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Enhancing Eye Disease Diagnosis with Deep Learning on Fundus Images

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Abstract: Eye diseases such as diabetic retinopathy, glaucoma, and age-related macular degeneration are significant causes of visual impairment globally. Manual diagnosis requires specialized expertise and is time-consuming. This project proposes an automated system for detecting and classifying multiple eye diseases using fundus images. Utilizing the ODIR dataset, our approach applies transfer learning with pretrained VGG16 and ResNet50 models, coupled with data augmentation techniques to mitigate class imbalance. Explainability is enhanced using LIME to visualize critical image regions influencing model decisions. The system is deployed with a user-friendly Streamlit interface, providing accessible and interpretable results for clinical settings.

Keywords: Eye disease detection,fundus images,VGG16, Transfer learning, LIME

I. INTRODUCTION

Eye diseases such as diabetic retinopathy, glaucoma, cataracts, and age-related macular degeneration are major causes of vision impairment and blindness worldwide. Early detection is essential for timely treatment, yet traditional diagnostic methods are time-consuming, require expert interpretation, and are often inaccessible in under-resourced areas.

Advancements in deep learning, especially Convolutional Neural Networks (CNNs), have significantly improved the ability to analyze medical images. Pre-trained models like VGG16 when fine-tuned through transfer learning, offer high accuracy even with limited domain-specific data. These models are well-suited for the classification of retinal
fundus images, which are critical in diagnosing a range of ocular conditions.

This project proposes a multi-label classification system using VGG16 trained on the Ocular Disease Intelligent Recognition (ODIR) dataset. To address the issue of dataset imbalance, we applied techniques such as data augmentation, oversampling, and under sampling. These steps help the model learn effectively across all disease categories.

To enhance trust and transparency in predictions, we incorporated Local Interpretable Model-Agnostic Explanations (LIME). LIME visualizations highlight important regions in the fundus image that influenced the model's decision, which is crucial for clinical validation.
Finally, we developed a user-friendly web interface using Streamlit. This allows healthcare professionals to upload fundus images, receive predictions, and view explanatory heatmaps—all in real-time. The system is designed to be low-cost, scalable, and suitable for deployment in clinics and rural health centers.

By integrating deep learning, explainability, and usability, this project aims to support early and accessible detection of eye diseases, particularly in areas lacking specialist care.

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II. RELATED WORK

Kumar et al. [1] focused on using basic image techniques to catch early signs of diseases like diabetes or stroke just by looking at the eye. They didn't use AI — instead, they used stuff like color slicing and gradient filters to find blood vessel issues. By checking these patterns over time, they could spot changes and predict health risks early. It's a straightforward and cost-effective way to support doctors and reduce manual effort.

Ali et al. [2] ran several CNN models like LeNet, AlexNet, and VGG16 on OCT eye scans to detect conditions like CNV and DME. VGG16 turned out to be the most accurate, especially with careful tuning and dropout layers to avoid overfitting. Their study shows that with solid preprocessing and model tweaking, even older architectures can perform like champs.

Jain et al. [3] built their own CNN model, LCDNet, to sort eye images into healthy or diseased. They cleaned up the data, resized the images, and added more examples using data augmentation. With careful training and validation, they hit super high accuracy — up to 99.7%. It shows how a clean setup and a simple model can still go a long way.

Grassmann et al. [4] built a system called DeepSeeNet that mimicked how eye doctors grade macular degeneration. It looked at both eyes and gave a severity score from 0 to 5, trained on thousands of patient images. Interestingly, it outperformed actual specialists at spotting some early warning signs. It's one of those rare cases where the AI actually did better than the experts — at least in some tasks.

Gulshan et al. [5] focused on diabetic retinopathy and built a deep learning model to spot it in fundus images. They trained it on over 35,000 images and used tons of image tweaks like cropping and flipping to improve results. The model wasn't just accurate — it also did well in figuring out which eye had the issue. It's a big step toward fast, automated DR screening in clinics.

Burlina et al. [6] trained deep CNNs to classify stages of AMD and then combined their predictions using a random forest model. They used a huge dataset, focused on the macular region, and still managed solid performance even in older patients. The combo of CNNs and ensemble learning helped boost reliability and make the system more robust.

Li et al. [7] built a system to spot multiple eye conditions at once using transfer learning. They tested two setups — one where each eye got its own model, and another where both images were combined. The separate model approach actually worked better. Using models like VGG16 and ResNet, they were able to pick up multiple diseases from just one scan. It's a smart way to scale up screening for all kinds of eye issues.

III. METHODOLOGY

The proposed system is designed to automate the detection of multiple eye diseases using retinal fundus images. The pipeline includes image acquisition, preprocessing, model training using transfer learning, explainability via LIME, and user interaction through a Streamlit-based interface.

1)Data Acquisition

We used the ODIR (Ocular Disease Intelligent Recognition) dataset, which contains 6931 fundus images labeled across eight categories: Normal, Diabetic Retinopathy (DR), Glaucoma, Age-related Macular Degeneration (AMD), Cataract, Hypertension, Myopia, and Other abnormalities. The dataset is highly imbalanced and includes left and right eye images with associated metadata.

2) Image Preprocessing

To prepare the data for model training, all images were resized to 224×224 pixels. Normalization was

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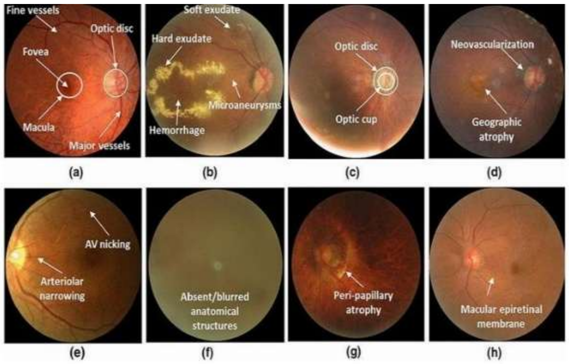

Fig.1: Samples of Dataset

applied to scale pixel values. Data augmentation techniques such as horizontal flipping, rotation, brightness adjustment, and zooming were implemented to enhance generalization and address class imbalance.

3) Model Architecture

Two pre-trained deep learning models—VGG16 and ResNet50—were used. Final dense layers were replaced to support multi-label classification with sigmoid activation. Dropout and batch normalization were added to reduce overfitting. Training was performed using the Adam optimizer and categorical cross-entropy loss.

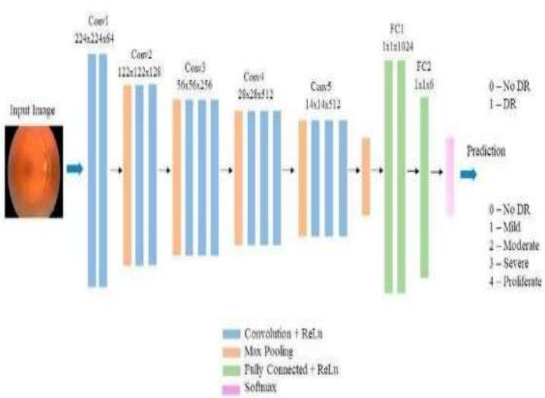

Fig.2: Architecture of VGG16 model(source:researchgate.net)

4)Handling Class Imbalance

Oversampling (SMOTE) and undersampling techniques were used alongside augmentation to ensure that minority classes were adequately represented during training.

5)Explainable AI(LIME)

To ensure interpretability, LIME was applied to visualize which parts of the fundus image influenced the model's predictions. This allows medical practitioners to validate results with visual justification.

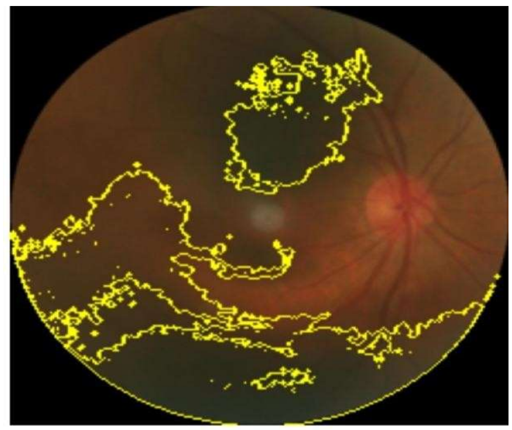

Fig.3: Explainable AI Lime

6)Interface and Deployment

A Streamlit web application was developed to allow users to upload fundus images, view predicted disease labels, and examine LIME-based heatmaps. This makes the system accessible for real-world clinical use, even in low-resource settings.

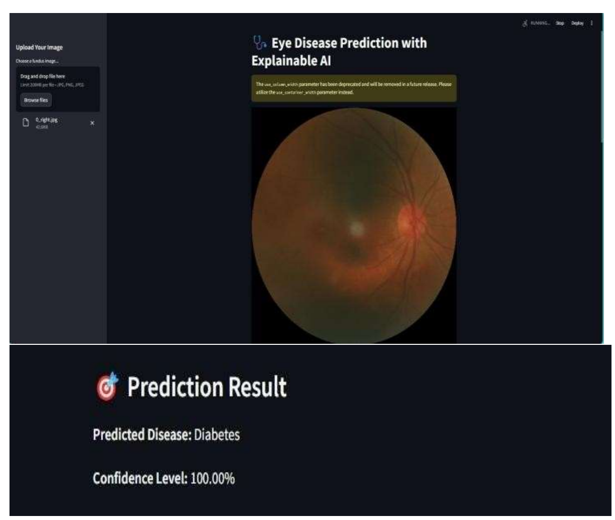

Fig 4: UI for the model

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IV. RESULT

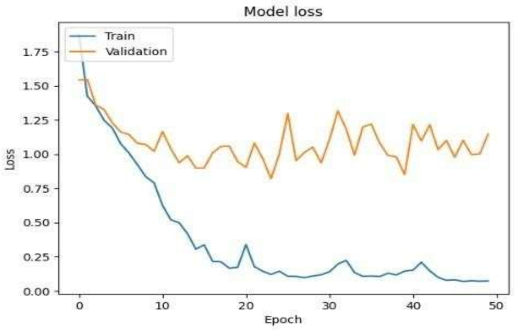

Fig.5 Graph of VGG16 model

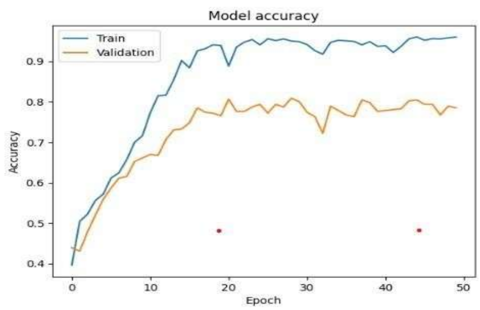

Fig.6 Graph of VGG16 model

Fig.7 :Confusion Matrix of VGG16

V. CONCLUSION

The eye disease prediction system demonstrates an innovative approach by integrating advanced deep learning models such as VGG16 and ResNet50 for diagnosing ocular conditions. This project emphasizes the importance of explainability in artificial intelligence through the incorporation of Explainable AI tools like LIME, which make the predictions transparent and interpretable for users, especially medical professionals. The application deployment using Streamlit ensures an intuitive and interactive interface to the nontechnical user and simplifies the operational workflow. In addition, Docker allows for easy portability and scalability across different platforms to ensur e smooth deployment and integration into clinical environments. Overall, this project has bridged the gap between AI-based healthcare solutions and practical usability by showing a promising solution in early and accurate eye disease detection.

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