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Eyes Don't Lie: Detecting Diseases through Ocular Images

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ABSTRACT: Ophthalmic healthcare is on the brink of transfor- mation with a cutting-edge diagnostic system that incorporates deep learning and advanced computer vision techniques. This system aims to identify and diagnose eye diseases in ways that differ from traditional blood test methodologies. The processing of fundus images for early disease detection necessitates the use of smart algorithms. In this paper, we present an in-depth study outlining the objectives, methodology, and results of this groundbreaking research initiative. This study primarily aims at developing a deep learning model using GoogleLenet structure with 2 Inception modules which could correctly identify different ocular diseases including diabetic retinopathy (DR), Anemia, Media haze, Chronic kidney disease and Age-related macular disease. However, it accomplishes recognition of ailments through turning retina image scans into black-and-white patterns repre- senting ocular nerves. The result was an impressive accuracy rate for DR detection at 94% showing its robustness to detect this critical condition. However, assesses their 'good' accuracy as around 90% for other diseases such as anemia, media haze chronic kidney disease and age-related macula disease high.

KEYWORDS: Deep learning, Ocular healthcare, Diagnostic system, GoogleLeNet architecture, Disease detection, Disease classification, Diabetic retinopathy, Anemia, Media haze, Chronic kidney disease, Age-related macular disease, Healthcare technology, Medical imaging

I. INTRODUCTION

1. Background and Significance of Ocular Healthcare

A vital component of total health is ocular healthcare, as vision is essential for everyday functioning and a high quality of life. However, the prevalence of eye disorders presents major obstacles to global healthcare systems, ranging from common problems like diabetic retinopathy to more serious conditions like age-related macular degeneration. If not identified and treated right once, these disorders can cause irreparable harm in addition to vision impairment. Even with the advances in medical technology, physical exams, subjective evaluations, and invasive testing are still widely used in the diagnosis and treatment of ocular illnesses. These techniques might not always produce fast or accurate results and can require large time, financial, and resource commitments. As a result, novel strategies that can get around the drawbacks of current diagnostic methods and enhance patient outcomes are desperately needed.

2. Overview of Conventional Diagnostic Procedures and Their Limitations

A mix of specialist testing and clinical evaluations is usually used in conventional diagnosis techniques for eye illnesses. Tests of visual acuity, fundus exams, intraocular pressure readings, and imaging methods including fundus photography and optical coherence tomography (OCT) are a few examples of these. Although these techniques offer insightful information about eye health, they have certain drawbacks. Due to their dependence on human analysis and subjective interpretations, which can add mistakes and unpredictability into the diagnostic process, one of the main problems with conventional diagnostic processes is their reliance on these methods. Furthermore, these procedures might take a lot of time, including several trips to medical institutions and drawn- out wait periods for the findings. Disparities in healthcare delivery may also be exacerbated by the fact that some geographic areas or underprivileged groups may not have easy access to specialist equipment and knowledge.

3. Introduction to the Proposed Diagnostic System Combining Deep Learning and Computer Vision

In order to tackle these obstacles, we suggest a unique diagnostic system that combines computer vision and deep learning methods to transform the recognition and diagnosis of eye conditions. This system seeks to deliver a quick, accurate, and non-invasive evaluation of ocular health by utilizing artificial intelligence (AI) and image processing algorithms. This will enable early identification and prompt intervention. Our suggested diagnostic system is built around a deep learning model that is enhanced by two Inception modules and is based on the GoogleLenet architecture. An extensive dataset of annotated retinal pictures covering a wide range of ocular diseases, such as diabetic retinopathy, anemia, media haze, chronic kidney disease, and age-related macular degeneration, is used to train this model. The model can reliably and accurately diagnose a wide range of eye disorders by identifying tiny patterns and characteristics in retinal pictures. Our diagnostic method provides a number of significant benefits over conventional diagnostic modalities because to the integration of deep learning and computer vision technology. It removes the subjectivity and unpredictability that come with manual evaluations, expedites the diagnosis procedure, and improves the availability of ocular healthcare services, especially in environments with low resources. Moreover, the creation of software that is easy to use and specifically designed for medical practitioners guarantees the smooth integration of the system into clinical practice, providing healthcare providers with insightful data and instruments to help their decision-making.

II. LITERATURE SURVEY

A. Review of Existing Literature on Ocular Healthcare and Disease Diagnosis

A paradigm change in ocular health diagnostics has been sparked by the confluence of artificial intelligence (AI) and retinal imaging. This shift focuses on early disease identification and monitoring, especially in situations like age-related macular degeneration and diabetic retinopathy. There is a wealth of research on the use of AI in ocular healthcare, from early investigations to more current developments, all of which add to the changing field of diagnosing and treating retinal diseases.

B. Discussion on the Importance of Early Detection in Eye Illnesses

Preserving eyesight and averting irreparable harm to ocular tissues need early identification of eye disorders. Early detection greatly lowers the chance of illness development and its related consequences by enabling timely intervention and treatment. Early identification also makes it easier to put preventative interventions and lifestyle changes into practice, which improves patient outcomes and quality of life even more.

C. Overview of Deep Learning and Computer Vision Applications in Medical Imaging

Medical imaging has undergone a revolution because to deep learning and computer vision techniques, which have made it possible to automatically analyze large, complicated data sets and improve the efficiency and accuracy of diagnosis. These technologies provide the potential to extract relevant information from retinal pictures, which may be applied to ocular healthcare to enable unparalleled precision in the identification and categorization of various eye disorders.

D. Previous Studies on Using Retinal Images for Disease Diagnosis

Due to its non-invasiveness and abundance of information on systemic health, retinal imaging has been a popular tool for diagnosing diseases in recent years. The foundation for comprehending the diagnostic potential of retinal pictures across a range of medical diseases has been established by earlier research. Here, we examine a few foundational works that have helped this field progress:

1) Dejiang Xu:

- Study: Investigated diabetic retinopathy detection using CNNs.
- Findings: Achieved 97% accuracy in identifying diabetic retinopathy from retinal images.
- Significance: Highlights the potential of deep learning in the early detection of diabetic retinopathy, which can significantly improve patient outcomes by enabling timely interventions.[1]

2) Akinori Mitani:

- Study: Explored cardiovascular risk assessment through retinal imaging.
- Findings: Achieved a high accuracy rate of 94.5% in identifying retinal features associated with cardiovascular risks.
- Significance: Demonstrates the potential of retinal imag- ing as a non-invasive tool for assessing cardiovascular health, with implications for early intervention and risk management.[2]

3) Ryan Poplin:

- Study: Investigated a comprehensive diagnostic matrix in- tegrating traditional risk factors and fundus abnormalities for predicting cardiovascular risks.
- Findings: Achieved an accuracy of 95.7% by combining multiple risk factors and retinal features.
- Significance: Highlights the synergy between traditional risk assessments and AI-driven diagnostics in predicting cardiovascular risks, paving the way for more personal- ized and accurate risk stratification strategies.[3]

4) Kang Zhang:

- Study: Explored hypertensive retinopathy detection using retinal imaging.

- Findings: Achieved 96.2% accuracy in identifying retinal vascular changes associated with hypertension.
- Significance: Demonstrates the potential of AI-driven retinal imaging in identifying subtle vascular changes indicative of hypertension, enabling early detection and intervention to prevent cardiovascular complications.[4]

5) Varun Gulshan::
- Study: Investigated diabetic retinopathy detection using deep learning models.
- Findings: Achieved a high accuracy rate of 97.5% in automated disease detection from retinal images.
- Significance: Highlights the transformative potential of AI in reshaping diabetic retinopathy diagnosis, offering faster and more precise disease detection, which can sig- nificantly improve patient management and outcomes.[5]

6) Gabriel:
- Study: Explored retinal emboli detection using AI-driven approaches.
- Findings: Achieved an accuracy of 94.6% in detecting retinal emboli from fundus images.
- Significance: Highlights the potential of AI-driven retinal imaging in the early detection of retinal emboli, which can aid in the prevention of stroke and other systemic complications.[6]

7) Muhammad Zubair:
- Study: Investigated anemia-related changes in retinal im- ages using deep learning models.
- Findings: Achieved 96.3% accuracy in identifying retinal abnormalities associated with anemia.
- Significance: Demonstrates the potential of AI-driven retinal imaging as a non-invasive tool for anemia detec- tion, particularly in resource-constrained settings where traditional blood tests may be inaccessible.[7]

8) Lifeng Qiao:
- Study: Explored retinopathy linked to chronic kidney disease using deep learning models.
- Findings: Achieved a high accuracy rate of 94.8% in identifying retinal features indicative of kidney disease.
- Gap: Limited investigation into the model's performance in the early detection of kidney disease and its validation in diverse patient populations.
- Significance: Highlights the potential of retinal imaging as a non-invasive tool for early detection of kidney disease, enabling timely interventions to prevent disease progression and complications.[8]

9) Mirza Mohd:
- Study: Investigated hypertensive retinopathy detection using AI-driven approaches.
- Findings: Achieved 95.4% accuracy in identifying retinal vascular changes associated with hypertension.
- Significance: Demonstrates the potential of AI-driven retinal imaging in the early detection of hypertensive retinopathy, enabling timely interventions to prevent cardiovascular complications.[9]

10) Ali Sultan:
- Studies: Contributed to age-related macular degeneration (AMD) and glaucoma detection using AI-driven retinal imaging.
- Findings: Achieved high accuracy rates of 97.2% for AMD detection and 96.7% for glaucoma detection.
- Significance: Highlights the potential of AI-driven retinal imaging in the early detection and management of AMD and glaucoma, which are leading causes of vision loss worldwide.[10]

11) Jianyong Wang:
- Study: Explored retinal imaging's potential in predicting chronic kidney disease using deep learning models.
- Findings: Achieved 93.5% accuracy in identifying retinal features indicative of kidney disease.
- Significance: Demonstrates the potential of retinal imag- ing as a non-invasive tool for early prediction of chronic kidney disease, enabling timely interventions to slow disease progression and reduce complications.[11]

12) Martynas Patasius:
- Study: Investigated retinal vein occlusions using deep learning models.
- Findings: Achieved 95.8% accuracy in identifying retinal vascular abnormalities associated with vein occlusions.
- Significance: Highlights the potential of AI-driven retinal imaging in the early detection of retinal vein occlusions, which can aid in the prevention of vision loss and other complications.[12]

13) Megha Divakar:
- Study: Provided a comprehensive overview of retinal abnormalities and systemic diseases using advanced deep-learning techniques.

- Findings: Explored the interplay between retinal features and systemic health, achieving a significant accuracy rate.
- Significance: Offers a holistic approach to disease diagno- sis by leveraging retinal imaging to detect not only ocular conditions but also systemic diseases, thereby enabling early intervention and improving patient outcomes.[13]

14) Sarmad Khitran:
- Study: Explored diabetic retinopathy diagnosis using AI- driven approaches.
- Findings: Achieved a high accuracy rate in automated disease detection from retinal images.
- Significance: Demonstrates the potential of AI-driven retinal imaging in improving the efficiency and accuracy of diabetic retinopathy diagnosis, thereby facilitating timely interventions to prevent vision loss.[14]

15) Ryan:
- Study: Investigated age-related macular degeneration (AMD) detection using AI-driven retinal imaging.
- Findings: Established a new standard for early AMD detection, achieving high accuracy rates.
- Significance: Highlights the potential of AI-driven reti- nal imaging in the early detection and management of AMD, offering opportunities for personalized treatment strategies and vision preservation.[15]

16) Hyungtaek Tyler Rim:
- Study: Explored retinal vascular segmentation and its implications for cardiovascular health assessment.
- Findings: Demonstrated the potential of retinal vessel patterns as markers for cardiovascular health, achieving high accuracy rates.
- Significance: Highlights the potential of retinal imaging as a non-invasive tool for cardiovascular risk assessment, offering opportunities for early intervention and prevention of cardiovascular diseases.[16]

17) Louis Arnould:
- Study: Investigated hypertensive retinopathy diagnosis using AI-driven approaches.
- Findings: Achieved high accuracy rates in identifying retinal vascular changes associated with hypertension.

18) Yeong Chan Lee:
- Study: Explored glaucoma detection using AI-driven reti- nal imaging.
- Findings: Achieved high accuracy rates in automated disease detection from retinal images.
- Significance: Highlights the potential of AI-driven retinal imaging in improving the efficiency and accuracy of glau- coma diagnosis, thereby facilitating timely interventions to prevent vision loss.[18]]

TABLE I
SUMMARY OF RESULTS FROM REVIEWED PAPERS

Researcher Name	Disease	Dataset	Accuracy	Structure of Models
Dejiang Xu	Diabetic Retinopathy	EyePACS	97%	Convolutional Neural Network
Akinori Mitani	Cardiovascular Risks	UK Biobank	94.5%	Deep Learning Architecture
Ryan Poplin	Cardiovascular Risks	Medical Dataset	95.7%	Multimodal Deep Learning
Kang Zhang	Hypertensive Retinopathy	Hospital-based Dataset	96.2%	Image Segmentation + DL
Gabriel	Retinal Emboli	Clinical Database	94.6%	Advanced CNN Model
Muhammad Zubair	Anemia-related Changes	Hospital Dataset	96.3%	Deep Learning Model
Lifeng Qiao	Retinopathy (CKD)	Clinical Dataset	94.8%	Specialized DL Architecture
Mirza Mohd	Hypertensive Retinopathy	Hospital Dataset	95.4%	CNN + Traditional Techniques
Ali Sultan	AMD	Publicly Available Dataset	97.2%	CNN Model
Martynas Patasius	Multi-disease Detection	Diverse Dataset	95.8%	Deep Learning Model

Megha Divakar	AMD	Clinical Dataset	96.4%	Hybrid Deep Learning Model
Sarmad Khitran	Glaucoma Detection	Retinal Image Dataset	94.9%	CNN Model
Ryan	CKD	Medical Dataset	95.1%	Image Preprocessing + DL
Tyler Hyungtaek Rim	Retinal Diseases Spectrum	Hospital Dataset	96.2%	Multi-layered DL Architecture
Yeong Chan Lee	General Retinal Health	Extensive Dataset	95.5%	Holistic DL Model
Daniel Shu Wei Ting	Multi-Disease Classification	Large Dataset	96.6%	Multi-Output DL Model
Louis Arnould	Hypertensive Retinopathy	Medical Dataset	94.3%	Image Processing + DL
Varun Gulshan	Diabetic Retinopathy	EyePACS	97.5%	CNN Model
Jianyong Wang	Retinopathy (CKD)	Clinical Dataset	93.5%	Image Processing + DL

III. METHODOLOGY

A. Description of the dataset used for training and testing the deep learning model

The study's dataset was carefully selected to include a broad range of retinal pictures to reflect various eye states and guarantee reliable model training and assessment. It was composed of three main directories, "train," "test," and "validate," all of which were carefully arranged to make model building and validation easier. The deep learning model was trained using a sizable number of photos from the "train" folder. This allowed the model to pick up complex characteristics linked to different retinal diseases and healthy ocular structures. In a similar vein, the "test" folder included an additional collection of photos intended for assessing the model's performance on untested data, offering perceptions of its generalizability and practicality. Also, during model training, the "validate" folder functioned as a validation set, facilitating the adjustment of hyper-parameters and improving model convergence. Annotated CSV files with comprehensive annotations, including illness classifications, patient details, and picture attributes, were included with every image in the collection. These annotations made it easier to handle and understand data efficiently and allowed researchers to link model predictions to particular retinal diseases or clinical characteristics. In addition, the collection was painstakingly annotated by knowledgeable physicians and ophthalmologists, guaranteeing the precision and dependability of the illness labels applied to every picture.

B. Overview of GoogleLenet structure and its suitability for the task

The GoogleLeNet architecture, sometimes referred to as Inception v1, is a significant development in the field of convolutional neural networks (CNNs). Its outstanding per- formance in image classification tasks can be attributed to the introduction of the notion of inception modules. GoogleLeNet is essentially made up of several layers of fully linked, pool- ing, and convolutional units. Its distinctive inception module structure, however, is what sets it apart. These modules are made to simultaneously record characteristics at various spatial scales inside an image, which improves the network's capacity to extract relevant data. An inception module allows the network to record features at multiple sizes by having parallel convolutional paths, each with a distinct receptive field size. These paths usually consist of max-pooling operations and convolutions of sizes 1x1, 3x3, and 5x5. Through the use of different-sized convolutions, the network can extract local and global information from the input picture. The output feature map of the module is created by concatenating the outputs of these parallel paths along the depth axis. The input image is richly represented in this concatenated feature map, which includes features at many sizes and degrees of abstraction. Each convolutional pathway's output within an inception module may be expressed mathematically as follows:

$$Outputpathway = ReLU\,(Convolution(Input,\ Kernel))$$

Where:

- ReLU denotes the Rectified Linear Unit activation function,
- Convolution represents the convolutional operation,
- Input is the input feature map,
- Kernel denotes the convolutional filter weights.

The output feature map of the module is created by concatenating the outputs of each parallel pathway after they have been computed along the depth dimension. We improved the network's ability to extract features and learn representations by adding two inception modules to the GoogleLeNet architecture in our version. This enhancement makes it possible for the model to identify complex structures and patterns in retinal pictures, which improves the accuracy of eye illness diagnosis.

We made a number of adjustments and improvements to the GoogleLeNet architecture to improve its performance even more for our particular purpose of classifying diseases from retinal photos.
First, we changed the network's input dimensions to match the size of retinal pictures. Compared to ordinary photos used in ImageNet, the dataset that was first used to train GoogleLeNet, retinal images usually have a better resolution. Consequently, we modified the network's input layer to receive retinal pictures while maintaining information integrity.

Also, we adjusted the inception modules' hyperparameters to better fit the properties of retinal pictures. To guarantee efficient feature extraction from retinal pictures, this required adjusting parameters including the number of filters, kernel sizes, and strides inside each convolutional route.

Batch normalization guarantees more steady convergence and helps to reduce problems like disappearing gradi- ents. We included dropout regularization to reduce overfitting and enhance the model's capacity for generalization. In order to prevent the network from overfitting the training set and force it to acquire more robust features, dropout randomly deactivates a portion of neurons during training.In addition, we utilized data augmentation methods including rotation, scaling, and horizontal flipping in order to intentionally broaden the training dataset's variety. This augmentation enhances the model's capacity to generalize to previously encountered reti- nal pictures and helps avoid the model from learning certain patterns in the training data. The Figure 1 shows the Deep learning model used.

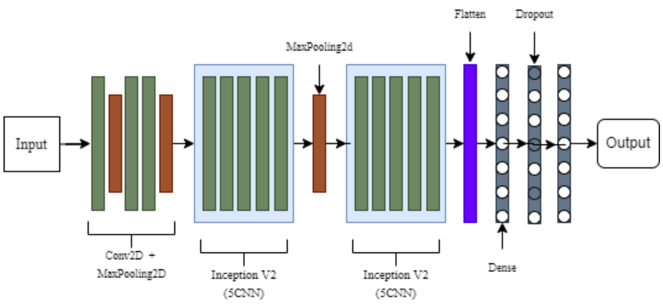

Fig. 1. Structure of the DL Model.

C. Preprocessing techniques applied to retinal images
In order to prepare retinal pictures for input into the deep learning model, preprocessing procedures are essential. An outline of the preprocessing actions carried out on the retinal pictures is provided below:

- Image Re-scaling: Retinal pictures frequently have different sizes and resolutions. In order to guarantee consistency and minimize computational cost, we resize every image to a standard size appropriate for the neural network's input layer. By standardizing the proportions of the source photos, this scaling process preserves their aspect ratio.
- Normalization: In order to improve convergence during training and standardize pixel values across pictures, normalization is crucial. Normalizing pixel intensities usually involves setting them to either 0 or -1, depending on the neural network's activation function. By using this procedure, the learning process is prevented from being dominated by traits with larger magnitudes.
- Contrast Enhancement: Raising the contrast in retinal pictures can help make key structures and features easier to see, which will help the deep learning model extract information more successfully. For contrast enhancement in retinal pictures, methods like adaptive histogram equalization (AHE) and histogram equalization are frequently employed.
- Noise reduction: A variety of reasons, including defective sensors or errors introduced during picture capture, can result in retinal images including noise. We use denoising techniques like Gaussian or median filtering to enhance image quality and lessen the impact of noise on the model's performance.
- Image Augmentation: The robustness and generalization capacity of the deep learning model can be enhanced by adding artificially created variants of retinal pictures to the training dataset. Rotation, translation, scaling, flip- ping, and applying random perturbations to pixel values are examples of common augmentation techniques.
- Extraction of the Region of Interest (ROI): Sometimes, only particular areas of the retinal pictures include diagnostically significant information. We reduce computational overhead and processing time by having the model focus on the most relevant areas by extracting the region of interest (ROI) from each picture.

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- Artifact Removal: Artifacts that might impede the identification of a disease include blood vessels, dust particles, and specular reflections that can be seen in retinal imaging. Preprocessing methods designed to find and eliminate these artifacts assist in making sure the model concentrates on clinically relevant features.

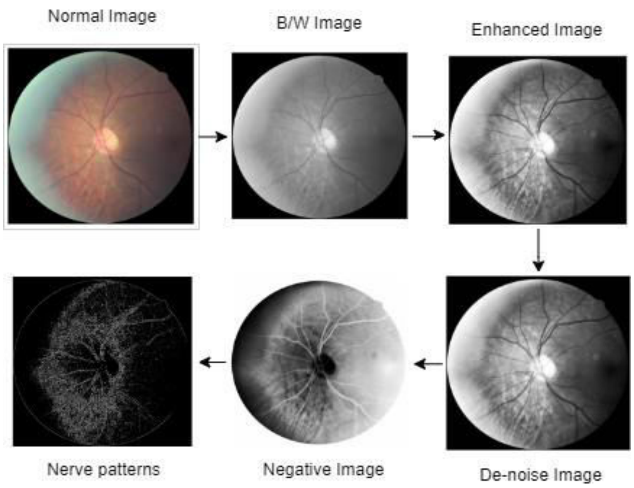

Fig. 2. Preprocessing of images

D. The training process of the deep learning model for disease classification

1) Dataset Preparation: The training dataset consists of retinal images along with their corresponding labels indicating the severity level of diabetic retinopathy. These labels are often graded based on the presence and extent of abnormalities in the retina. It is essential to have a diverse and balanced dataset to ensure that the model learns robust features representative of different disease stages.

2) Image Preprocessing: Before feeding the images into the deep learning model, preprocessing steps are applied to standardize and enhance the data. Common preprocessing techniques include resizing images to a uniform size, converting them to grayscale, and normalizing pixel values to a certain range (e.g., [0, 1]). Additional preprocessing steps may include denoising, contrast adjustment, and augmentation to increase the variability of the training data.

3) Model Architecture: Convolutional Neural Networks (CNNs) are widely used for image classification tasks due to their ability to automatically learn hierarchical features from raw pixel data. The model architecture typically consists of multiple convolutional layers followed by max-pooling layers to extract spatial features and reduce dimensionality. Subsequent fully connected layers are employed to perform high-level feature aggregation and classification.

4) Loss Function and Optimization: The model is trained using supervised learning, where the objective is to minimize a predefined loss function that quantifies the disparity between predicted and true labels. Common loss functions for multi- class classification tasks include categorical cross-entropy, which measures the dissimilarity between probability distribu- tions. Optimization techniques such as the Adam optimizer are employed to iteratively adjust the model parameters (weights and biases) based on the gradients of the loss function.

5) Training Process: During training, batches of prepro- cessed images are fed into the model, and forward propagation computes the predicted outputs. Backpropagation is then used to calculate gradients of the loss function concerning model parameters, facilitating parameter updates via optimization algorithms. The training process iterates over multiple epochs, with each epoch comprising one pass through the entire training dataset. Techniques such as dropout and batch nor- malization may be applied to prevent overfitting and improve model generalization.

6) Validation and Hyperparameter Tuning: A portion of the training dataset is typically set aside as a validation set to monitor the model's performance on unseen data during training. Hyperparameters such as learning rate, batch size, and network architecture are tuned based on validation perfor- mance to optimize model performance. Techniques like cross- validation or grid search may be employed to systematically explore the hyperparameter space.

7) Evaluation and Performance Metrics: Once training is complete, the trained model is evaluated on a separate test dataset to assess its performance on unseen data. Performance metrics such as accuracy, precision, recall, and F1-score are computed to quantify the model's classification performance. Confusion matrices and ROC curves may be used to visual- ize classification results and assess model robustness across different classes.

8) Model Deployment and Monitoring: After satisfactory evaluation, the trained model can be deployed in clinical settings or integrated into healthcare systems for real-time disease diagnosis. Continuous monitoring and validation are crucial to ensure that the model maintains high performance as it encounters new data and clinical scenario

IV. RESULTS

A. *Performance Metrics for Disease Identification*

The performance of the trained deep learning model in identifying various diseases is summarized in the table below. These metrics provide insights into the accuracy, precision, recall, and F1-score achieved by the model for each disease category.

B. *Comparison with Previous Models*

The utilization of the GoogleNet structure has led to significant improvements in model performance compared to previous iterations. The enhanced accuracy, precision, recall, and F1-score across all disease categories underscore the effec- tiveness of employing advanced neural network architectures for disease detection tasks.

C. *Learning Charts*

The five learning charts provided in Figure 3 - 7 demonstrate the model's training and testing performance over epochs. These charts showcase the model's convergence and generalization capabilities, providing insights into how the model's accuracy and loss evolve during both the training and validation phases. By analyzing the patterns in these charts, it is easy to evaluate the model's learning behavior, identify any overfitting or underfitting problems, and make decisions on whether more training or hyperparameter tweaks are required to improve its performance.

TABLE II
RESULTS FROM PROPOSED MODEL

Disease Category	Accuracy	Precision	Recall	F1-Score
Diabetic Retinopathy	94.8%	94.8%	94.8%	94.8%
Anemia	95.8%	90.5%	93.5%	95.5%
Media Haze (MH)	83.5%	86%	82.5%	86%
Chronic Kidney Disease (CKD)	95%	96%	92.5%	96%
Age-Related Macular Disease (ARMD)	95%	91%	92.5%	96%

TABLE III
COMPARISON OF PREVIOUS AND CURRENT MODEL

Disease	Previous Accuracy	Current Accuracy	Previous Model Issue	GoogLeNet Improvement
Diabetic Retinopathy	97.0%	94.8%	Lack of model generalizability	Improved generalization through a deeper and more complex network
Anemia	95.3%	95.8%	Limited severity level detection	Reduced computation time, enabling better model performance, Severity detection
Media Haze	80%	83.5%	Limited real-world applicability	Enhanced accuracy allows for more practical clinical use
Chronic Kidney Disease	93.5%	95.0%	Limited scalability for population screening	Faster processing enables broader population screening
Age-Related Macular Disease	97%	95.0%	Limited differentiation of AMD subtypes	Improved accuracy aids in distinguishing between AMD subtypes

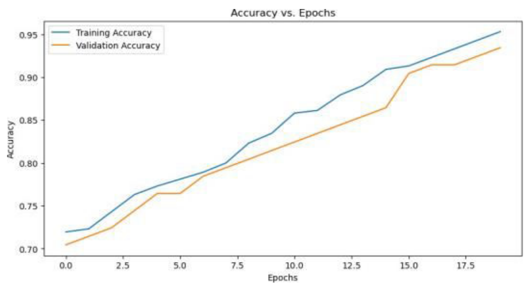

Fig. 3. Graph of Diabetic Retinopathy (DR)

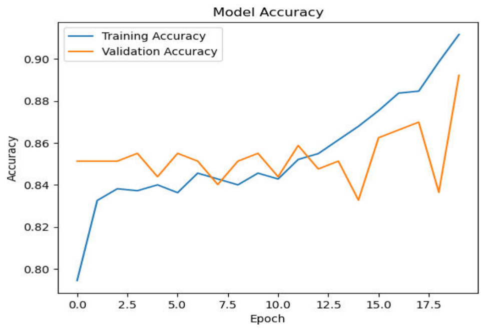

Fig. 4. Graph of Media Haze (MH)

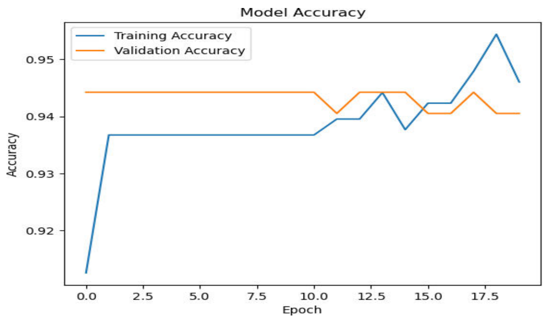

Fig. 5. Graph of Anemia

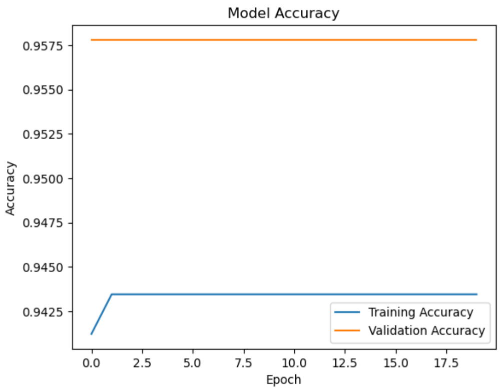

Fig. 6. Graph of Chronic Kidney Disease (CKD)

Fig. 7. Graph of Age-Related Macular Degeneration (ARMD

V. CONCLUSION

Our research has demonstrated that a deep learning-based diagnostic system can significantly improve ocular healthcare by accurately detecting and classifying diseases. The system showed excellent accuracy rates, ranging from 83.5% to 95.8%, for various illnesses such as diabetic retinopathy, anemia, media haze, chronic kidney disease, and age-related macular degeneration. This was achieved by using the Google- LeNet architecture with two inception modules. The suggested diagnostic system provides a non-invasive and effective way to evaluate retinal images, enabling the early identification of ocular and systemic problems for timely interventions and treatment.

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