IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

OPTISCAN: EYE DISEASE DETECTION & CLASSIFICATION

Roshni Narkhede[1], Avadhut Shedage[2], Adinath Raut[3], Amol Lokhande[4]
Associate Professor, Computer Engineering Department [1]
Student, Computer Engineering Department [2,3,4],
Nutan Maharashtra Institute of Engineering & Technology, Pune, Maharashtra[1,2,3,4]

Abstract : The project aims to develop a cost-effective and user-friendly eye disease detection and classification system tailored for children and adults in economically disadvantaged areas. The proposed system consists of a mobile or a Desktop Application. The system receives as input a picture of an unadorned human eye. The image of the eyes can be captured through a simple mobile camera or laptop camera without much concerned of surrounding light or illumination. The system can detect eye diseases like cataract, glaucoma and other diseases that require the intervention of doctors for disease prediction. The proposed method utilizes an algorithm that makes use of 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.**

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 problems can range from mild to severe, including conditions like Diabetic Retinopathy (DR), Glaucoma, Cataracts, and Age-Related Macular Degeneration (AMD), all of which have the potential to cause 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.

LITERATURE REVIEW

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.

PROPOSED METHODOLOGY

The objective is to develop a cost-effective and user-friendly eye disease classification system for children in economically disadvantaged areas, utilizing deep learning model 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.

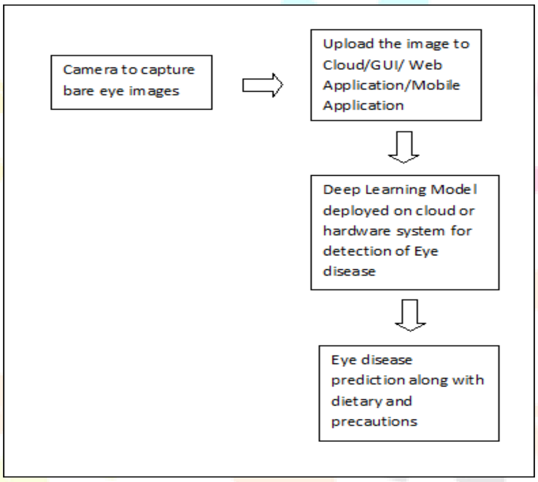


fig. 1 block diagram of the proposed eye disease prediction system

Following are the Steps of the proposed method:

1. **Obtaining the dataset :** The dataset employed in this study is ODIR (Ocular Disease Intelligent Recognition) [6]. It serves as a valuable and 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). Consisting of 5000 color fundus photographs in total. 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 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

fig. 2 a sample view of the ODIR dataset

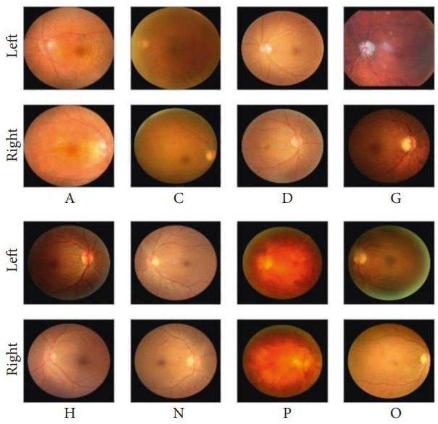
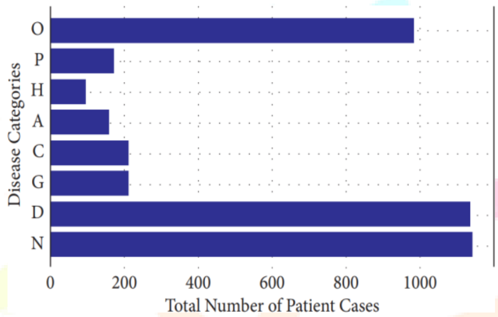


fig. 3 distribution of the dataset represented as a bar chart.



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 activitation 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 .

4. **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 max-pooling layers with 2 × 2 filters and a stride of 2. This design choice minimizes hyper parameters, distinguishing VGG-19 in its architecture. The network comprises convolution and max-pooling 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 fully connected layer, every neuron is linked to all neurons in the previous layer, allowing the model to learn from the features of the preceding layer. 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.

5. **Normalization :** In this project, normalization methods played a key role in improving model performance and accelerating 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 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.

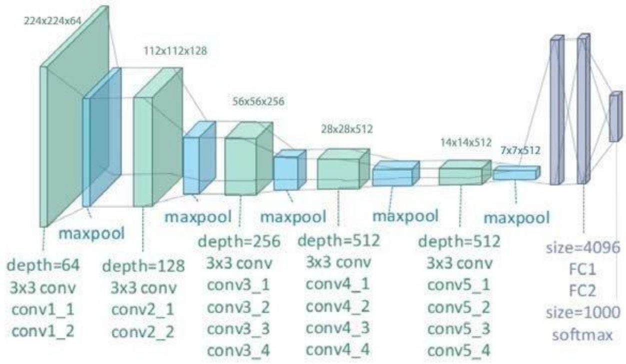


fig. 4 vgg19 architecture

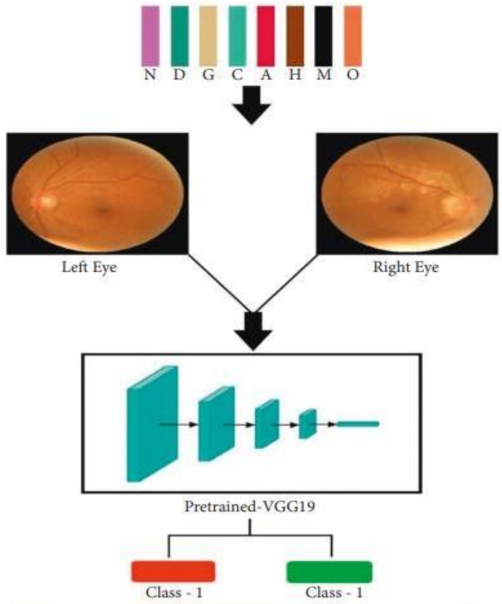


fig. 5 illustration of the proposed method for eye- disease prediction.

FUTURE SCOPE

Eye disease detection through deep learning is a rapidly developing field with great promise for the improvement of early diagnosis, treatment planning, and patient management. Use of Convolutional Neural Networks (CNN) and VGG19 has already yielded promising results for the identification of diseases like diabetic retinopathy, glaucoma, and age-related macular degeneration. The potential of the technology in the future is enormous, with many areas likely to be improved:

1. Enhanced Precision By Advanced Architectures : Coming developments are sure to feature increasingly sophisticated deep learning architectures such as Vision Transformers (ViTs) and their hybrids that combine CNN and attention. These are likely to provide still better feature extraction and classification than CNN and VGG19 currently.

2. Real-Time Disease Monitoring and Prediction : With the trend of edge computing and cloud-based models of AI increasing, real-time detection of eye disease will become increasingly feasible. This will allow doctors to precisely diagnose disease in real-time with the assistance of wearable or mobile devices.

3. Multi-Modal Data Fusion : Fundus camera imaging, OCT, and other modality fusion with deep learning will increase disease predictions. CNN and VGG19-based models can be trained multimodal input for increased inspection.

4. Personalized and AI-Focused Treatment Plans : AI systems can assist ophthalmologists through the generation of personalized treatment plans depending on trends of disease history. Future models based on CNN will incorporate patient history, genetics, and surroundings for precise recommendation.

5. Deployment in Low-Resource Settings :One of the key contributions of deep learning in eye disease detection is its suitability to be used in remote and low-resource environments. AI-driven mobile apps powered by CNN and VGG19 can help detect eye diseases where ophthalmologists are not readily available.

6. Federated Learning for Privacy-Preserving AI : Future development will be founded on federated learning, whereby models are trained from decentralized data without sharing confidential patient data. This will facilitate privacy and improve the generalization capacity of CNN and VGG19 models.

7. Automating Eye Screening Programs : Deep learning can be used in mass screening programs to automate early diagnosis of eye diseases in high-risk populations. Governments and health care providers can use AI-powered tools for low-cost mass screening.

8. Robotics and Surgery Assistance Integration : AI-based robotic systems in the future can assist ophthalmologists with precision surgeries. Models based on CNN and VGG19 can be utilized to study real-time information during surgery to improve the outcome of complex procedures.

CONCLUSION

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.

REFERENCES

1. *Ahmed Al Marouf; Md MozaharulMottalib; Reda Alhajj; Jon Rokne; Omar Jafarullah; An Efficient Approach to Predict Eye Diseases from Symptoms Using Machine Learning and Ranker-Based Feature Selection Methods, PMID: 36671598*
2. *Stewart Muchuchuti; SerestinaViriri; Retinal Disease Detection Using Deep Learning Techniques: A Comprehensive Review; PMID: 37103235*
3. *Hao Gu, Youwen Guo, Lei Gu, Anji Wei, Shirong Xie, Zhengqiang Ye, Jianjiang Xu, Xingtao Zhou, Yi Lu, Xiaoqing Liu; Deep learning for identifying corneal diseases from ocular surface slit-lamp photographs.*
4. *Wenben Chen, Ruiyang Li, QinjiYu , Andi Xu , Yile Feng , Ruixin Wang , Lanqin Zhao , Zhenzhe Lin Yahan Yang , Duoru Lin , Xiaohang Wu , Early detection of visual impairment in young children using a smartphone-based deep learning systemPMID: 36702948*
5. *Abu Kowshir Bitto; Imran Mahmud; Multi categorical of common eye disease detect using convolutional neural network: a transfer learning approach, Bulletin of Electrical Engineering and Informatics 11(4):2378-2387*
6. *https://www.kaggle.com/datasets/andrewmvd/o cular-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 Learningp. 109960T, Maryland, USA, 2019.*
8. *N. Li, T. Li, C. Hu, K. Wang, and H. Kang, "A Benchmark of Ocular Disease Intelligent Recognition: One Shot for MultiDisease Detection," 2021, https://arxiv.org/abs/2102.07978.*
9. *H. Singh Gill, O. Ibrahim Khalaf, Y. Alotaibi, S. Alghamdi, and F. Alassery, "Fruit image classification using deep learning," Computers, Materials & Continua, vol. 71, no. 3, pp. 5135–5150, 2022.*
10. *H. Singh Gill, O. Ibrahim Khalaf, Y. Alotaibi, S. Alghamdi, and F. Alassery, "Multi-model CNN-RNN-LSTM based fruit recognition and classification," Intelligent Automation & Soft Computing, 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," Intelligent Automation & Soft Computing, vol. 32, no. 1, pp. 339–359, 2022.*