A Review Paper On Ai-Powered Retinal Disease Classifier Using Fundus Images

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Abstact— **Retinal pathologies like diabetic retinopathy, cataract, and glaucoma constitute the most prevalent causes of avoidable blindness globally. Specialist ophthalmologist access continues to be a rarity, especially in areas where resources are scarce, even though the detection needs to be done early. To automatically identify and classify the four classes—Cataract, Diabetic Retinopathy, Glaucoma, and Normal—a fundus image-based AI-powered retinal disease classifier is proposed in this study. With an optimized pre-trained ResNet-18 model for multi-class classification, it utilizes transfer learning. To improve generality, the hand-collected dataset was preprocessed with augmentation, normalization, and resizing methods. Stratified splitting was used for balanced training (70%), validation (15%), and test (15%) sets. With overall accuracy of 90%, the model was optimized across three epochs using Adam optimizer and cross-entropy loss. Performance testing under diabetic retinopathy (0.97) and cataracts (F1-score: 0.91) included exceptionally high F1-score and recall; detection of glaucoma, however, was tough (F1-score: 0.84). From confusion matrix analysis, it was revealed that the majority of the misclassifications between glaucoma and normal ones reflected higher diversity in the dataset along with more sophisticated feature extraction. The model was implemented as a web application based on Flask for improving clinical utility with real-time prediction in a user-friendly interface even accessible to non-professionals. The approach has widespread scope for mass retinal screening, especially in telemedicine and rural medicine. Though the initial results are encouraging, glaucoma detection needs to be improved, diversity of datasets should be increased, and explain ability should be ensured. To alleviate the worldwide burden of preventable blindness, this study helps in the development of affordable AI-powered ophthalmology solutions.**

Keywords — **(CNN), Fundus Imaging, Retinal Disease Classification, Diabetic Retinopathy, Cataract, Glaucoma, ResNet-18, Transfer Learning, Medical Image Analysis, Telemedicine, Flask Web Application, Automated Screening, Preventable Blindness.**

I. INTRODUCTION

Vision is one of the most significant senses for human beings, and it significantly enhances quality of life and enables communication with the external world. Any form of visual impairment can lead to important functional limitations, social isolation, and a reduction in productivity. Almost half of the 2.2 billion people living with blindness or visual impairment worldwide can be avoided or treated by early diagnoses and timely intervention, says the World Health Organization (WHO).

More than 103 million people worldwide had diabetic retinopathy in 2020, and it is estimated this number would rise rapidly as diabetes is increasingly becoming prevalent. Diabetic retinopathy is a leading cause for blindness in adults in their productive years. Because these are often used for screening and diagnostic purposes as a result of their capability for obtaining a complete image of significant retinal features including the optic disc, macula, fovea, and retinal blood vessels, their use is routine. Artificial intelligence (AI), in particular machine learning (ML) and deep learning (DL), has significantly improved over the last decade in capabilities for handling hard pattern recognition problems. These frameworks are particularly suitable for complex and high-dimensional information, such as fundus images, since they are able to learn discriminative features directly from raw photos without manually constructed feature engineering. problems, developing multi-classification and multi-label classification models which are able to distinguish between several retinal diseases at a single instance is required. models, there are still few publicly available datasets of multi-disease fundus photographs. images. On a range of datasets, the system shall achieve high accuracy and generalization performance by extracting relevant features in an automatic manner using deep learning techniques, handling class imbalance by means of preprocessing and augmentation strategies.

II. LITERATURE REVIEW

1.AI-Powered Deep Learning for Retinal Image Analysis in Diabetic Retinopathy Detection:
Diabetic Retinopathy (DR) is a diabetes-related eye disease and one of the leading causes of preventable blindness worldwide, making early and accurate detection essential. Recent advances in artificial intelligence, particularly deep learning, have shown significant potential in automated medical image analysis. This work presents an AI-powered deep learning approach for retinal image analysis using fundus images to detect diabetic retinopathy at early stages. Convolutional Neural Networks (CNNs) are employed to automatically learn discriminative features from retinal images, enabling reliable classification of DR severity with minimal human intervention. The proposed system aims to improve screening efficiency, reduce dependency on manual diagnosis, and support ophthalmologists in timely decision-making, thereby enhancing the effectiveness of large-scale diabetic retinopathy screening programs.

2.A low-cost AI-Powered System for Early Detection of Diabetic Retinopathy and Ocular Diseases in Resource-Limited Settings:
Diabetic Retinopathy and other ocular diseases are major causes of vision impairment, particularly in resource-limited settings where access to specialist care and advanced diagnostic tools is limited. This study presents a low-cost AI-powered system for the early detection of diabetic retinopathy and common ocular diseases using retinal fundus images. The proposed approach leverages deep learning techniques to automatically analyze retinal images and identify disease-related features with high accuracy while maintaining affordability and ease of deployment. By minimizing the need for expensive equipment and expert interpretation, the system aims to enable scalable, community-level screening and early diagnosis. This solution has the potential to reduce preventable blindness by facilitating timely referral and treatment in underserved healthcare environments.

3.Advancing AMD screening with an offline, AI-powered smartphone-based fundus camera: A prospective, real-world clinical validation:
Age-related Macular Degeneration (AMD) is a leading cause of irreversible vision loss among the elderly, highlighting the need for accessible and efficient screening solutions. This study advances AMD screening through an offline, AI-powered smartphone-based fundus camera designed for real-world clinical use. The proposed system integrates a portable, low-cost fundus imaging device with a deep learning model capable of analyzing retinal images without internet connectivity. A prospective clinical validation is conducted to assess performance in real-world settings, demonstrating reliable detection of AMD while maintaining practicality and affordability. This approach enables early screening in remote and underserved areas, supports clinicians with rapid decision-making, and promotes wider adoption of retinal health screening outside traditional hospital environments.

4.Innovative Approach for Diabetic Retinopathy Severity Classification: An AI-Powered Tool using CNN-Transformer Fusion:
Diabetic Retinopathy (DR) is a progressive retinal disorder that requires accurate severity classification for timely treatment and vision preservation. This work presents an innovative AI-powered approach for diabetic retinopathy severity classification using a CNN–Transformer fusion model. The proposed system combines the strong local feature extraction capability of Convolutional Neural Networks with the global contextual understanding of Transformer architectures to effectively analyze retinal fundus images. By integrating both spatial and long-range dependencies, the model enhances classification accuracy across multiple DR severity stages. The approach aims to support ophthalmologists with reliable automated assessment, reduce diagnostic variability, and improve large-scale screening and clinical decision-making in diabetic eye care.

III. METHODOLOGY

1.Dataset Preparation and Splitting: - The dataset preparation process utilized a Python-driven pipeline to organize raw fundus images of four retinal diseases Cataract, Diabetic Retinopathy, Glaucoma, and Normal into a standardized format for AI training. To ensure a fair and unbiased model, images were first shuffled to eliminate ordering bias and then partitioned into three stratified subsets: 70% for training and feature learning, 15% for validation and hyperparameter tuning, and 15% for final testing.

This automated workflow maintained class balance across all subdirectories and preserved metadata integrity using the shutil.copy2() function. Ultimately, this rigorous preprocessing prevents data leakage and ensures the resulting deep learning pipeline can provide an unbiased estimate of diagnostic performance in real-world scenarios.

Class	Training Images	Validation Images	Testing Images
Cataract	726	155	157
Diabetic Retinopathy	768	164	166
Glaucoma	704	151	152
Normal	751	161	162

TABLE 1: DISTRIBUTION OF IMAGES AFTER DATASET SPLITTING

2.Data Preprocessing and Augmentation: - To ensure uniformity and compatibility with the model, retinal images were preprocessed through a standardized pipeline. All images were resized to 224 × 224 pixels to match ResNet-18 requirements and reduce computational cost. Pixel intensities were then normalized using ImageNet mean and standard deviation to support effective transfer learning and faster convergence. To improve robustness and reduce overfitting, training images were augmented using random horizontal flips and rotations between –10° and +10°, simulating real-world clinical variations. Validation and test images were only resized and normalized, without augmentation, to preserve their original characteristics and enable an unbiased evaluation of model generalization on unseen data.

3.Data Loading: - Effective data loading is essential for training deep learning models. In this work, PyTorch's DataLoader was used to load images from structured dataset directories with batching, shuffling, and parallel loading to improve efficiency and generalization. A batch size of 32 balanced GPU utilization and gradient stability, providing diverse samples for robust updates. Training data were shuffled each epoch to prevent overfitting, while shuffling was disabled for validation and test sets to ensure consistent evaluation. This controlled approach enabled stable gradient convergence, efficient resource usage, and reliable performance assessment for the retinal disease classification model.

4.Model Architecture and Modification: - The system employs the ResNet-18 architecture, which addresses challenges like vanishing gradients through residual learning. Pretrained on ImageNet, it already captures complex visual features, making it well-suited for transfer learning in medical imaging. For retinal disease classification, the original final layer was replaced to predict the four target classes, while the pretrained layers were retained and fine-tuned. This strategy enables faster training, high accuracy, and efficient use of limited data, resulting in a reliable tool for automated detection of eye diseases.

5.Model Training: - The Adam optimizer, appropriate for four-class classification tasks, was used for model training. The learning rate was set at 0.001 and Cross-Entropy Loss function was used. Three epochs were used for the training process, utilizing a GPU when it was available for fast computation and a CPU otherwise. To assess performance for the set used for training, for every epoch the loss and accuracy for the training was calculated. Concurrently, validation accuracy was monitored to assess the generalizability of the model as well as detect any potential indication of overfitting.

Epoch	Loss	Accuracy	Validation Accuracy
1	0.5677	0.7989	0.8082
2	0.3427	0.8739	0.8716
3	0.3088	0.8949	0.8685

TABLE 2: MODEL TRAINING AND VALIDATION PERFORMANCE PER EPOCH.

6.Model Evaluation: After training, the optimal model weights were saved as retinal_model.pth, enabling instant deployment and reproducible results without retraining. The model was evaluated on an independent test set using a classification report that measured precision, recall (sensitivity), and F1-score for each disease class. Additionally, a confusion matrix and heatmap were generated to visualize performance, highlighting correct classifications along the diagonal and identifying patterns of misclassification among retinal disease categories.

7.Web Application Design and Deployment: - The system was developed as a web-based application that integrates a user-friendly interface with a deep learning model for retinal disease prediction from fundus images. The backend was implemented using

Flask and supports a fine-tuned ResNet-18 convolutional neural network pretrained on ImageNet. The final fully connected layer was modified to classify four categories: cataract, diabetic retinopathy, glaucoma, and normal, and the optimized model weights were saved as *retinal_model.pth* and loaded at application startup. Uploaded images are processed through a PyTorch transformation pipeline involving resizing to 224 × 224 pixels, tensor conversion, and normalization using ImageNet parameters. During inference, the model runs in evaluation mode, and torch.max() is used to identify the class with the highest prediction probability. The frontend, built with HTML and CSS, features a glassmorphism-styled upload interface with a gradient background, while JavaScript enables image preview before submission. Upon upload, Flask handles preprocessing and model inference, and the predicted label is dynamically displayed on the same page. This seamless integration enables real-time inference, making the system suitable for quick, accurate retinal disease classification in clinical and educational settings.

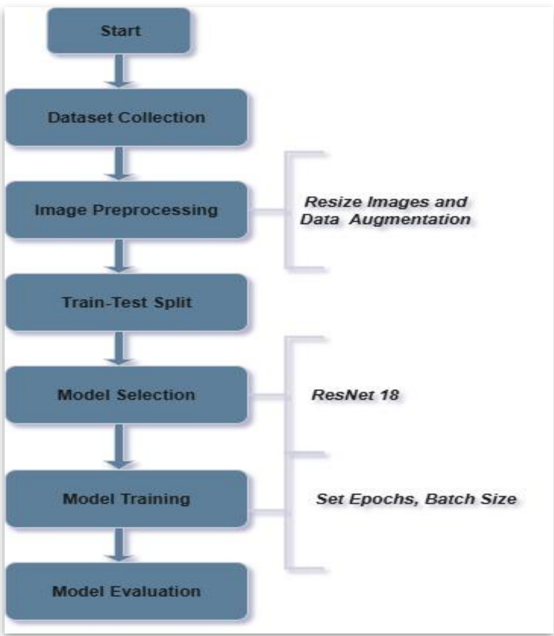

FIGURE 1: FLOWCHART OF THE AI-POWERED RETINAL DISEASE CLASSIFIER USING FUNDUS IMAGES.

IV. RESULT

The retinal fundus image dataset was divided into training (70%), validation (15%), and testing (15%) sets using a randomized process to ensure fair evaluation. All images were resized and normalized to match the ResNet-18 input requirements, while data augmentation techniques such as rotation and flipping were applied only to the training set to improve generalization. The pre-trained ResNet-18 model was fine-tuned for three epochs using the Adam optimizer and cross-entropy loss.

The model achieved an overall accuracy of 90% on the test dataset. Diabetic Retinopathy showed the best performance with perfect recall, indicating all cases were correctly identified. Cataract detection was also strong, with balanced precision and recall. Glaucoma classification demonstrated high precision but lower recall, suggesting that some glaucoma cases were missed due to overlapping visual features with normal images. The Normal class achieved consistent performance, confirming the model's reliability.

Class	Precision	Recall	F1-score	Support
Cataract	0.89	0.93	0.91	157
Diabetic Retinopathy	0.93	1.00	0.97	166
Glaucoma	0.94	0.76	0.84	152
Normal	0.84	0.88	0.86	162

TABLE 3: CLASSIFICATION REPORT OF THE RETINAL DISEASE CLASSIFIER.

Explanations: - A confusion matrix confirmed minimal misclassification, and the trained model was saved as retinal_model.pth. The classifier was deployed as a Flask-based web application, allowing users to upload retinal images and receive instant disease predictions. This deployment transforms the deep learning model into a practical, easy-to-use clinical support tool, enabling faster and more accessible retinal disease screening.

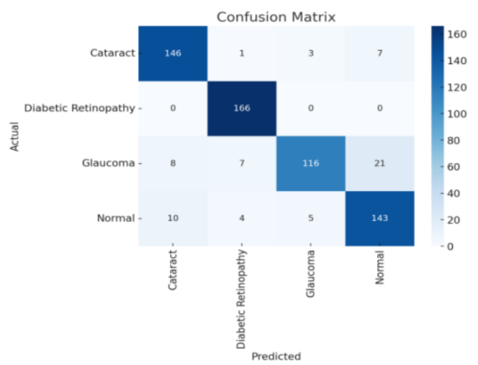

FIGURE 2: CONFUSION MATRIX OF DISEASE CLASSIFICATION.

Deployment of Flask Web Application: - The trained ResNet-18 model was deployed as a lightweight Flask web application with a simple and user-friendly interface, enabling both clinicians and non-technical users to perform retinal disease classification without programming knowledge. Users upload fundus images, which are automatically resized, normalized, and processed by the model in real time. The system then displays the predicted disease class clearly, transforming the deep learning model into a practical and accessible clinical support tool.

Clinical Implications and Observations: - The demonstration shows the real-world clinical applicability of the retinal disease classifier. The Flask-based deployment enables quick and efficient retinal screening in practical settings. While the model performs accurately for diabetic retinopathy and cataract, some glaucoma cases are misclassified, indicating the need for more data and improved feature extraction. Overall, the system successfully bridges the gap between research and practical diagnostic use.

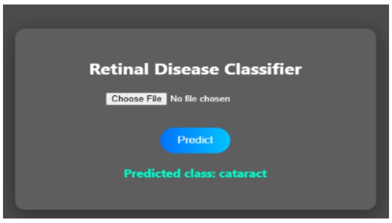

FIGURE 3: PREDICT OF DISEASE CLASSIFICATION

V. CONCLUSION

This research highlights the transformative potential of artificial intelligence in ophthalmology through the development of a ResNet-18 based retinal disease classifier that achieves 90% accuracy in identifying normal fundus, diabetic retinopathy, cataract, and glaucoma. Beyond its technical performance, the project's true impact lies in its practical deployment via a Flask-based web application, which bridges the gap between complex deep learning models and real-world clinical accessibility, particularly in low-resource or rural settings where trained ophthalmologists are scarce. While the system excels in detecting cataracts and diabetic retinopathy—the latter being crucial for preventing blindness through early intervention—it faces a significant challenge with glaucoma due to the limitations of using a single imaging modality (fundus photography) for a disease that often requires structural analysis like OCT or IOP testing. Despite this, the study underscores the importance of data pre-processing and efficient design, ensuring the tool remains scalable and functional on low-end hardware to promote global health equity. To evolve into a fully robust clinical tool, future work must focus on integrating multimodal data, improving model explainability through techniques like Grad-CAM, and expanding datasets to include more diverse populations. Ultimately, this work serves as a foundational step toward a global, AI-driven screening infrastructure that can provide affordable, real-time diagnostic support to prevent avoidable blindness worldwide.

APPLICATIONS

1.Early retinal disease detection
2.Diabetic retinopathy screening
3.Glaucoma detection
4.Cataract classification
5.Mass eye screening programs
6.Tele-ophthalmology services

ADVANTAGES

1.Early and accurate disease detection
2.Fast and automated screening
3.Reduced workload for ophthalmologists
4.Cost-effective diagnosis
5.High scalability for mass screening
6.Non-invasive diagnostic approach

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