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Cost-Effective Real-Time Eye Disease Detection and Classification Using Deep Learning Techniques

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***Abstract*— In this project, we introduce an affordable and user-friendly system for classifying eye diseases, specifically targeting children in underprivileged areas. By leveraging the VGG-19 Convolutional Neural Network, our system achieves an impressive accuracy of 98.10% in categorizing fundus images into classes such as Cataract, Diabetes, Glaucoma, Normal, and others. Complementedby a ReactJS-based graphical user interface anda Python backend, the system ensures seamlessuser interaction. In addition to image classification, the system offers personalized dietary recommendations, significantly enhancing its user-centric impact. Our approach represents a substantial advancement in early eye disorder detection, addressing healthcare disparities and promoting visual health among underserved communities, particularly children.**

Keywords*— Eye disease detection, Deep learning, Fundus Image Analysis, Machine Learning in Ophthalmology, VGG-19 Model, Healthcare Access in Underserved Communities, Affordable Healthcare Technology, Early Detection and Intervention, Userfriendly Healthcare Solutions

I. INTRODUCTION

India ranks fourth in the world for both use and production of electricity. India has a surplus ofpower producing capability, but it lacks theinfrastructure to supply energy to everyone whoneeds 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 a need for living comfortably and must be used and managed appropriately. 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 andbackgrounds. Vision issues can be small orserious, like Diabetic Retinopathy (DR), Glaucoma, Cataract, and Age-Related MacularDegeneration (AMD), 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 issue is that there aren't enough eye doctors for all the patients. Checking eyes manually takes a lot of time and needs experts.So, we use computer help to diagnose eye problems. But, eye diseases differ a lot betweenplaces 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 isto 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 easy to use and doesn't cost a lot. We hope it helps people in slums, especially kids, have healthier eyes. Thegoal is for folks to take care of their eyes betterand 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 REVIEW

Recent advancements in eye disease predictionand detection have showcased the potential of machine learning and deep learning techniques.

[1] The paper titled "An Efficient Approach to Predict Eye Diseases from Symptoms Using Machine Learning and Ranker-Based Feature Selection Methods" proposes a model for predicting common eye diseases, with Support Vector Machine (SVM) achieving remarkable accuracy (99.11%).

[2] 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.

[3] "Deep Learning for Identifying Corneal Diseases from Ocular Surface Slit-Lamp Photographs" introduces a novel hierarchical deep learning network, demonstrating high accuracy and suggesting its potential for computer-assisted corneal disease diagnosis.

[4] Addressing early detection in young children, the paper titled "Early Detection of Visual Impairment in Young Children Using a SmartphoneBased 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.

[5] "Multi Categorical of Common Eye Disease Detect Using Convolutional Neural Network: A Transfer Learning Approach" employs transfer learning with various CNN architectures, emphasizing the efficiency of Inception-v3 in distinguishing between normal eyes, conjunctivitis, and cataract eyes. These studies collectively contribute to advancing tools for early diagnosis and treatment in ophthalmology.

III. PROPOSEDMETHODOLOGY

The objective is to develop a cost-effective anduserfriendly eye disease classification system for children in economically disadvantaged areas, utilizing deep learning model deployed via web application or mobile application. Theproject aims to enhance early detection and intervention, addressing eye health disparities in underserved communities, particularlyslums.

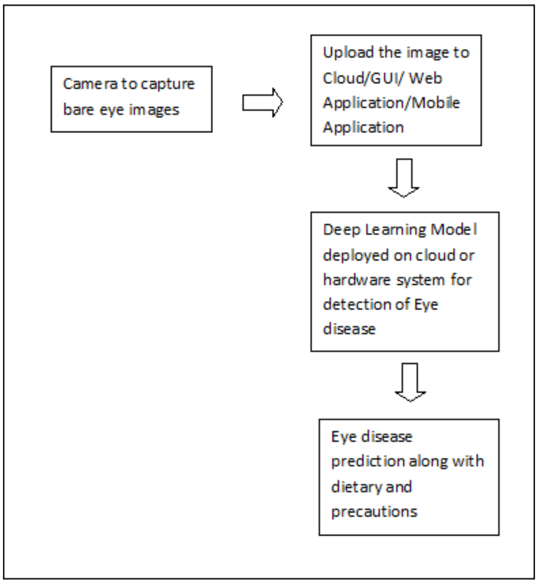

Figure 1 Block diagram of the proposed eye disease prediction system

Following are the Steps of the proposed method:

A. **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.

Table 1 Distribution of images in the ODIR dataset

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

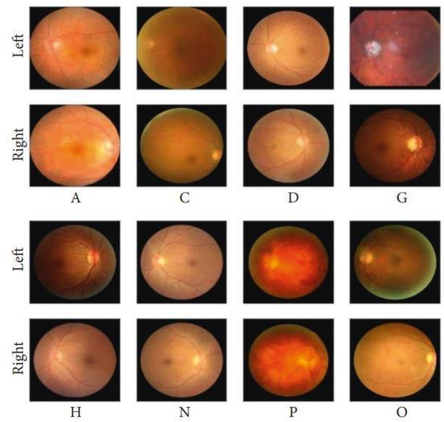

Figure 2 A sample view of the ODIR dataset

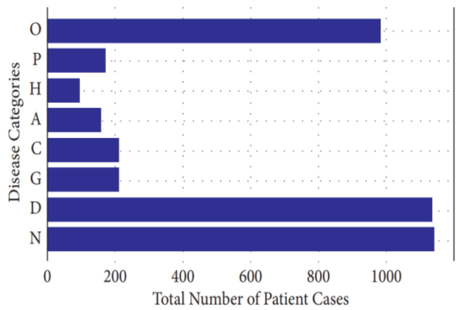

Figure 3 Distribution of the dataset represented as a bar chart.

B. **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.

C. **Training data on CNN model**
The dataset was trained using simple CNN model with CNN layers, pooling 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

D. **VGG-19 architecture**
VGG-19, a Convolutional Neural Network (CNN)-based model, adopts a structured approach using 3 × 3 filters with a single stride, consistently applying the same padding and utilizing maxpooling layers with 2 × 2 filters and a stride of 2. This design choice minimizes hyperparameters, distinguishing VGG-19 in its architecture. The network comprises convolution and maxpooling layers organized similarly, along with two Fully Connected (FC) layers. Notably, the VGG-19 network boasts over 138 million trainable parameters, emphasizing its scale. Fig. 4 illustrates the detailed architecture of the VGG-19 network. Following the classification layer, which integrates a densely connected classifier and a dropout layer, a sequence of convolutional layers (conv1, conv2, conv3, conv4, and conv5) is applied. In a densely connected layer, each neuron connects to all neurons in the preceding layer, enabling learning from prior layer features. The activation method for the densely connected layer needs explicit specification to ensure optimal functioning. For an accurate classification, the data was processed using Normalization

E. **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

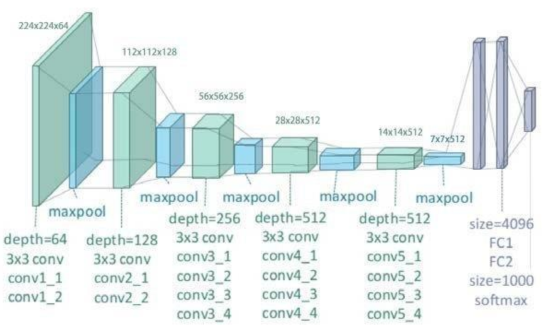

Figure 4 VGG19 architecture

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 aimedto 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.

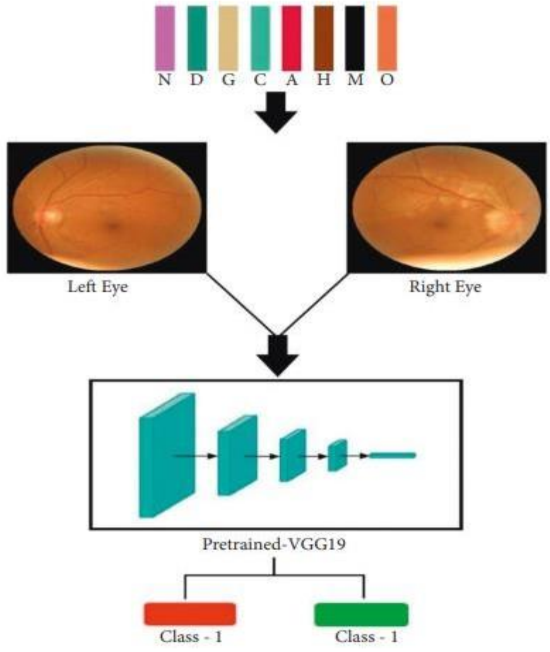

Figure 5 Illustration of the proposed method for eye- disease prediction.

F. **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. The GUI provides real-time feedback on the status of image processing and the subsequent classification results, ensuring a 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 modelis 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 innovativehealth 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 diseasedetection. 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.

G. **Handling Potential Biases in the Dataset and Model**

To ensure the accuracy and fairness of our eye disease detection system, we implemented several strategies to handle potential biases arising from the demographics of underprivileged areas

Algorithm and Model Training:

a. ***Dataset Diversity:*** Diverse Data Sources: We sourced eye images from multiple datasets to ensure representation from various demographics, including different ages, genders, ethnicities, and socioeconomic backgrounds. This approach helps the model generalize across diverse populations.

b. ***Data Augmentation:*** To increase the diversity of our training data, we applied augmentation techniques such as rotation, scaling, and color adjustments. These transformations simulate various lighting conditions and image qualities.

c. ***Preprocessing and Normalization:*** **Standardization:** We standardized all images to reduce variations due to differing lighting and camera quality. This involved normalizing pixel values and applying consistent preprocessing steps

H. ***Image Normalization:*** Techniques such as histogram equalization were used to ensure uniformity in image contrast and brightness, thus mitigating biases from different image capture environments.

I. **Balanced Training**: Our training dataset was balanced across different classes to prevent the model from being biased towards more prevalent conditions.

J. **Cross-Validation**: We employed cross-validation strategies to train and validate the model on different subsets of the data, enhancing robustness and reducing the risk of overfitting to any particular demographic.

K. **Bias Detection and Mitigation**: Fairness Metrics: We used fairness metrics to assess the model's performance across various demographic groups, evaluating accuracy, sensitivity, and specificity for different subpopulations.

L. **Regular Audits:** Periodic audits of model predictions were conducted to identify and correct any biases. Misclassifications were analyzed, and the model or dataset was adjusted accordingly.

M. **Community Feedback and Iteration:** Local Engagement: We engaged with local healthcare providers and community representatives to gather feedback on the system's performance and address any perceived biases.

N. **Iterative Improvements:** Based on the feedback, we iterated on the model by incorporating additional data and refining preprocessing and training processes to enhance fairness and accuracy. By implementing these measures, we aimed to create a system that is both accurate and equitable, ensuring that it serves the needs of underserved communities effectively. 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.

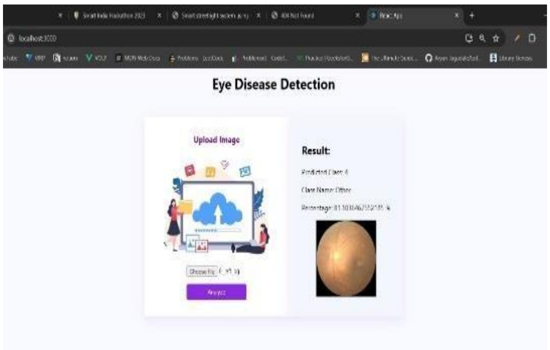

Figure 6 (a) GUI interface with Fundus image uploaded

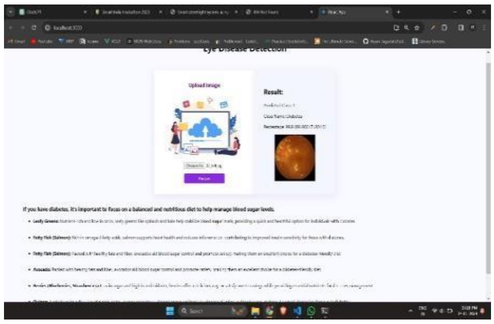

Figure 7 (b) GUI prediction along with health care recommendation

Generation of Recommendations and Tailoring to Individual Users. The recommendations generated by our eye disease detection and classification system are based on a robust and systematic approach that ensures both accuracy and relevance to individual users. The following steps outline the generation process and the factors considered in tailoring recommendations:

a) Data Collection and Pre-processing :

a. **Image Capture:** The input to the system is a bare image of the human eye, captured using a simple mobile or laptop camera. To account for varying conditions, the system is designed to function effectively without stringent requirements on lighting or camera quality.

b. **Image Preprocessing:** Images undergo preprocessing steps such as normalization and standardization to ensure uniform quality. This includes techniques like histogram equalization to manage differences in contrast and brightness.

b) *Model Training and Disease Detection:*

a. **VGG-19 Convolutional Neural Network (CNN) :** We employed the VGG-19 CNN model, known for its depth and ability to extract complex features from images. The model was trained on a diverse dataset to recognize and categorize eye conditions.

b. **Normalization Techniques:** Advanced normalization techniques were used to enhance the model's performance and reduce the impact of variations in the input images.

c) *Categorization and Recommendation Generation:*

a. **Classification into Five Classes:** The system classifies fundus images into five distinct categories: Cataract, Diabetes, Glaucoma, Normal, and Other. This classification forms the basis of the recommendations provided.

b. **Disease-Specific Recommendations:** Once classified, the system generates tailored recommendations based on the detected condition. These recommendations are formulated considering the typical progression of the disease and standard medical guidelines.

d) *Factors Considered in Tailoring Recommendations:*

a. **User Demographics:** Recommendations are tailored to consider the user's age, which is a significant factor in the prevalence and progression of eye diseases. For example, glaucoma and cataracts are more common in older adults, whereas diabetes-related eye issues may be pertinent across a broader age range.

b. **Local Healthcare Resources:** The system integrates information about available healthcare resources in the user's locality. This ensures that recommendations are practical and actionable, taking into account the accessibility of medical facilities and specialists.

c. **Feedback Loop:** Users and healthcare providers can provide feedback on the recommendations. This feedback is used to refine and improve the system continuously, ensuring that it remains relevant and effective.

d. **Cultural and Socioeconomic Factors:** The system is designed to be sensitive to the cultural and socioeconomic contexts of the users. Recommendations consider these factors to ensure they are appropriate and feasible for implementation in underserved communities.

e) *User Interface and Accessibility*

a. **User-Friendly Interface:** The system features an intuitive interface that is easy to navigate, even for individuals with limited technical skills. Clear instructions and visual aids are provided to assist users in capturing high-quality images and understanding the recommendations.

b. **Language Support:** To cater to diverse populations, the system supports multiple languages and includes options for both text and audio guidance.

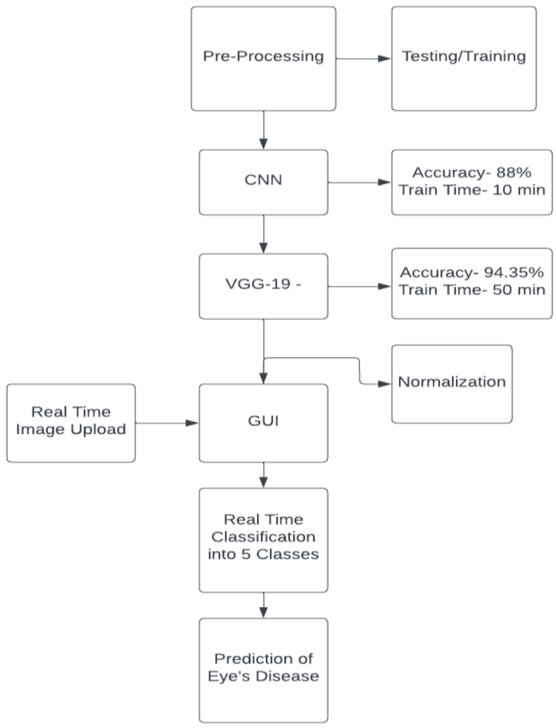

Figure 8 Architectural pipeline of the proposed intelligent and low-cost system for eye disease prediction

IV. 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. 9 (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.

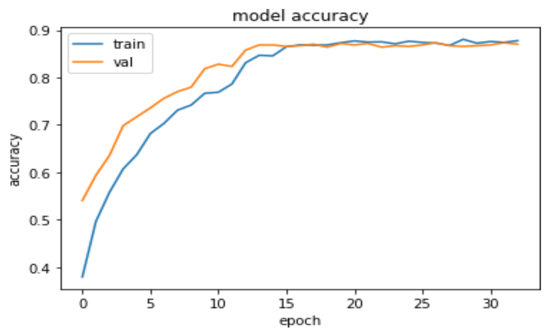

Figure 9 (a) Model accuracy of CNN

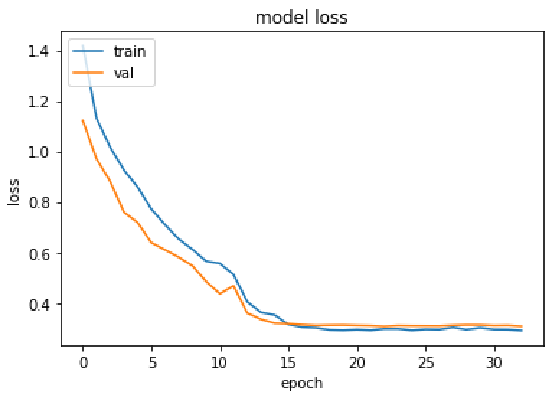

Figure 9 (b) Model loss of CNN model

To further improve the accuracy of the classification in the proposed method, VGG-19 model, a pre-trained CNN using TensorFlow 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 94.35%. Fig. 10 (a) and (b) the model accuracy and model loss using CNN+VGG-19.

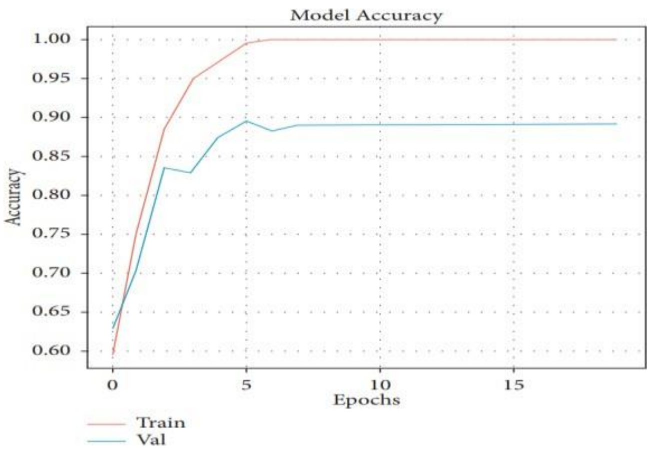

Figure 10 (a) Model accuracy with CNN+VGG-19

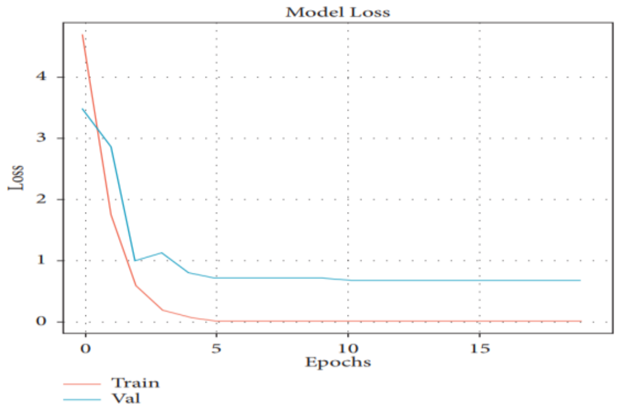

Figure 10 (b) Model loss with CNN+VGG-19

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 theclassification of individual eye diseases from the dataset using VGG-19 model.

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*

Figure 11 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 model 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 Glucoma. These images were uploaded for eye disease prediction using the GUI for validation of the proposed method. Fig. 11 demonstrates the models capability to predict images along with the health care instructions. Fig. 11 presents an image of eye with no disease.

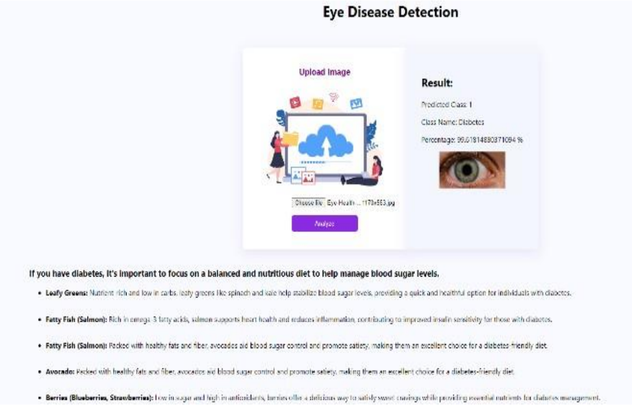

Figure 11 Classification of real time image using proposed model

Fig. 12 (a) and (b) demonstrates a case for Glucoma prediction from real time image obtained using Android mobile camera and upload on the GUI.

Figure 12 (a) Real eye image with Glucoma captured using Android mobile camera and upload on GUI

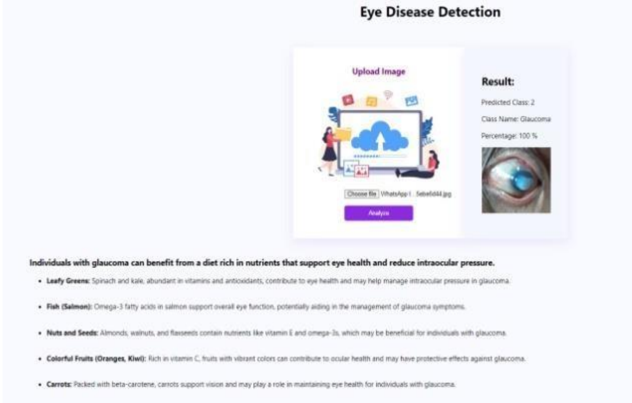

Figure 12 (b) Predictions and health care instruction for real eye image with Glucoma captured using Android mobile camera and upload on GUI

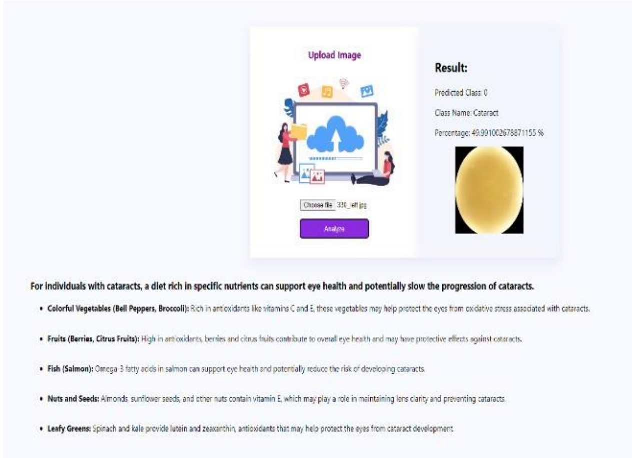

Figure 13 Classification of Fundus image uploaded on GUI

Real-World Impact of the System on Visual Health Outcomes in Underserved Communities. The proposed eye disease detection and classification system is designed to have a significant positive impact on visual health outcomes, particularly among children and older adults in underserved communities. Here's an evaluation of its real-world impact :

A. *Early Detection and Intervention:*

a. **Timely Diagnosis:** By facilitating early detection of eye diseases such as cataract, glaucoma, and diabetic retinopathy, the system enables timely medical intervention. Early treatment can prevent the progression of these diseases, significantly reducing the risk of vision loss.

b. **Increased Awareness:** The system raises awareness about eye health, encouraging individuals to seek regular check-ups and adhere to treatment plans.

B. *Accessibility and Affordability:*

a. **Low-Cost Solution:** Utilizing readily available mobile or laptop cameras makes the system cost-effective, removing financial barriers to accessing eye health services.

b. **Ease of Use:** The user-friendly interface ensures that even individuals with limited technical skills can use the system effectively, broadening its reach.

C. *Impact on Children:*

a. **Improved Educational Outcomes:** Early detection of vision problems in children can lead to prompt treatment, preventing visual impairments that can hinder educational performance and development.

b. **Preventing Long-Term Disabilities:** By addressing eye health issues early, the system helps prevent long-term disabilities, promoting better quality of life and future opportunities for children.

D. *Impact on Older Adults:*

a. **Preservation of Independence:** Early detection and management of eye diseases common in older adults, such as cataracts and glaucoma, can preserve their vision, helping them maintain independence and quality of life.

b. **Reduced Healthcare Burden:** Preventing severe vision loss reduces the need for more extensive medical treatments and caregiving, alleviating the overall healthcare burden on families and communities.

E. *Community Health Improvement:*

a. **Widespread Screening:** The system's scalability allows for widespread screening in community centers, schools, and local clinics, reaching a large population in underserved areas.

b. **Empowering Local Healthcare Providers:** By integrating with local healthcare resources, the system empowers community health workers and local clinics to offer more comprehensive eye care services.

F. *Feedback and Continuous Improvement:*

a. **Iterative Refinement:** Continuous feedback from users and healthcare providers ensures that the system evolves to meet the specific needs of the community, enhancing its effectiveness and user satisfaction.

b. **Data-Driven Insights:** Aggregated data from the system can inform public health strategies and resource allocation, further improving community health outcomes.

By providing early detection, affordable access, and tailored recommendations, it addresses critical gaps in healthcare delivery. Specifically, for children and older adults, the system can prevent vision loss, enhance quality of life, and reduce the overall burden on healthcare systems. The real-world impact of this system lies in its ability to democratize eye care and bring essential health services to those who need them most.

V. 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 Otherclasses. 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.

REFERENCES

[1] A. Al Marouf, M. MozaharulMottalib, R. Alhajj, J. Rokne, and O. Jafarullah, "An Efficient Approach to Predict Eye Diseases from Symptoms Using Machine Learning and Ranker-Based Feature Selection Methods," *PMID: 36671598*.

[2] S. Muchuchuti and S. Viriri, "Retinal Disease Detection Using Deep Learning Techniques: A Comprehensive Review," *PMID: 37103235*.

[3] H. Gu, Y. Guo, L. Gu, A. Wei, S. Xie, Z. Ye, J. Xu, X. Zhou, Y. Lu, and X. Liu, "Deep Learning for Identifying Corneal Diseases from Ocular Surface Slit-Lamp Photographs."

[4] W. Chen, R. Li, Q. Yu, A. Xu, Y. Feng, R. Wang, L. Zhao, Z. Lin, Y. Yang, D. Lin, and X. Wu, "Early Detection of Visual Impairment in Young Children Using a Smartphone-Based Deep Learning System," *PMID: 36702948*.

[5] A. K. Bitto and I. Mahmud, "Multi-Categorical Detection of Common Eye Diseases Using Convolutional Neural Network: A Transfer Learning Approach," *Bull. Electr. Eng. Informatics*, vol. 11, no. 4, pp. 2378–2387.

[6] "A. Mvd, 'Ocular Disease Recognition (ODIR5K),' Kaggle," *Available: https://www.kaggle.com/datasets/andrewmvd/ocular-disease-recognition-odir5k*.

[7] Y. Elloumi, M. Akil, and H. Boudegga, "Ocular Diseases Diagnosis in Fundus Images Using a Deep Learning: Approaches, Tools, and Performance Evaluation," in *Proc. Real-Time Image Processing and Deep Learning*, 2019, p. 109960T, Maryland, USA.

[8] N. Li, T. Li, C. Hu, K. Wang, and H. Kang, "A Benchmark of Ocular Disease Intelligent Recognition: One Shot for Multi-Disease Detection," 2021, [Online]. Available: https://arxiv.org/abs/2102.07978.

[9] H. S. Gill, O. I. Khalaf, Y. Alotaibi, S. Alghamdi, and F. Alassery, "Fruit Image Classification Using Deep Learning," *Comput. Mater. Continua*, vol. 71, no. 3, pp. 5135–5150, 2022.

[10] H. S. Gill, O. I. Khalaf, Y. Alotaibi, S. Alghamdi, and F. Alassery, "Multi-Model CNN-RNN-LSTM Based Fruit Recognition and Classification," *Intell. Autom. Soft Comput.*, vol. 33, no. 1, pp. 637–650, 2022.

[11] M. Rajalakshmi, V. Saravanan, V. Arunprasad, O. Khalaf, and C. Karthik, "Machine Learning for Modeling and Control of Industrial Clarifier Process," *Intell. Autom. Soft Comput.*, vol. 32, no. 1, pp. 339–359, 2022

[12] A. Chaudhari, P. Shelke, P. Thombare, and S. Sandbhor, "Real Time Eye Disease Detection and Classification System Using Deep Learning," Indian Patent – 202421031655.