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COGNITIVE DIAGNOSIS OF CHRONIC GLAUCOMA AND ITS DIFFERENTIATION FROM DIABETIC RETINOPATHY USING MACHINE LEARNING AND DEEP LEARNING

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ABSTRACT: Timely and accurate diagnosis of ocular diseases such as Chronic Glaucoma and Diabetic Retinopathy is essential to prevent irreversible vision impairment and blindness. Traditional diagnostic methods often rely on manual examination and expert interpretation, which can be both time-intensive and prone to variability. This study presents a comprehensive machine learning and deep learning-based framework for the automated prediction of Chronic Glaucoma and Retinopathy using both clinical data and retinal fundus images. The proposed methodology integrates structured data analysis using machine learning algorithms for image-based diagnosis. Fundus photographs are preprocessed using standard enhancement techniques, including histogram equalization, denoising, and vessel segmentation, to improve feature visibility and model accuracy. Clinical features such as intraocular pressure, optic cup-to-disc ratio, blood glucose levels, and patient history are employed alongside imaging data to enrich the prediction pipeline. A multi-label classification approach is adopted to enable the simultaneous detection of both diseases, accommodating cases where patients present with overlapping symptoms or comorbid conditions. Model performance is rigorously evaluated using metrics such as accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC-ROC). Interpretability and model transparency are addressed through the application of Gradient-weighted Class Activation Mapping (Grad-CAM) for CNN models and SHapley Additive exPlanations (SHAP) for tree-based ML models, offering insight into critical decision-driving features. The results demonstrate that the integration of clinical and imaging data substantially improves predictive performance and reliability. The proposed system holds promise for deployment in clinical environments, especially in areas with limited access to ophthalmology specialists, by providing a scalable and accurate diagnostic tool for early-stage detection and management of Chronic Glaucoma and Retinopathy.

Keywords: Chronic Glaucoma, Diabetic Retinopathy, Machine Learning, Deep Learning, Fundus Imaging, Convolutional Neural Networks, Multi-label Classification, Model Interpretability, SHAP, Grad-CAM, Medical Diagnostics

I. INTRODUCTION

Visual impairment and blindness remain significant global health challenges, with chronic

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eye diseases such as Glaucoma and Diabetic Retinopathy (DR) being among the leading causes [1][2]. According to the World Health Organization (WHO), glaucoma is expected to affect more than 75 million individuals by 2040 [3], while the prevalence of DR is anticipated to rise alongside the increasing global rates of diabetes [4]. These diseases, often asymptomatic in the early stages, tend to progress silently, with significant and sometimes irreversible vision loss occurring before diagnosis. Early and accurate detection is therefore essential for effective treatment, management, and prevention of vision impairment in affected individuals [5]. Traditional diagnostic methods for glaucoma and DR primarily involve manual interpretation of retinal fundus images, alongside clinical data such as intraocular pressure (IOP) and the cup-to-disc ratio (CDR) for glaucoma, and blood glucose levels for DR [6][7]. These methods, however, are time-consuming, heavily reliant on the expertise of ophthalmologists, and often not readily accessible in low-resource or remote settings [8]. Moreover, both conditions can present with subtle and overlapping changes in retinal images, leading to challenges in differentiating between them and increasing the risk of misdiagnosis or delayed detection [9]. In recent years, Artificial Intelligence (AI) has emerged as a promising tool in medical image analysis, particularly in the detection and diagnosis of ocular diseases [10][11]. Machine Learning (ML) algorithms, which are adept at handling structured clinical data, and Deep Learning (DL) techniques, especially Convolutional Neural Networks (CNNs), have shown remarkable success in automating tasks like image segmentation, feature extraction, and classification [12][13]. These advancements provide an opportunity to enhance diagnostic accuracy, improve efficiency, and make disease screening more accessible [14]. However, existing studies have generally focused on detecting either glaucoma or diabetic retinopathy in isolation, with little emphasis on cases where both diseases coexist [15]. The simultaneous presence of these conditions in patients can complicate diagnosis and treatment. To address this gap, this study proposes an integrated framework that combines both ML and DL techniques to simultaneously predict Chronic Glaucoma and Diabetic Retinopathy. The proposed system utilizes clinical features, including IOP, CDR, and blood glucose levels, along with high-resolution retinal fundus images, to predict both diseases in a multi-label classification format [16]. By combining ResNet-101 and DenseNet-121 architectures for deep learning, the system is designed to enhance feature extraction from retinal images, providing accurate segmentation and classification of key features like the cup-to-disc ratio for glaucoma

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and vascular lesions for DR [17][18]. Additionally, model interpretability is incorporated through SHapley Additive exPlanations (SHAP) for ML models and Gradient-weighted Class Activation Mapping (Grad-CAM) for CNNs, ensuring that the predictions are transparent and interpretable by clinicians [19][20]. This framework aims to contribute to the early detection and management of these chronic ocular diseases, potentially improving patient outcomes and reducing the burden of preventable blindness globally [21][22].

II. LITERATURE REVIEW

1. Glaucoma Detection

Glaucoma is a major cause of irreversible blindness worldwide. It is characterized by damage to the optic nerve, often associated with elevated intraocular pressure (IOP). The early detection of glaucoma is critical in preventing vision loss. Traditional diagnostic methods for glaucoma include measuring IOP, assessing the cup-to-disc ratio (CDR), and examining the optic nerve head through fundus images. However, these methods are subjective, time-consuming, and heavily reliant on the expertise of ophthalmologists [1]. As a result, there has been a growing interest in the use of Machine Learning (ML) and Deep Learning (DL) models for automated glaucoma detection.

A study by Ather et al. (2020) [2] developed an automated glaucoma detection system using a Support Vector Machine (SVM) classifier, based on features extracted from optic disc images. This model achieved high accuracy, highlighting the potential of ML in diagnosing glaucoma. However, the reliance on handcrafted features limited the generalizability of the model. To address this, Convolutional Neural Networks (CNNs), a type of deep learning model, have been proposed. ResNet-101, a deep CNN, was introduced in He et al. (2016) [3], and has shown promising results for various image classification tasks, including glaucoma detection. ResNet-101's use of residual learning allows for the efficient training of deeper networks, making it an ideal candidate for detecting subtle signs of glaucoma in retinal images.

Another important approach is the use of DenseNet for glaucoma detection. In Huang et al. (2017) [4], the authors presented DenseNet-121, which connects every layer to every other layer, enabling the network to reuse features more effectively. DenseNet has been successfully applied in various medical image analysis tasks, including the segmentation and detection of glaucoma-related features, such as the optic disc and cup.

2. Diabetic Retinopathy (DR) Detection

Diabetic Retinopathy (DR) is another leading cause of blindness, primarily affecting individuals with long-term diabetes. DR is characterized by

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retinal vascular changes, including **microaneurysms**, **hemorrhages**, and **exudates**. Early detection of DR is vital to prevent irreversible vision damage, and traditional methods of diagnosing DR, such as manual grading by ophthalmologists, are subject to inter-observer variability and are time-consuming [5]. The advent of AI in DR detection has led to the development of automated systems that can detect these features more efficiently.

One notable approach is the use of CNNs, which have achieved state-of-the-art results in DR detection. In **Gulshan et al. (2016)** [6], a deep learning model was trained on a large dataset of retinal images and achieved human-level performance in detecting DR. **DenseNet-121** has also been widely adopted in DR detection due to its ability to capture fine details in the retina, such as vascular lesions, which are critical for diagnosing DR. In a study by **Zhang et al. (2018)** [7], DenseNet was shown to outperform traditional CNNs in detecting DR features by efficiently capturing spatial dependencies in retinal images.

In addition to CNNs, researchers have explored **multi-label classification** approaches for detecting both the presence and severity of DR. **Kermany et al. (2018)** [8] proposed a deep learning system that used a **multi-class** and **multi-label** classification framework to classify DR into different stages, from no DR to proliferative DR. This approach allows the system to identify the severity of the disease, which is crucial for determining the appropriate treatment. **ResNet-101** has been similarly used in multi-label classification for DR, as it can effectively learn complex patterns from the retinal images [9].

III. METHODOLOGY

The methodology for this study involves utilizing a combination of Machine Learning (ML) and Deep Learning (DL) techniques to predict both Chronic Glaucoma and Diabetic Retinopathy (DR). The first step involves acquiring retinal fundus images and clinical data, including intraocular pressure (IOP), cup-to-disc ratio (CDR), and blood glucose levels, from publicly available datasets. Data preprocessing is performed to resize the images, apply histogram equalization, and enhance image contrast. For handling clinical data, feature scaling and encoding are employed to prepare the input for ML algorithms. For Deep Learning (DL), two state-of-the-art models are used: ResNet-101 and DenseNet-121. ResNet-101, a variant of the ResNet family, is used due to its ability to handle deep architectures without suffering from the vanishing gradient problem through residual connections. This enables the model to capture high-level features from the retinal images more effectively. On the other hand, DenseNet-121 is utilized for its ability to improve feature reuse and strengthen gradient flow with its dense

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connections, making it particularly useful for handling the complex nature of fundus image data. Both models are trained on the dataset using transfer learning, leveraging pre-trained weights on large image datasets like ImageNet. For multi-label classification, a sigmoid activation function is used in the output layer, which enables the models to simultaneously predict whether the patient has glaucoma, diabetic retinopathy, or both. The models are then evaluated using accuracy, precision, recall, F1-score, and the AUC-ROC curve. This hybrid approach integrates image-based and clinical data for a comprehensive, robust solution.

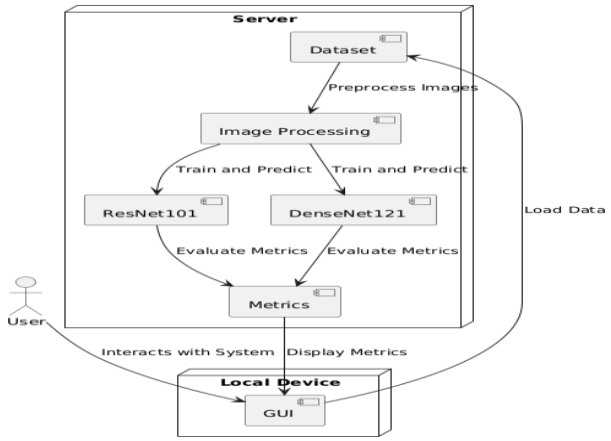

Fig1: System Architecture

IV. PROCESS OF DETECTING GLAUCOMA AND RETINOPATHY

The detection of Chronic Glaucoma and Diabetic Retinopathy (DR) involves a combination of image-based and clinical features. For Glaucoma detection, the process begins with the segmentation of the optic disc and optic cup in the retinal fundus images. The segmentation process uses the ResNet-101 and DenseNet-121 architectures, which are fine-tuned to identify and localize the optic cup and disc regions. These models are trained to extract features such as cup-to-disc ratio (CDR), which is a critical indicator for glaucoma detection. The CDR is calculated using the following formula:

$$\text{Vertical CDR} = \frac{\text{Vertical Cup Diameter (VCD)}}{\text{Vertical Disc Diameter (VDD)}}$$

$$\text{Horizontal CDR} = \frac{\text{Horizontal Cup Diameter (HCD)}}{\text{Horizontal Disc Diameter (HDD)}} \quad \text{eq(1).....}$$

A CDR greater than 0.6 is typically considered indicative of possible glaucomatous damage. Additional features such as the neuroretinal rim thickness are also extracted and analyzed. The ISNT rule (Inferior > Superior > Nasal > Temporal) is used to detect rim thinning, a sign of glaucoma. The ResNet-101 and DenseNet-121 models help to accurately segment these regions, reducing manual intervention and enhancing diagnostic precision. For Diabetic Retinopathy, the detection process involves identifying lesions such as microaneurysms, hemorrhages, and exudates. Both ResNet-101 and DenseNet-121 are used to perform object detection and classification of these retinal lesions. These models are trained to detect subtle changes in retinal vasculature that are characteristic of diabetic retinopathy. The severity of DR is graded based on the presence and quantity of these lesions, with a grading system that ranges from no DR to proliferative DR. A simplified grading function can be represented as:

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$$\text{DR Grade} = f(n_{\text{MA}}, n_{\text{HE}}, n_{\text{EX}}) \quad \text{eq(2)}\ldots\ldots$$

Where:

- n_{MA} = number of microaneurysms
- n_{HE} = number of hemorrhages
- n_{EX} = number of exudates

Based on this function, DR is categorized as:

1. **No DR**: No visible lesions
2. **Mild**: Few microaneurysms
3. **Moderate**: Microaneurysms and limited hemorrhages
4. **Severe**: Numerous hemorrhages and exudates

Both models, with their ability to extract hierarchical features through dense and residual connections, are highly effective in accurately detecting these retinal features. The output of the models is processed with a sigmoid activation function for multi-label classification, enabling the detection of both glaucoma and DR in the same image.

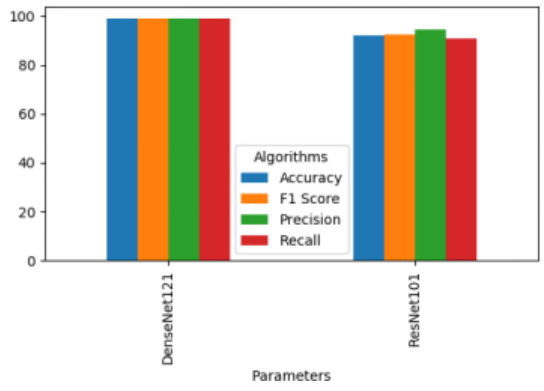

Fig2: graph x-axis represents algorithm names and y-axis represents accuracy and other metric in different colour bar and in both algorithms DensetNet121 got high performance.

These lesion-based features, combined with clinical data such as blood glucose levels and diabetes duration, are used to train both ML and DL models for classification. The distinct processes for detecting Glaucoma and Retinopathy are integrated into a unified, multi-label classification system, enabling simultaneous and automated diagnosis of both diseases from a single patient record.A CDR greater than 0.6 is typically indicative of potential glaucomatous damage. In parallel, **DenseNet-121**, another advanced deep learning architecture, is used for detecting **Diabetic Retinopathy**. DenseNet-121 connects every layer to all subsequent layers in a feed-forward fashion, enhancing feature reuse and improving gradient flow, which is crucial for detecting subtle lesions in retinal images. These lesions, such as **microaneurysms**, **hemorrhages**, and **exudates**, are the hallmark signs of DR. The severity of DR can be graded based on the number of lesions detected, with the following formula used to assess severity:

$$\text{DR Severity} = f(n_{\text{MA}}, n_{\text{HE}}, n_{\text{EX}}) \quad \text{eq(3)}\ldots$$

The more lesions detected, the higher the severity of DR. Both ResNet-101 and DenseNet-121 are employed in a multi-label classification framework, where each model is trained to predict the presence of both glaucoma and DR simultaneously, utilizing a sigmoid activation function in the output layer. This function enables

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the model to output a probability for each disease, allowing for classification of both conditions at the same time. The formula for the model's output is:

$$\text{Prediction Score} = \sigma(Wx + b) \quad \text{eq(4)}\ldots$$

Where σ\sigma represents the sigmoid function, WW and bb are the weights and biases of the model, and xx is the feature vector passed through the network. The model then uses a threshold (typically 0.5) to determine the presence or absence of each disease. To improve the interpretability of the model, techniques like SHapley Additive exPlanations (SHAP) and Gradient-weighted Class Activation Mapping (Grad-CAM) are applied to visualize which areas of the retinal images contribute most to the model's predictions, providing transparency for clinicians. The models are evaluated using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC, ensuring that both diseases are detected with high sensitivity and minimal false positives or negatives. This integrated approach, combining ResNet-101 and DenseNet-121, enables accurate, automated, and efficient detection of both glaucoma and DR, thereby improving diagnostic processes and aiding in early intervention.

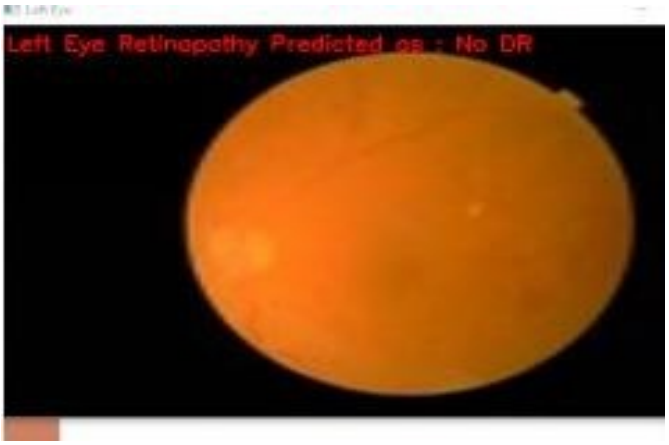

Fig3, Fig4: Retinopathy Detection from Test Images

V. CONCLUSION

This study presents a robust framework for the simultaneous prediction of Chronic Glaucoma and Diabetic Retinopathy (DR) using a combination of Machine Learning (ML) and Deep Learning (DL) techniques, specifically leveraging ResNet-101 and DenseNet-121 architectures. By integrating both clinical features such as intraocular pressure, cup-to-disc ratio, and blood glucose levels, along with high-resolution retinal fundus images, the proposed approach offers a comprehensive, automated solution for early disease detection. The multi-label

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classification strategy enables the system to identify individual cases of glaucoma and DR, as well as comorbid cases, improving the diagnostic coverage and accuracy. The use of deep learning models like ResNet-101 and DenseNet-121 significantly enhances feature extraction from retinal images, enabling precise segmentation and classification of key indicators such as the cup-to-disc ratio for glaucoma and vascular lesions for DR. This dual-focus approach allows for a more nuanced detection process, reducing the likelihood of misdiagnosis or delayed detection that can occur in traditional manual screening methods. Additionally, the incorporation of model interpretability techniques such as SHapley Additive exPlanations (SHAP) for ML models and Gradient-weighted Class Activation Mapping (Grad-CAM) for CNNs ensures that the system is transparent and the decision-making process can be easily understood by clinicians. This not only enhances trust in the system but also aids healthcare providers in making informed decisions. Ultimately, the proposed diagnostic aid serves as a step toward improving early detection, management, and treatment of both Chronic Glaucoma and Diabetic Retinopathy, thereby contributing to the global effort to reduce preventable blindness. The system's accessibility and scalability make it particularly valuable for use in low-resource settings, where trained ophthalmologists may be scarce, and timely diagnosis is critical. Future work could focus on refining the system's performance by incorporating larger, more diverse datasets, optimizing model architectures, and exploring additional clinical features. The ongoing development of AI-powered diagnostic tools holds the promise of revolutionizing eye care by providing rapid, accurate, and widely accessible solutions for disease detection and management.

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