IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

OPTISCAN: DEEP LEARNING-BASED EYE DISEASE DETECTION & CLASSIFICATION

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Abstract: The project is intended to create a cost-effective and easy-to-use eye disease detection and classification system for children and adults in economically underprivileged regions. The system proposed is either a mobile or a Desktop Application. The system takes as input a photo of an unadorned human eye. The picture of the eyes can be taken through a basic mobile camera or laptop camera without too much worry about light or lighting. The system can identify eye diseases such as cataracts, glaucoma, and other diseases where intervention by doctors for disease prediction is needed.

The proposed method utilizes an algorithm that makes use of the VGG-19 Convolutional Neural Network (CNN) model with normalization techniques to categorize fundus images into five distinct classes: Cataract, Diabetic, Glaucoma, Normal, and Other.

The primary objective is to provide an accessible technology for early detection and intervention of eye disorders in underserved communities. By employing a robust deep-learning model, we intend to enhance visual health outcomes and overall well-being among children and adults in these regions. The user-friendly interface and affordability of the system play pivotal roles in facilitating its seamless deployment and effective use, addressing the healthcare access disparity prevalent in these communities.

Index Terms - Eye Disease Classification, Children's Eye Health, Fundus Image Analysis, Machine Learning in Ophthalmology, VGG-19 Model, Healthcare Access in Underserved Communities, Affordable Healthcare Technology, Early Detection and Intervention, User-friendly Healthcare Solutions

I. INTRODUCTION

India ranks fourth in the world for both use and production of electricity. India has a surplus of power producing capability, but it lacks the infrastructure to supply energy to everyone who needs it. The Indian government showed a program named "Power for all" to build the infrastructure. India's electricity industry is controlled by fossil fuels, such as coal. Only renewable energy is increased by the government. Electricity is essential for a comfortable life and should be utilized and conserved responsibly. Currently, a human operator from the electricity board visits the residence, diagnosing eye problems from pictures is tough, and it affects people of all ages and backgrounds. Vision issues can be mild to severe, involving conditions such as Diabetic Retinopathy (DR), Glaucoma, Cataracts, and Age-Related Macular Degeneration (AMD), all of which can lead to blindness. Here's a worrying stat: over 400 million people might have Diabetic Retinopathy by 2030. These eye diseases are a big global problem because they can't be cured, and if not caught early, they can make you blind. The challenge lies in the shortage of eye doctors to meet the demand of patients. Manual eye examinations are time-consuming and require specialized expertise. So, we use computer help to diagnose eye problems. But, eye diseases differ a lot between places and people due to age, gender, job, lifestyle, money, cleanliness, and culture.

In poor areas, like slums, it's hard to get eye care. This is a big deal, especially for kids and young people who are more at risk. Our plan is to use computer smarts (deep learning) to find and classify eye diseases. We want to catch problems early, especially where there isn't much help. Our system is user-friendly and affordable. We hope it helps people in slums, especially kids, have healthier eyes. The goal is for folks to take care of their eyes better and for doctors to step in early, lowering eye problems in poor areas. This paper talks about how we use computer smarts and a mix of pictures to make our system better at finding eye issues, hoping to improve eye care for people in these areas.

II. Literature Survey

Recent advancements in eye disease prediction and detection have showcased the potential of machine learning and deep learning techniques. The paper "An Efficient Approach to Predict Eye Diseases from Symptoms Using Machine Learning and Ranker-Based Feature Selection Methods" introduces a model designed to predict common eye diseases, with the Support Vector Machine (SVM) demonstrating impressive accuracy of 99.11% [1]. In the realm of retinal abnormalities, the comprehensive review titled "Retinal Disease Detection Using Deep Learning Techniques: A Comprehensive Review" underscores the success of Deep Convolutional Neural Networks (DCNNs) and vision transformers (ViTs) for Computer-Aided Diagnosis (CAD), while advocating for further exploration of ensemble CNN architectures [2]. The paper "Deep Learning for Identifying Corneal Diseases from Ocular Surface Slit-Lamp Photographs" presents an innovative hierarchical deep learning network, showing high accuracy and highlighting its potential for aiding in the computer-assisted diagnosis of corneal diseases [3]. Addressing early detection in young children, the paper titled "Early Detection of Visual Impairment in Young Children Using a Smartphone-Based Deep Learning System" presents the Apollo Infant Sight (AIS), a Smartphone-based mHealth system, showcasing its efficacy in identifying visual impairment in young children across various ophthalmic disorders [4]. Finally, the paper "Multi Categorical of Common Eye Disease Detection Using Convolutional Neural Network: A Transfer Learning Approach" utilizes transfer learning with several CNN architectures, highlighting the effectiveness of Inception-v3 in differentiating between normal eyes, conjunctivitis, and cataract eyes [5]. Together, these studies play a significant role in enhancing tools for the early diagnosis and treatment of eye diseases in ophthalmology.

III. Problem statement

Eye diseases such as cataract, glaucoma, and diabetic retinopathy pose significant global health challenges, particularly in underserved communities where early detection is limited due to a lack of medical infrastructure and trained professionals. Conventional diagnostic methods rely on expert evaluation of fundus images, making timely detection difficult and costly. The advancement of deep learning models, particularly Convolutional Neural Networks (CNNs) such as VGG-19, offers a promising solution for automating eye disease detection and classification. However, challenges such as variations in image quality, lighting conditions, and disease manifestations hinder accurate classification. This project aims to develop a cost-effective and user-friendly system that leverages deep learning techniques for the automated detection and classification of common eye diseases using fundus images. By deploying this model through a mobile or desktop application, the system seeks to enhance accessibility to early diagnosis and intervention, particularly in economically disadvantaged regions.

IV. System Overview

The objective is to develop a cost-effective and user-friendly eye disease classification system for children in poor areas, utilizing deep learning models deployed via web application or mobile application. The project aims to enhance early detection and intervention, addressing eye health disparities in underserved communities, particularly slums.

Fig. 1 presents the block diagram of the system.

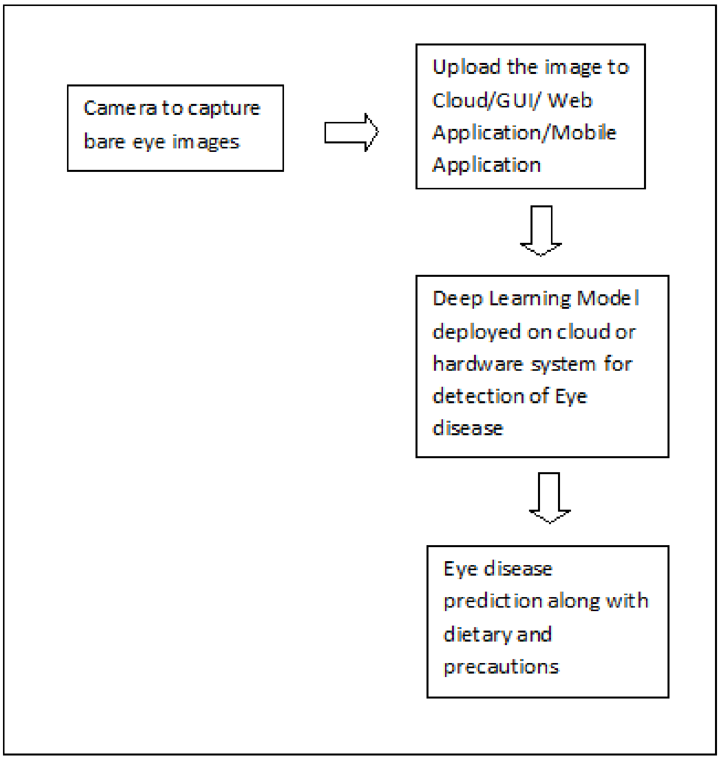

Fig. 1 Block diagram of the proposed eye disease prediction system

The following are the steps of the implementation:

1. Obtaining the dataset

The dataset employed in this study is ODIR (Ocular Disease Intelligent Recognition) [6]. It stands out as a comprehensive resource on Kaggle for detecting eye diseases. This dataset consists of fundus images categorized into eight groups of ocular diseases, including normal (N), myopia (M), hypertension (H), diabetes (D), cataract (C), glaucoma (G), age-related macular degeneration (A), and other abnormalities/diseases (O). With a total of 5000 color fundus photographs. Table 1 provides detailed information about image distributions in the ODIR dataset, and sample images are shown in Figure 2. Figure 3 further details the distribution of images with a bar chart, where the x-axis represents the number of patients, and the y-axis represents disease categories. The chart illustrates that the normal (N) class has the highest number of patient cases (1135), followed by the diabetes (D) class. Interestingly, the hypertension (H) class exhibits the lowest number of patient cases.

No. of classes	Labels	Training cases
1	Normal (N)	1135
2	Diabetes (D)	1131
3	Glaucoma (G)	207
4	Cataract (C)	211
5	Age-related macular degeneration (A)	171
6	Hypertension (H)	94
7	Pathological myopia (M)	177
8	Other diseases /abnormalities (O)	944

Table 1: Distribution of images in the ODIR dataset

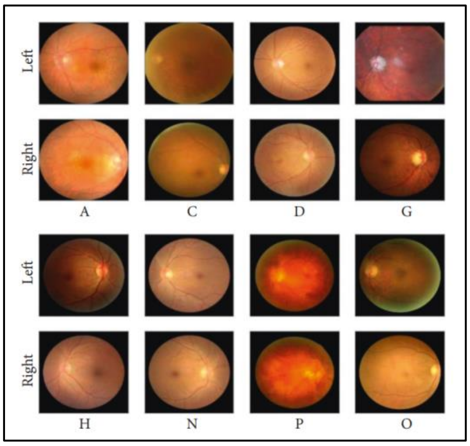

Fig. 2 A sample view of the ODIR dataset

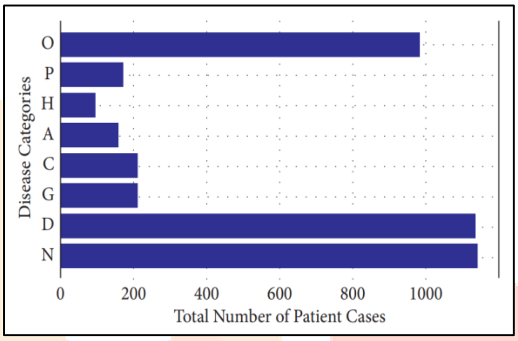

Fig. 3 Distribution of the dataset represented as a bar chart.

2.Pre-processing and Testing/Training Split

For consistency, all images were resized to 224 × 224. The dataset is split into training and testing subsets, with over 3500 cases used for training.

3.Training data on CNN model

The dataset was trained using simple CNN model with CNN layers, poolong layers, stride and ReLU as the activation function. The CNN layer demonstrated an accuracy of 85% for almost all classes. The results of the CNN model were further passed on to pre-trained VGG16 deep learning model to further improve the accuracy.

Working of the CNN Model

The CNN model in this study followed a structured architecture where:

Convolutional Layers were used to extract important spatial features from the images. These layers applied multiple filters to detect patterns such as edges, textures, and shapes.

Pooling Layers, particularly max pooling, were introduced to reduce the spatial dimensions while preserving the most essential features. This helped in reducing computational costs and preventing overfitting.

Strides were used to control how the convolution filters moved across the image, optimizing feature extraction and reducing redundancy.

Activation Function (ReLU) was applied to introduce non-linearity, allowing the model to learn complex patterns in the data.
After training the dataset using the CNN model, the network demonstrated an **accuracy of 85%** across almost all classes, indicating its effectiveness in feature extraction and classification.

Enhancing Accuracy with VGG16

While the CNN model performed well, its accuracy was further improved by passing the results through a pre-trained VGG16 deep learning model. VGG16 is a widely recognized deep convolutional neural network that consists of 16 layers, known for its deep architecture and ability to learn hierarchical representations of images.

The pre-trained VGG16 model, trained on large datasets such as ImageNet, was leveraged for transfer learning. Instead of training a deep model from scratch, the pre-trained weights were used, which allowed the model to generalize better with limited data.

The output features from the initial CNN model were fed into VGG16, allowing the model to refine and enhance the classification results further.

VGG16's deeper architecture helped in capturing more intricate patterns, improving overall classification performance.

By combining the CNN model with VGG16, the classification accuracy was significantly enhanced, demonstrating the power of transfer learning and deep feature extraction. This approach helped in overcoming limitations such as limited data availability and computational constraints, leading to improved generalization and robust performance across different classes.

4.VGG-19 architecture

VGG-19 is a **deep Convolutional Neural Network (CNN)** that follows a structured and uniform design for image recognition and classification tasks. It was developed as an extension of the VGG architecture and consists of **19 layers**, including convolutional and fully connected layers. This network is known for its deep yet straightforward architecture, which has proven to be highly effective in computer vision tasks.

Architecture and Design of VGG-19

VGG-19 follows a consistent architectural approach, where 3 × 3 convolutional filters with a single stride are used throughout the network. The same padding is applied uniformly to retain spatial dimensions, and max pooling layers with 2 × 2 filters and a stride of 2 are incorporated after sets of convolutional layers to progressively reduce the feature map size.

One of the key aspects of the VGG-19 architecture is its minimal hyper parameter tuning, as it follows a fixed configuration for convolutional and pooling layers. The deep structure allows it to capture highly complex image patterns and features, making it suitable for various deep learning applications.

The **VGG-19 architecture** consists of the following:

1. **Convolutional Layers (Conv Layers)**:

The network is structured into five convolutional blocks, labelled as conv1, conv2, conv3, conv4, and conv5. Each convolutional layer employs a ReLU (Rectified Linear Unit) activation function, introducing non-linearity to enhance learning capabilities.

The depth of the network increases as the number of filters doubles in each subsequent block.

2. **Max Pooling Layers**:

After every convolutional block, max pooling is applied using a 2 × 2 filter with a stride of 2. This operation significantly reduces the spatial dimensions while retaining the most crucial features.

Max pooling helps control overfitting by reducing computational complexity.

3. **Fully Connected (FC) Layers**:

VGG-19 incorporates two fully connected layers following the convolutional blocks. Each neuron in these layers is connected to all neurons in the preceding layer, enabling the network to learn complex feature representations.

A dropout layer is included to prevent overfitting by randomly deactivating certain neurons during training.

4. **Classification Layer**:

The final layer of VGG-19 consists of a SoftMax classifier, which assigns probabilities to different output classes. This layer determines the final classification output based on learned patterns from the preceding layers.

Trainable Parameters and Model Complexity

VGG-19 is a computationally expensive model, with over 138 million trainable parameters. This large number of parameters enables it to learn intricate patterns and variations within the dataset, making it highly effective for image recognition, object detection, and deep learning applications. However, due to its complexity, training VGG-19 requires substantial computational power, memory, and GPU resources.

5. Normalization

In this project, normalization techniques were integral for enhancing model performance and convergence during training. The process involved scaling the pixel values of the fundus images to a standardized range, typically [0, 1]. This normalization was crucial to ensure

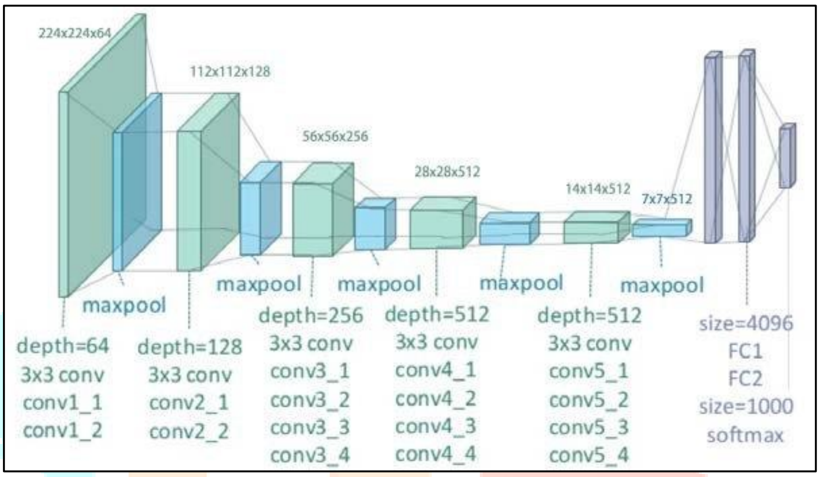

Fig. 4 VGG19 architecture

that the neural network effectively learned patterns and features across all images, preventing dominant pixel intensity values from disproportionately influencing the training process. The normalization step aimed to achieve consistency in input data, promoting more stable and efficient training of the VGG-19 Convolutional Neural Network. By scaling the input features, the model's ability to generalize across different fundus images and diverse eye conditions was significantly improved, contributing to the overall robustness and effectiveness of the eye disease classification system.

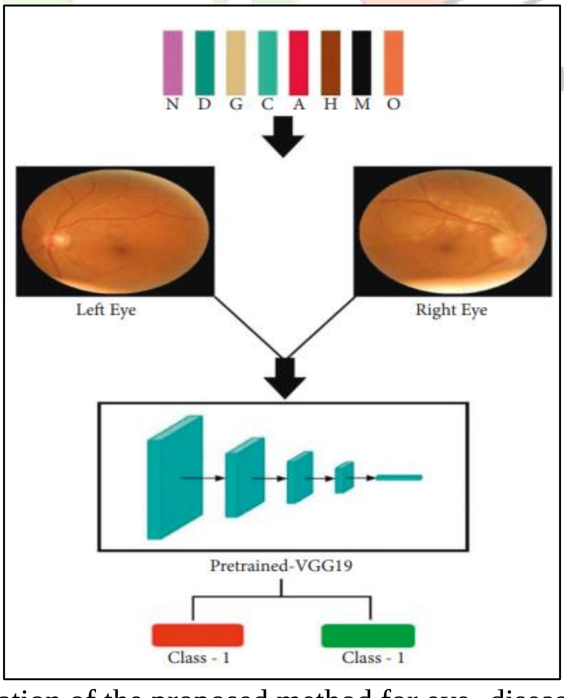

Fig. 5 Illustration of the proposed method for eye- disease prediction.

6. GUI implementation for real time eye disease prediction

The development of a user-friendly and intuitive Graphical User Interface (GUI) plays a pivotal role in the accessibility and usability of proposed eye disease classification system. Implemented in Python, the GUI serves as the interactive platform through which users can effortlessly upload eye or fundus images for real-time disease detection. Users can easily upload eye or fundus images through an intuitive file upload mechanism, facilitating seamless interaction with the system. GUI provides real-time feedback on the status of image processing and the subsequent classification results, ensuring responsive user experience. The GUI is intricately linked with the proposed CNN+VGG-19 model implemented in the Python backend. Upon image upload, the GUI triggers the model for real-time disease classification. The communication between the GUI and the model is designed to be efficient and instantaneous, providing users with immediate insights into the detected eye diseases. In addition to real-time eye disease detection, our Graphical User Interface (GUI) goes beyond mere classification by incorporating an innovative health recommendation feature. This feature aims to empower users with personalized guidance on healthy practices based on the detected eye diseases. Fig. 6 (a) demonstrates the GUI. The GUI development represents a pivotal aspect of our project, bridging the gap in healthcare access by providing an easily navigable platform for real-time eye disease detection. The use of Python, coupled with user-centric design principles, contributes to the overall success of our system in reaching and benefiting the communities it serves.

Beyond medical images, our project showcases versatility by accommodating both retina and normal camera images. This adaptability enhances usability, making our tool comprehensive for various applications as demonstrated in results and discussion section.

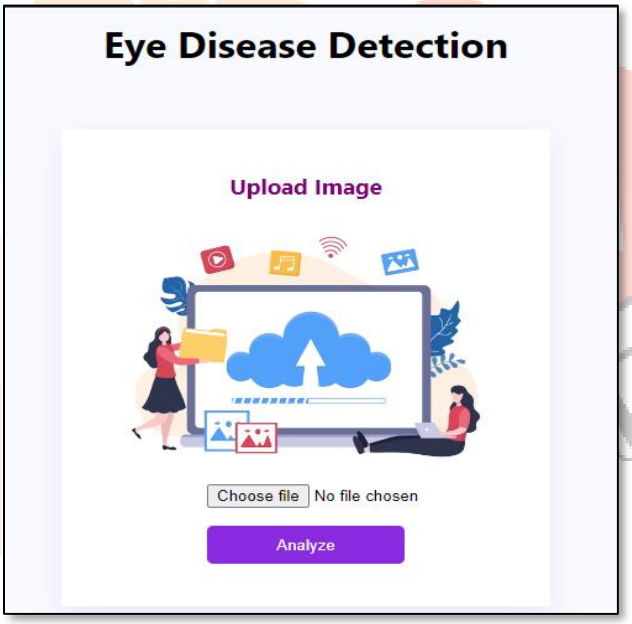

Fig. 6 GUI to upload Eye/Fundus Image

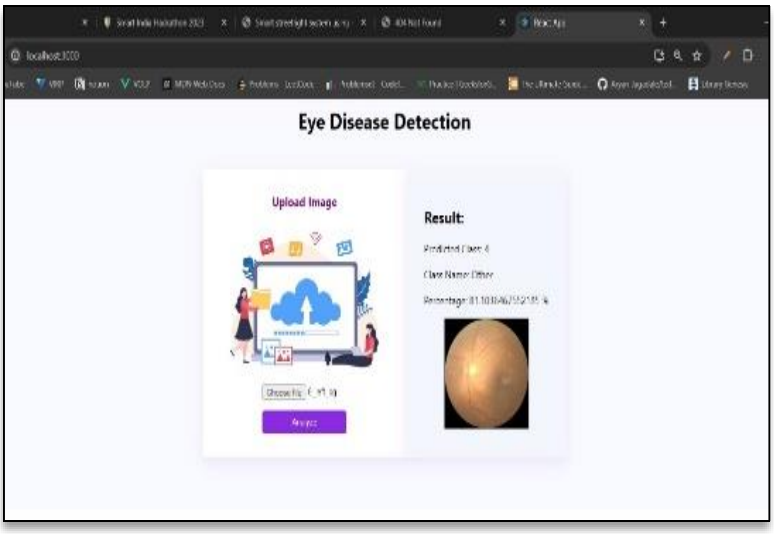

Fig. 6 (a) GUI interface with Fundus image uploaded.

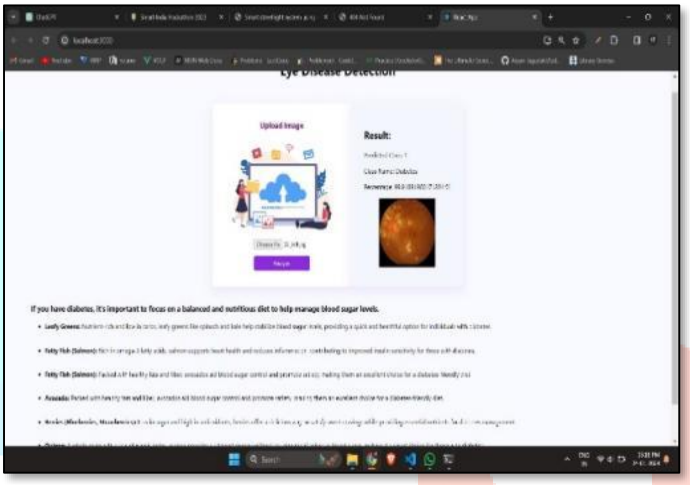

Fig. 6 (b) GUI prediction along with health care recommendation

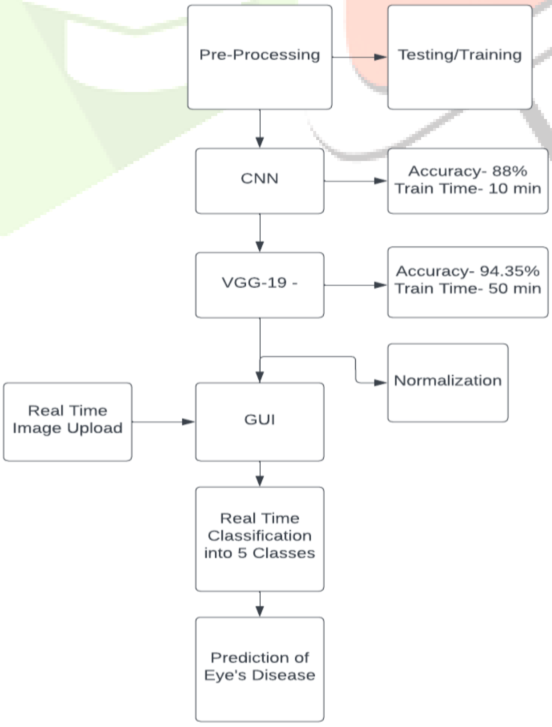

Fig. 7 Architectural pipeline of the proposed intelligent and low-cost system for eye disease prediction

V. RESULTS AND DISCUSSION

The following section presents the experimental analysis of the proposed method along with the results and discussion. Accuracy is used as the performance metrics for the classification of eye disease. The proposed method is compared with few state of the art methods for eye disease classification.

A. Experimental Analysis, Results and Discussion for Eye Disease Classification using proposed model

Fig. 8 (a) and (b) demonstrates the model accuracy and model loss using along the CNN model. The CNN exhibited an accuracy of approximately 88% in classifying fundus images into specified categories (Cataract, Diabetes, Glaucoma, Normal, and Other). The initial testing phase not only assessed the dataset's compatibility with a CNN but also paved the way for exploring more advanced architectures, such as the VGG-19 model.

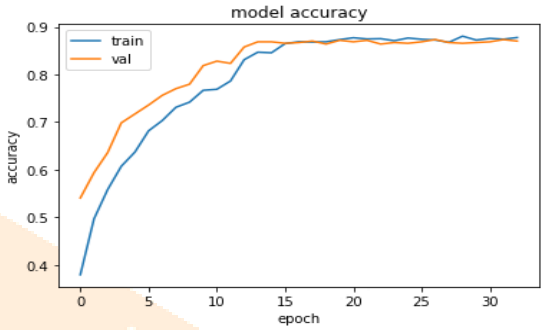

Fig. 8 (a) Model accuracy of CNN

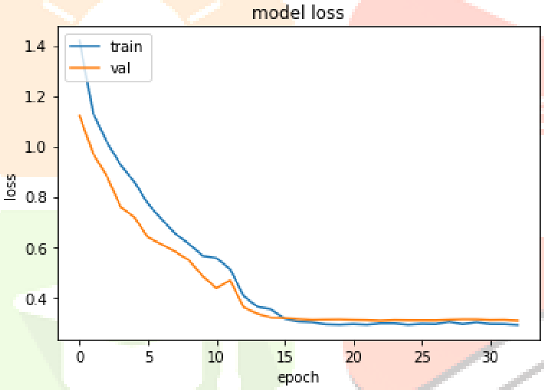

Fig. 8 (b) Model loss of CNN model

To further improve the accuracy of the classification in the proposed method, VGG-19 model, a pre-trained CNN using Tensor Flow was integrated with the initial CNN mode. The Fundus images were resized and normalized for VGG-19 compatibility, enhancing overall performance. Validation tests refined the model's ability to classify fundus images, resulting in an identified accuracy improvement to 96 to 99% Fig 9 (a), (b). the model accuracy and model loss using CNN+VGG-19.

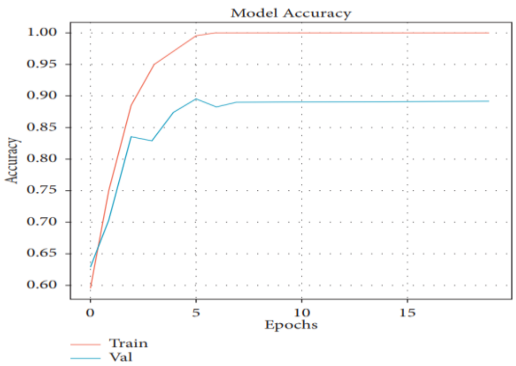

Fig. 9 (a) Model accuracy with CNN+VGG-19

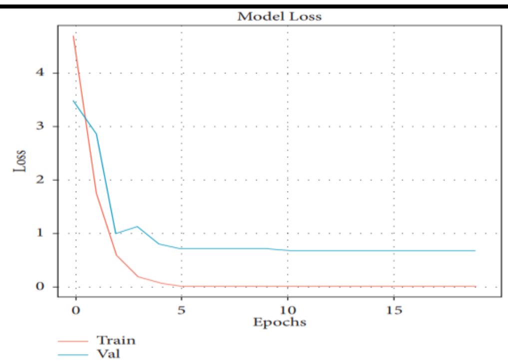

Fig. 9 (b) Model loss with CNN+VGG-19

Table 2 demonstrates the performance comparison of the proposed model for eye disease classification with other state of the art methods in literature. Table 3 demonstrates the classification of individual eye diseases from the dataset using VGG-19 model.

Table 2 Performance comparison of proposed method for eye disease classification with other deep learning models.

Paper reference	**Model name**	**Accuracy (%)**
Proposed model	CNN+VV-19	98.10
[7]	VGG Net	89.75
[8]	VGG-19	97.94
[9]	VGG-16	81.76
	EfficientNetB5	87.25
[10]	EfficientNetB6	86.52
	DenseNet169	86.76
[11]	VGG-16 (off-site)	85.4
	VGG-16 (on-site)	86.28

Table 3 Classification of individual eye diseases from the dataset using only VGG-19 model.

	Precision	Recall	F1-score	Support
Cataract	0.91	0.91	0.91	45
Diabetes	0.93	0.95	0.94	276
Glaucoma	0.78	0.77	0.77	47
Normal	0.99	0.99	0.99	425
Other	0.91	0.88	0.90	199
accuracy		0.94	992	
macro avg	0.90	0.90	0.90	992
weighted avg	0.94	0.94	0.94	992

B. Experimental Results for Real time classification for proposed models using GUI

For the experimental analysis of real time images, real time images using Android mobile phone camera were captured for the following cases: normal eye with no disease, images of eyes having cataract and images of eyes having Glaucoma. These images were uploaded for eye disease prediction using the GUI for validation of the proposed method. Fig. 10 demonstrates the model's capability to predict images along with the health care instructions. Fig. 10 presents an image of an eye with no disease.

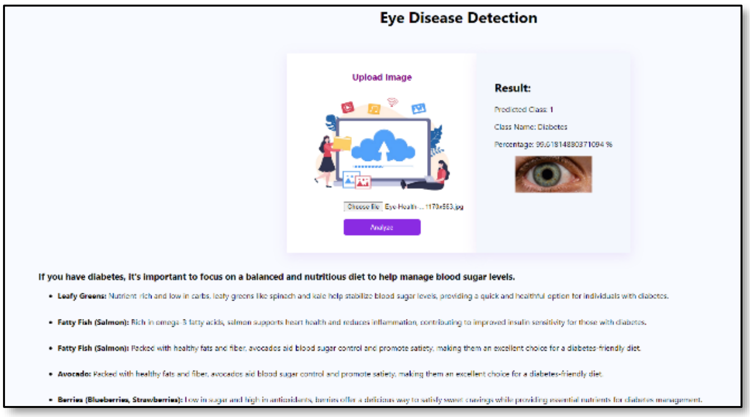

Fig. 10 Classification of real time image using proposed model.

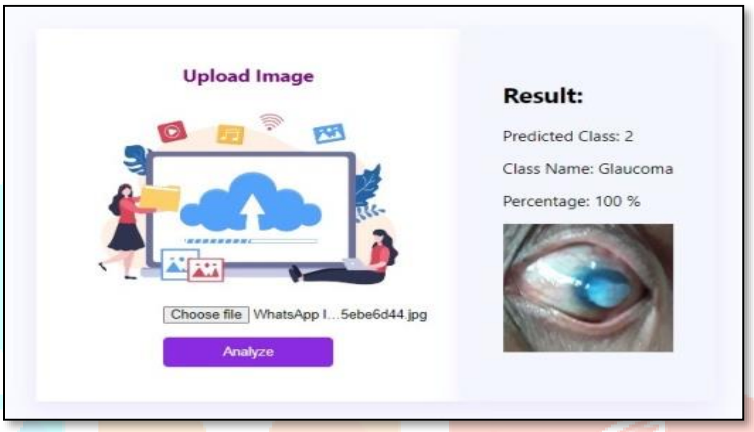

Fig. 11 (a) Real eye image with Glaucoma captured using Android mobile camera and upload on GUI.

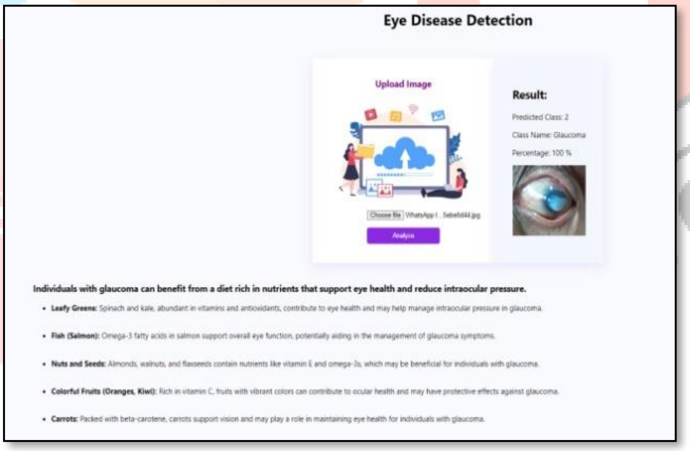

Fig. 11 (b) Predictions and health care instruction for real eye image with Glaucoma captured using Android mobile camera and upload on GUI.

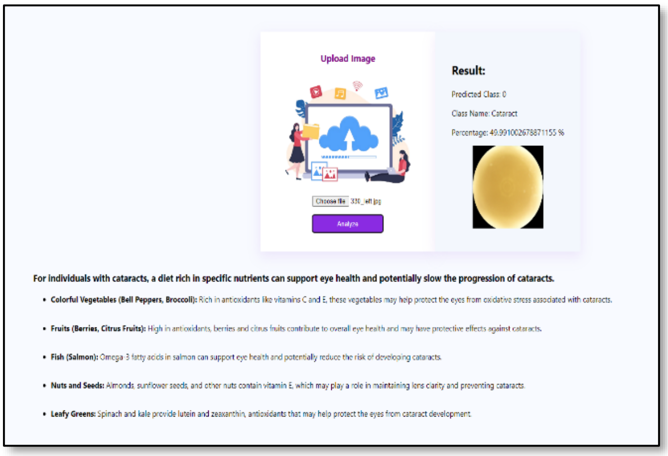

Fig. 12 Classification of Fundus image uploaded on GUI.

VI. CONCLUSIONS

In conclusion, our project introduces a cost- effective and user-friendly eye disease classification system, focusing on children in economically disadvantaged areas. Leveraging the VGG-19 Convolutional Neural Network, we achieved a remarkable 98.10% accuracy in categorizing fundus images into Cataract, Diabetes, Glaucoma, Normal, and Other classes. The system, complemented by a ReactJS GUI and Python backend, facilitates seamless user interaction. Beyond image classification, our innovation extends to personalized dietary recommendations, enhancing the user-centric impact. Overall, our approach demonstrates a significant advancement in early detection of eye disorders, addressing healthcare disparities and promoting visual well-being in underserved communities, particularly among children.

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