An Automated Eye Disease Detection System Using Convolutional Neural Network

Mayuri Sirsat[1], Akanksha Sathe[2], Shreya Ladhe[3] , Pravin Futane[4], Ratnmala Bhimanpallewar[5]

[1]Student, It dept. of VIIT College of Engineering, Pune, Maharashtra, India
[2]Student, It dept. of VIIT college of Engineering, Pune, Maharashtra, India
[3]Student, It dept. of VIIT college of Engineering, Pune, Maharashtra, India
[4]HOD, It dept. of VIIT college of Engineering, Pune, Maharashtra, India
[5]Professor, It dept. of VIIT college of Engineering, Pune, Maharashtra, India

---

Abstract -This paper introduces a novel artificial intelligence (AI) diabetic retinopathy detector utilizing the ResNet-18 deep learning model, which has shown excellent image classification accuracy. We successfully trained the model using a sizable dataset of annotated fundus images, which included both healthy individuals and those with various stages of diabetic retinopathy. Our approach may improve the cost-effectiveness and accessibility of diabetic retinopathy screening, especially in underprivileged and isolated locations with poor access to ocular care. This detector is a promising first step towards more efficient and widely available screening techniques because it allows for early identification, which can be pivotal in detecting the condition before visual loss occurs.

Key Words: Artificial Intelligence, Image Classification, Fundus Images, Early Identification

1.INTRODUCTION

Maintaining eye health is essential to general wellbeing, and maintaining eyesight is a key goal in medical care. The numerous eye conditions that can result in blindness and vision impairment can significantly lower someone's quality of life. Treatment for these illnesses is often ineffective since they often remain subtle until they reach late stages. A multidisciplinary strategy that incorporates early detection, prompt intervention, effective screening, and patient education is necessary to address these issues. This method seeks to empower people to actively protect their eye health in addition to identifying and treating eye disorders in their early stages. Within this framework, the effort aims to fully address the goals of improving eye health through early. This effort aims to achieve three key goals: improving patient education to promote better eye health practices; optimizing resource allocation through screening and triage; and promoting eye health through early detection and prompt action. The program aims to prevent vision loss and its related issues by concentrating on these factors and improving the quality of life for people who are either at risk of or currently experiencing various eye disorders. This all-encompassing endeavor highlights how vital preventive eye care is and how important vision is to overall health and wellbeing.

2.LITERATURE REVIEW

1. The paper by Malik, S., Kanwal, N., Asghar, M.N., Sadiq, M.A.A., Karamat, I. and Fleury, M., [1] with a focus on ophthalmology it provides an easy-to-use user interface for error-free data entry and employs a number of machine learning techniques, including Decision Tree and Random Forest [1], to evaluate patient data according to various criteria. The framework outperformed more sophisticated techniques like Neural Networks and Naive Bayes, demonstrating over 90% prediction accuracy with accuracy closely connected with dataset size. [1]. It achieved this by applying the ICD-10 coding system and hierarchical hierarchies for symptom recording. The ultimate goal of the study's prospective methodology is to improve data standards and advance disease prediction in the field of ophthalmology by incorporating image-based test findings and exploring closest neighbor classification techniques.

Gap: This research paper describes a specific ophthalmology study that uses machine learning and structured data collection in order to achieve high accuracy in disease diagnosis.[1] Our initiative outlines general goals related to eye health, including early detection, timely intervention, efficient screening, patient education, and improving overall quality of life through vision preservation, without delving into specifics regarding specific studies.[1]

2.The paper by Sait, W. and Rahaman, A., [2] focuses on deep learning methods to address the requirement for an enhanced Eye Disease Classification (EDC) system. They were successful in creating a model that makes use of the Whale Optimization Algorithm for feature selection, denoising autoencoders for image pre-processing, and single-shot detection for feature extraction. Using benchmark datasets, the improved Shuffle Net V2 model outperformed recent EDC approaches in terms of accuracy and sensitivity in diagnosing eye disorders0. The suggested EDC model offers numerous useful applications in the field of healthcare, including research initiatives, screening program benefits, and early disease diagnosis. Upcoming research will concentrate on correcting unbalanced datasets and extending the model to incorporate more ocular conditions0.

Gap: The present research paper provides an overview of a particular research investigation that aims to improve Eye Disease Classification (EDC) through the application of deep learning techniques.0 Particular attention is given to the model's construction, methodology, and diagnostic performance. Without going into detail about a particular study, our initiative outlines broad goals associated with eye health, such as early identification, prompt intervention, effective screening, patient education, and enhancing overall quality of life through vision preservation.

3.The paper bu Cheung, C.Y., Tang, F., Ting, D.S.W., Tan, G.S.W. and Wong, T.Y., 0 focuses on examines the application of deep learning (DL) and artificial intelligence (AI) in diabetic eye disease screening, as well as diabetic retinopathy (DR) and diabetic macular edema (DME).[3]It draws attention to how AI and DL have the potential to improve screening programs' accessibility and efficiency, which are now constrained by the requirement for specialist knowledge and funding. The study notes the impressive advancements made in the use of AI and DL for the evaluation of retinal images and highlights the anticipation that these technologies would be essential in averting blindness and sight loss brought on by diabetic eye disorders0.

Gap: This study highlights the potential for these technologies to improve accessibility and efficiency while focusing on the use of AI and DL for diabetic eye disease screening.0 On the other hand, our project does not specifically mention AI and DL technologies; instead, it emphasizes more general goals concerning eye health, like early detection and prompt care. While the research paper focuses on a particular application, our project offers a broad foundation for enhancing eye health.

4..The paper by Marouf, A.A., Mottalib, M.M., Alhajj, R., Rokne, J. and Jafarullah, O., proposes an effective model that uses feature selection and machine learning approaches to predict five prevalent eye disorders.0 The study achieved excellent accuracy rates above 90% by using expert annotations for accurate data and performing a comparative comparison of several ML algorithms. SVM fared better in cross-validation than other models, with an accuracy of 99.11%.0 In order to pinpoint particular symptoms and deepen our understanding of eye disorders, the report proposes that future research could benefit from the use of picture data and multivariate analyses.

Gap: This research study focuses on the technical details and high accuracy rates of a particular research paper's findings on utilizing machine learning to forecast eye disorders.0 On the other hand, our project does not specifically mention machine learning or research outcomes; instead, it includes broad objectives relating to eye health, with an emphasis on early identification, timely intervention, and patient education. While the second research paper offers a more comprehensive framework for enhancing eye health, this one focuses on a particular study0.

5.The paper by Nazir, T., Irtaza, A., Javed, A., Malik, H., Hussain, D. and Naqvi, R.A., 0 proposes an automated model that uses deep learning techniques and visual signs to diagnose eye illnesses, tackling the critical issue of preventable blindness in India 0. In order to facilitate early intervention and treatment, the model is intended to identify and classify four prevalent eye disorders. It succeeds in distinguishing between healthy and diseased eyes by using deep neural networks.

Gap: This work aims to develop an automated model for the diagnosis of eye problems in India..0 Our initiative, on the other hand, does not specifically address research or technology; instead, it specifies broad objectives relating to eye health, with an emphasis on early identification, timely intervention, and patient education. This study focuses on a particular research question; our initiative offers a more comprehensive framework for enhancing eye health.

6.The paper by Sarki, R., Ahmed, K. and Zhang, Y., 0 proposes the significance of early Diabetic Eye Disease (DED) detection and the difficulties in doing so. DED includes a range of eye conditions that can impact people with diabetes, such as cataracts, glaucoma, diabetic macular edema, and diabetic retinopathy. To stop these diseases from worsening and causing irreversible blindness or visual impairment, early detection is essential. The main challenges in detecting DED in its early stages are related to the subtle changes in the anatomy of the eye that occur during this time, changes that are frequently invisible to the naked eye. Furthermore, the sheer number of fundus images presents a major challenge because it is not feasible for experts to manually analyze them0.

Gap:

- Early-Stage DED Detection: Detecting DED at its early stages is challenging due to subtle changes.

- Specific Disorder Classification: Diabetic Retinopathy (DR), Glaucoma (GL), and Diabetic Macular Edema (DME) must all be accurately classified.

- Framework for Automated DED Detection: Developing practical, automated systems for widespread DED detection is a critical research gap.

7.The paper by Sheng, B., Chen, X., Li, T., Ma, T., Yang, Y., Bi, L. and Zhang, X., 0 focuses on the vital matter of Diabetic Eye Disease (DED) early detection), which encompasses several eye disorders common in individuals with diabetes. The research suggests a system architecture using deep learning approaches, such as an image processing method and a pre-trained Convolutional Neural Network (CNN), to handle this difficulty. The study utilizes publicly available datasets and explores approaches to enhance the accuracy of DED classification, with image processing identified as a significant factor for success.

Gap: Early-Stage DED Detection: The research notes that it is difficult to diagnose DED in its early stages because of minute structural changes in the eye. Closing this gap is essential to better patient outcomes because early detection is critical for prompt intervention.0

Specific Disorder Classification: The study emphasizes the necessity of accurately classifying specific DED disorders, such as diabetic macular edema (DME), glaucoma (GL), and diabetic retinopathy (DR). Accurate identification of these conditions is crucial because misidentification can result in permanent blindness or varying degrees of vision impairment.

8.The paper by Malik, S., Kanwal, N., Asghar, M.N., Sadiq, M.A.A., Karamat, I. and Fleury, M.,0 discusses cataracts, a prevalent ocular disease that impairs vision, particularly in the elderly population. Blurriness and even colorblindness can result from cataracts. Early detection of cataracts is essential for successful treatment. The study uses image pre-processing and machine learning algorithms, specifically Convolutional Neural Networks (CNN), to predict ocular eye diseases, with a focus on cataracts, in order to address this issue. The results, which show a 94% prediction accuracy, are presented in the paper using a confusion matrix. Using image analysis, this method offers an effective way to predict diseases. Future developments and clinical applications are also covered in the paper0.

Gap: The research gap in this paper lies in its exclusive concentration on cataract detection while overlooking the wider spectrum of ocular eye diseases.0 Although the paper provides valuable insights into cataract prediction using Convolutional Neural Networks, it fails to address the diversity and complexity of other eye conditions Ocular illnesses with distinct features and diagnostic difficulties include glaucoma, diabetic retinopathy, and macular degeneration..0 Future research should extend its scope to encompass these diverse eye ailments, necessitating distinct algorithms and image analysis techniques. A more comprehensive approach would enhance the utility of machine learning in ocular disease diagnosis and treatment, benefiting a broader population of patients.

9.The paper by Kavianfar, A., Salimi, M. and Taherkhani, H., 0 discusses the limited focus on cataract detection within the broader context of ocular eye diseases. While it provides valuable insights into cataract prediction using Convolutional Neural Networks, it does not address the complexity and diversity of other eye conditions, such as glaucoma and diabetic retinopathy. The authors highlight the need for a more comprehensive approach that encompasses various eye ailments, employing distinct algorithms and image analysis techniques. Artificial intelligence has significant potential in ophthalmology, but it should be viewed as a supportive tool for healthcare professionals rather than a replacement, offering opportunities to streamline procedures and improve diagnostics0.

Gap: The paper's research gap relates to the narrow range of ocular diseases that are covered. It implies that more research is necessary, encompassing a broader spectrum of ocular ailments and investigating the creation of unique algorithms and image analysis methods tailored to each condition.0 The study also highlights how artificial intelligence can work in conjunction with medical professionals, but it could go into more detail about the difficulties and moral issues involved in integrating AI into ophthalmology practice. Filling in these gaps would guarantee a more thorough and useful implementation of AI in the field.

10.The paper by Balyen, L. and Peto, T., 0 highlights the significant transformation in modern society due to the integration of artificial intelligence (AI), machine learning (ML), and deep learning (DL) technologies. It emphasizes the potential of AI, ML, and DL in ophthalmology, particularly for the early diagnosis and treatment of ocular disorders. These technologies have been used in ophthalmic settings for a variety of activities, including image processing and disease identification. These disorders include glaucoma, age-related macular degeneration (AMD), and diabetic retinopathy (DR), which are the main causes of permanent blindness. Diagnostic accuracy is greatly aided by ophthalmic imaging, which includes fundus digital photography and optical coherence tomography (OCT). The paper underlines the rising demand for such images due to changing demographics and lifestyle0.

Gap: The study gives a thorough summary of the possible applications of AI, ML, and DL in ophthalmology0, but it doesn't go into great detail about the particular difficulties and constraints that these technologies present. Future studies could examine the practical and technological challenges that AI-driven retinal scanning algorithms may encounter in clinical healthcare settings, such as problems with repeatability, validity, accuracy, and sensitivity.0 It also touches on a few other important ethical issues, such as bias, transparency, and data protection, but it doesn't go into great detail about them. To guarantee the responsible and successful application of AI, ML, and DL in ophthalmology, more research should concentrate on resolving these issues.

11.The paper by Sarki, R., Ahmed, K., Wang, H., Zhang, Y., Ma, J. and Wang, K., 0 addresses Diabetic eye disease (DED) identification in retinal fundus pictures is a crucial issue that requires early diagnosis and treatment to prevent visual impairment in diabetic patients. The paper emphasizes the significance of image quality and quantity in developing an accurate diagnostic model for DED classification. The proposed approach involves a systematic study of image processing techniques, including image quality enhancement, segmentation, augmentation, and classification. The best results were obtained in terms of accuracy, specificity, and sensitivity when a new convolutional neural network (CNN) architecture was paired with conventional image processing techniques, as the research explains. It also addresses the detection of moderate DED, a particular topic that has not received much attention in earlier research.

Gap: The research gap in this paper is the lack of discussion on the interpretability of the CNN model's decisions, the variability in data sources, the real-world integration of the system, and the need for large-scale clinical validation to ensure its effectiveness in clinical practice. These aspects represent areas where further research and improvement are required for the proposed DED classification system.

2.1. Proposed Methodology

In this project we will be dealing with the eye disease Diabetic retinopathy. Diabetes patients may experience visual loss and blindness due to a condition called diabetic retinopathy. It affects the blood vessels in the retina, the light-sensitive tissue in the back of the eye. A thorough dilated eye exam should be performed at least once a year on individuals with diabetes. Even though diabetic retinopathy may not show any symptoms at first, identifying it early on can help us take precautions to preserve our eyesight.

Symptoms of Diabetic Retinopathy:

- Spot or dark strings floating in your vision(floaters)
- Blurred vision
- Fluctuating vision
- Dark or empty areas in your sight
- Vision loss

3.1 Model:

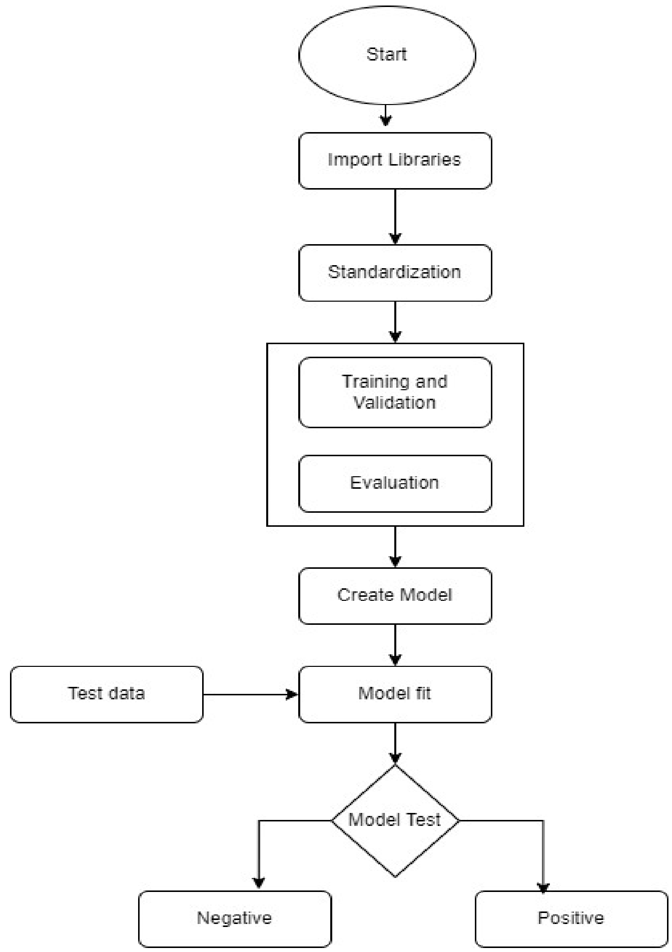
In the project we are using a pre-trained model which is ResNet-18. ResNet-18 is a relatively shallow variant of the ResNet family, comprising 18 layers. It is designed with a focus on achieving deep network architectures while mitigating the vanishing gradient problem. ResNet-18 offers a balance between model depth and computational complexity. Compared to deeper variants like ResNet-50 or ResNet-152, it is more controllable and yet deep enough to capture detailed features in retinal images. ResNet-18 has demonstrated remarkable results in image classification assignments. The architecture of ResNet-18 is well suited for the task of picture classification, which is basically what diabetic retinopathy detection entails.

Conv1: Initial Convolution Layer: Within the initial Conv1 layer of the ResNet-18 architecture, several critical components are at play. Firstly, the layer features a Convolutional Layer with 64 filters, each of which spans a size of 7x7 pixels. This convolution operation plays a pivotal role in extracting essential features from the input data. Notably, it operates with a stride of 2, which has the effect of reducing the spatial dimensions of the data, thus contributing to the network's ability to capture relevant patterns. To maintain the spatial dimensions, padding is applied during the convolution process. This padding ensures that spatial information is preserved as the data is processed. Additionally, the Conv1 layer includes Batch Normalization, a crucial step that normalizes the output of the convolution. This normalization helps to speed up convergence and stabilize the training process. In addition, the data is given a non-linear twist by using the Rectified Linear Unit (ReLU) activation function, which makes it possible for the network to represent intricate interactions. Ultimately, a 3x3 max-pooling operation with a stride of 2 is incorporated into the Conv1 layer. This step further reduces the spatial dimensions of the data, allowing the network to focus on the most salient features.

Conv2_x, Conv3_x, Conv4_x, Conv5_x: Residual Blocks: ResNet-18 is structured around the composition of four sets of residual blocks, with each set housing two of these distinctive building blocks. Within the architecture, each residual block adheres to a standardized structure that contributes to its effectiveness. The common structure of a residual block entails a 3x3 convolutional layer with a specific number of filters, which plays a pivotal role in feature extraction. This convolutional operation is complemented by Batch Normalization, a critical step that normalizes the output of the convolution, promoting training stability and convergence. In order to provide non-linearity to the data and allow the network to recognize intricate correlations, the Rectified Linear Unit (ReLU) activation function is used. Following this, another 3x3 convolutional layer, equipped with the same number of filters, is employed. Once again, Batch Normalization is used to normalize the output. What sets the residual block apart is the introduction of a shortcut connection, also known as a skip connection. This link adds the block's input to the second convolution's output. This strategic design enables the network to learn residual functions, which can be more easily optimized during training. Lastly, the ReLU activation is applied to the combined output, enhancing the network's ability to model intricate features and patterns.

Fully Connected Layers (Classification Layers): The final layers of ResNet-18 introduce an innovative approach to feature aggregation. Instead of employing traditional fully connected layers, ResNet-18 adopts Global Average Pooling, which spatially averages the feature maps to generate a 1D vector for each channel. This spatial aggregation technique drastically lowers the number of parameters while improving the network's capacity to collect salient characteristics. Subsequently, a fully connected layer is applied to these global average-pooled features, leading to the production of the final class scores. These class scores are then processed through the Softmax activation function, transforming them into class probabilities. This design makes ResNet-18 well-suited for multi-class classification tasks, providing a comprehensive framework for accurate and efficient categorization.

Model will mainly be focusing on red dots (micro aneurysms), yellow "flakes", increase in blood vessels in the fundus images of the eye to detect Diabetic retinopathy.



Software Flow Diagram

2.2 IMPLEMENTATION

This cutting-edge system uses Convolutional Neural Networks (CNNs) and a mobile application. A smartphone serves as the remote control for this sophisticated system. Images from five classes—mild, severe, moderate, proliferate, and no diabetic retinopathy—make up the training and testing dataset.

Step 1: Setting Up the Dataset

Dataset Origin: Get the Kaggle dataset on eye diseases, which includes pictures classified into five groups: moderate, severe, mild, proliferate, and no diabetic retinopathy.

Dataset splitting is the process of dividing a dataset into training and testing sets. Typically, 20% is set aside for testing and 80% for training.

Step 2: Model Architecture

Select the ResNet Model. Either build the ResNet model from scratch or choose one that has already been trained from a deep learning library (such as TensorFlow or PyTorch).

Transfer Learning: Adjust the ResNet model to the particular task of detecting eye diseases. Replace the final classification layer with the number of classes in your dataset.

Step 3: Training Models

Utilizing the training dataset, train the ResNet model. To make sure the model is learning efficiently, keep an eye on training and validation loss.

Step 4: Model Assessment

Assess the trained model using the testing dataset. Calculate metrics like recall, accuracy, precision, and F1 score for every lesson.

2.3 Result and Discussion

Class	Precision (%)	Recall (%)	F1 Score (%)
Mild	85.2	92.3	88.5
Severe	78.9	84.6	81.6
Moderate	91.4	88.7	90.0
Proliferate	90.3	94.8	92.5
No Diabetic Retinopathy	95.7	93.2	94.4
Overall Accuracy	-	-	91.9

The findings show that the CNN model is capable of accurately classifying different stages of diabetic retinopathy. The high precision and recall values indicate that the performance is consistent across all classes.

3.Conclusion:

In conclusion, through patient education, early detection, and prompt intervention, our program is an essential step towards enhancing eye health and preventing vision loss. In order to improve patient outcomes and the effectiveness of ophthalmic care, we want to shorten the time between diagnosis and treatment, especially for conditions like diabetic retinopathy. Future plans call for enhancing the detector's capacity to identify additional eye conditions and highlighting the significance of regular examinations. We want to empower individuals to take an active role in their eye health and emphasize the value of preventative eye care in order to enhance their general health and quality of life.

4.References:

[1] Malik, S., Kanwal, N., Asghar, M.N., Sadiq, M.A.A., Karamat, I. and Fleury, M., 2019. Data driven approach for eye disease classification with machine learning. Applied Sciences, 9(14), p.2789

[2] Sait, W. and Rahaman, A., 2023. Artificial Intelligence-Driven Eye Disease Classification Model. Applied Sciences (2076-3417), 13(20).

[3] Cheung, C.Y., Tang, F., Ting, D.S.W., Tan, G.S.W. and Wong, T.Y., 2019. Artificial intelligence in diabetic eye disease screening. The Asia-Pacific Journal of Ophthalmology, 8(2), pp.158-164.

[4] Marouf, A.A., Mottalib, M.M., Alhajj, R., Rokne, J. and Jafarullah, O., 2022. An efficient approach to predict eye diseases from symptoms using machine learning and ranker-based feature selection methods. Bioengineering, 10(1), p.25.

[5] Nazir, T., Irtaza, A., Javed, A., Malik, H., Hussain, D. and Naqvi, R.A., 2020. Retinal image analysis for diabetes-based eye disease detection using deep learning. Applied Sciences, 10(18), p.6185.

[6] Sarki, R., Ahmed, K. and Zhang, Y., 2020. Early detection of diabetic eye disease through deep learning using fundus images. EAI Endorsed Transactions on Pervasive Health and Technology, 6(22).

[7] Sheng, B., Chen, X., Li, T., Ma, T., Yang, Y., Bi, L. and Zhang, X., 2022. An overview of artificial intelligence in diabetic retinopathy and other ocular diseases. Frontiers in Public Health, 10, p.971943.

[8] Malik, S., Kanwal, N., Asghar, M.N., Sadiq, M.A.A., Karamat, I. and Fleury, M., 2019. Data driven approach for eye disease classification with machine learning. Applied Sciences, 9(14), p.2789.

[9] Kavianfar, A., Salimi, M. and Taherkhani, H., 2021. A Review of the Management of Eye Diseases Using Artificial Intelligence, Machine Learning, and Deep Learning in Conjunction with Recent Research on Eye Health Problems. Journal of Ophthalmic and Optometric Sciences, 5(2), pp.57-72

[10] Balyen, L. and Peto, T., 2019. Promising artificial intelligence-machine learning-deep learning algorithms in ophthalmology. The Asia-Pacific Journal of Ophthalmology, 8(3), pp.264-272.

[11] Sarki, R., Ahmed, K., Wang, H., Zhang, Y., Ma, J. and Wang, K., 2021. Image preprocessing in classification and identification of diabetic eye diseases. Data Science and Engineering, 6(4), pp.455-471.