deep learning is promising and rapidly expanding, offering transformative potential in ophthalmology. Here's a detailed breakdown of its future scope: Early and Accurate Diagnosis Improved accuracy: Deep learning models can outperform traditional diagnostic methods in detecting diseases like diabetic retinopathy, glaucoma, age-related macular degeneration (AMD), and cataracts. early detection: Models can catch early-stage conditions, even before symptoms appear, enabling preventive care Real-Time Screening in Remote Areas Tele-ophthalmology integration: Deep learning can enable real-time screening in rural or underserved areas via mobile apps and portable fundus cameras. reduced dependency on specialists: Automated analysis helps in areas lacking access to ophthalmologists.

VII. REFERENCES

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