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IDENTIFICATION OF RETINAL DISEASES USING ML

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Abstract— **Retinal diseases such as diabetic retinopathy, glaucoma, and age-related macular degeneration are major causes of vision loss and blindness worldwide. Early detection is critical for effective treatment and prevention. Recent advances in deep learning have shown promise in medical image analysis. This study presents a novel approach using convolutional neural networks (CNNs) to detect retinal diseases from retina images. The CNN is trained on a large, labeled dataset of retina images and includes multiple convolutional, pooling, and fully connected layers for classification. Data augmentation techniques are used to enhance the dataset's diversity and size. Our system effectively classifies retina images as normal or abnormal with high sensitivity and specificity, showing its potential for real-world applications. The motivation behind this work is the urgent need for accessible, early diagnosis of retinal diseases, especially in regions with limited access to ophthalmologists. Automated CNN-based analysis can significantly improve early detection rates, offering a scalable and cost-effective solution. This technology helps reduce preventable blindness and enhances quality of life by enabling timely and accurate screenings. Ultimately, it supports healthcare systems in managing retinal diseases more efficiently and equitably across different populations.**

Keywords— **Retinal diseases, Convolutional Neural Networks (CNN), Retina images, Disease detection, Medical image analysis.**

I. INTRODUCTION

Retinal diseases, including diabetic retinopathy major global health challenge that can result in irreversible vision loss if not diagnosed early. Timely and accurate detection plays a crucial role in preserving vision and improving patient outcomes. Traditionally, diagnosis relies on expert analysis of retinal images obtained through fundus photography or optical coherence tomography (OCT), which is often time-consuming, subjective, and prone to human error. This has led to growing interest in automated and scalable diagnostic solutions. Convolutional Neural Networks (CNNs), a powerful class of deep learning models, have shown great promise in medical image classification tasks. In retinal disease detection, CNNs can automatically learn hierarchical features from large datasets, identifying abnormalities such as hemorrhages, exudates, and vessel changes—key indicators of diseases like diabetic retinopathy. These models capture subtle image patterns often missed by the human eye, significantly improving both speed and accuracy. CNNs enable rapid analysis of large image volumes with minimal human intervention, making them ideal for large-scale screening, especially in underserved areas. They also reduce diagnostic subjectivity by providing consistent, data-driven results. Furthermore, CNNs can be continuously updated with new data to enhance performance over time. Their integration into healthcare systems supports early diagnosis, reduces costs, and increases accessibility to retinal disease screening worldwide. The adoption of artificial intelligence (AI) in healthcare, particularly through deep learning approaches like CNNs, is transforming the landscape of medical diagnostics. In retinal disease detection, CNNs have demonstrated capabilities not only in classification tasks but also in segmentation and localization of pathological regions. These models can be trained using labeled datasets to distinguish between healthy and diseased retinas with high accuracy. Advanced architectures such as ResNet, VGGNet, and Inception have further enhanced performance, enabling CNNs to handle variations in image quality, lighting conditions, and anatomical differences across patients. Data augmentation techniques, including rotation, zoom, and contrast adjustments, are commonly used to improve model generalization. Additionally, transfer learning allows pre-trained models to be fine-tuned for specific medical imaging tasks, reducing the need for large annotated datasets. Visualization tools like Grad-CAM (Gradient-weighted Class Activation Mapping) help interpret CNN decisions by highlighting image regions influencing predictions, which builds trust among clinicians. Integration of CNNs with mobile applications and cloud platforms enables real-time, remote screening, extending the reach of eye care services. In resource-limited settings, this technology can serve as a valuable support system for non-specialist healthcare workers. Despite their promise, CNN-based systems must be rigorously validated for clinical use, ensuring reliability, fairness, and robustness. Continued collaboration between medical experts and AI researchers is essential to develop models that are interpretable, generalizable, and ethically sound. As research advances, CNNs are expected to play a pivotal role in personalized medicine, enabling early, precise, and accessible diagnosis of retinal diseases on a global scale. To support the deployment of CNN-based diagnostic systems, a growing number of publicly available retinal image datasets—such as DIARETDB1, EyePACS, Messidor, and DRIVE—are being used for training and benchmarking models. These datasets include images annotated by ophthalmologists, providing ground truth labels for various retinal conditions. The diversity and size of these datasets are critical for developing models that are robust across different populations and imaging devices.

II. LITERATURE SURVEY

1. In the paper "Machine Learning and Artificial Intelligence-Based Diabetes Mellitus Detection and Self-Management: A Systematic Review," Chaki et al. (2020) review the use of machine learning (ML) and artificial intelligence (AI) techniques in the detection and management of diabetes. The paper examines various ML and AI models applied to medical data for early detection, prediction, and self-management of diabetes mellitus. The authors highlight the strengths and limitations of different approaches, such as support vector machines, decision trees, and deep learning models, in terms of accuracy and patient outcomes. The review emphasizes the potential of AI-driven technologies to improve early diagnosis and personalized management of diabetes, but it also addresses challenges like data privacy, integration with healthcare systems, and the need for larger, highquality datasets to validate these models.[1]
2. [Handayani, 2013] proposed a system for the classification of non-proliferative diabetic retinopathy using soft margin SVM. Hard exudates in the retinal fundus images are used to classify severity level of non-proliferative diabetic retinopathy. Mathematical morphology is applied to segment hard exudates. But the system does not include micoaneurysms and haemorrhage as the features.[2]
3. [Sangwan, 2015] described a system that identifies different stages of diabetic retinopathy based on blood vessels, haemorrhage and exudates. The features are extracted using image preprocessing and they are fed into the neural network.SVM based training provided into the data and classify the images into three categories as mild, moderate non proliferative diabetic retinopathy and proliferative diabetic retinopathy.
4. [Farrikh Alzami, 2019] described a system for diabetic retinopathy grade classification based on fractal analysis and random forest using MESSIDOR dataset. Their system segmented the images, then computed the fractal dimensions as features. They failed to distinguish mild diabetic retinopathy to severe diabetic retinopathy.[4]
5. In the paper titled "Diabetic Retinopathy: Detection and Classification Using AlexNet, GoogleNet, and ResNet50 Convolutional Neural Networks," Caicho et al. (2022) explore the use of deep learning models for the detection and classification of diabetic retinopathy from retinal images. The study compares three well-known convolutional neural network (CNN) architectures—AlexNet, GoogleNet, and ResNet50—to assess their effectiveness in accurately diagnosing diabetic retinopathy. By analyzing key performance metrics such as accuracy, precision, and recall, the authors demonstrate that ResNet50 performs the best among the three models due to its deeper architecture and ability to capture intricate features. The findings emphasize the potential of CNNs in enhancing automated medical diagnosis systems for diabetic retinopathy.[5]
6. Revathy et al. [3], used an SVM-based training approach to data and classified them into three classes as mild, moderate non-proliferative Diabetic Retinopathy and proliferative Diabetic Retinopathy. Approach used various classification algorithms and noted good accuracy with 82%.[6]
7. In the survey by Litjens et al. (2017), titled “A Survey on Deep Learning in Medical Image Analysis,” the authors provide a comprehensive review of the applications and advancements of deep learning techniques in the field of medical image analysis. The paper covers various deep learning methodologies, including convolutional neural networks (CNNs), and their impact on different aspects of medical imaging, such as image segmentation, classification, and anomaly detection. The review highlights significant achievements and challenges in implementing deep learning models for diagnosing diseases, improving image quality, and supporting clinical decision making. The authors also discuss future directions for research, including the need for more diverse and annotated datasets, improved model interpretability, and integration of deep learning systems into clinical practice. This survey offers valuable insights into how deep learning is transforming medical image analysis and identifies key areas for further development.[7]
8. In the paper by Islam and Indiramma (2020), titled “Retinal Vessel Segmentation Using Deep Learning – A Study,” the authors investigate the application of deep learning techniques for the segmentation of retinal vessels in fundus images. The study focuses on leveraging advanced deep learning models to accurately identify and delineate the complex network of blood vessels in the

retina, which is crucial for diagnosing and monitoring retinal diseases. This paper details the methodologies employed, including various deep learning architectures and their effectiveness in improving segmentation accuracy. The authors present their findings on the performance of these models in comparison to traditional segmentation techniques, highlighting improvements in precision and reliability. The research demonstrates the potential of deep learning to enhance retinal image analysis, offering a more robust and automated approach to vessel segmentation, which is essential for early detection and management of retinal conditions.[8]

III. DATASETS AND METHODS

a . Dataset

This study utilized the publicly available Kaggle dataset for Diabetic Retinopathy Detection. The datasets is of Kaggle competition 2019. It contains imbalanced data and to overcome the imbalance we have utilized binary classification the multiclass classification. The dataset was created from images sourced from various public retinopathy detection datasets. It contains 1700 images with diabetic retinopathy and 1700 images without DR and total images are 3400 . From this, we selected 1700 images with diabetic retinopathy , from this 1700 images are distributed in 4 types of images and 1700 normal images. The selected abnormal images feature exudates, hemorrhages, and microaneurysms. Diabetic retinopathy presence is determined by factors such as the appearance, count, distribution, size, and area of exudates, microaneurysms, and hemorrhages .

B. Steps

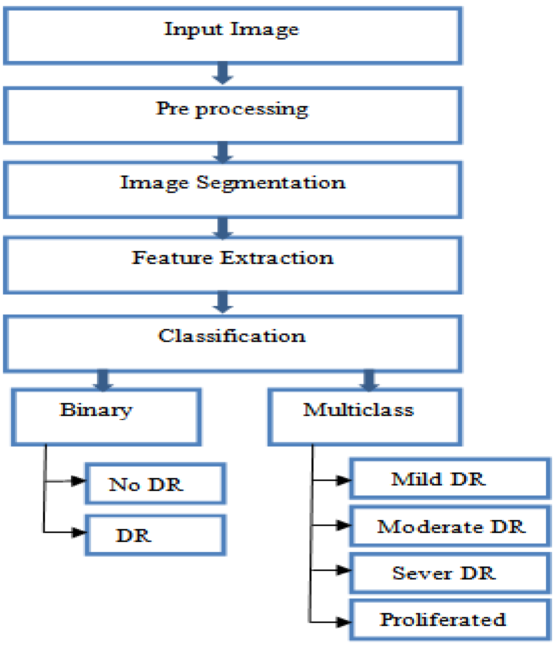


Fig . Flow Chart of Proposed Model

a. Input Image: The input for the detection of diabetic retinopathy (DR) typically comprises retinal images captured through non-invasive imaging techniques, such as fundus photography. These high-resolution images offer detailed visual information about the retinal structures, including the blood vessels, optic disc, macula, and potential pathological features such as microaneurysms, hemorrhages, exudates, and other abnormalities. The quality of the image, including factors such as resolution and lighting conditions, plays a crucial role in the accuracy of subsequent processing and analysis.

b. Pre-processing: Preprocessing is a critical step that prepares the input images for effective analysis by addressing issues like noise, illumination variations, and scale differences. The main goal of preprocessing is to enhance the quality of the image, reduce unwanted artifacts, and ensure consistency across different image sources. Common techniques involved in this step include:

- **Resizing**: Standardizes the image size for consistency.
- **Noise Reduction**: Removes irrelevant background noise using filters.
- **Contrast Adjustment**: Enhances the visibility of important features like lesions.

c. Image Segmentation : Image segmentation is the process of partitioning the retinal image into distinct regions that contain useful information for detecting diabetic retinopathy. This step is vital because it isolates the areas of interest, such as blood vessels, optic disc, macula, and potential lesions, from the rest of the image. Several segmentation techniques can be employed, such as:

- **Thresholding**: Converts the image into binary to highlight features.
- **Edge Detection**: Identifies boundaries of blood vessels and lesions.
- **Region-Based Methods**: Expands selected regions to include areas of interest.
- **Active Contours or Snakes**: Iteratively refine the boundary of a segmented region to match the contours of an object.

d. Feature Extraction : After segmentation, the next step is feature extraction, where significant characteristics that can help differentiate normal from abnormal retinas are identified and quantified. These features are critical for the machine learning model to understand and distinguish between the various stages and types of diabetic retinopathy. Key features commonly extracted from retinal images include:

- **Color Features**: Analyzes the color of exudates or hemorrhages.
- **Texture Features**: Measures patterns in lesion regions.

- **Shape Features**: Captures the size and shape of abnormalities.

e. Classification : Once the relevant features have been extracted, the next step is to classify the retinal image as either "normal" (no diabetic retinopathy) or "abnormal" (indicative of diabetic retinopathy). This step is performed using machine learning algorithms that are trained on a labeled dataset containing both normal and abnormal retinal images. Some of the commonly used classification algorithms in diabetic retinopathy detection include:

- **Support Vector Machines (SVM)**: Separates classes using a hyperplane, effective for high-dimensional feature spaces.
- **Convolutional Neural Networks (CNNs)**: Deep learning models that automatically learn features from raw images, excelling in medical image analysis.
- **Random Forests**: Combines multiple decision trees to improve accuracy, especially with complex or noisy data.
- **K-Nearest Neighbors (KNN)**: Classifies based on the majority vote of neighboring points, useful with small datasets..
- **Logistic Regression**: A simpler method used when the feature space is small, relying on a linear decision boundary..

f. DR , NO DR Classification : After classification, the final decision is made regarding whether the input retinal image is "NO DR" or "DR" with respect to diabetic retinopathy. The classification results are typically expressed in terms of probabilities, where a threshold can be applied to classify an image as NO DR or DR . The decision-making process may involve the following:

- **NO DR** : The image is classified as normal if no significant signs of diabetic retinopathy are present, such as exudates, hemorrhages, or microaneurysms .

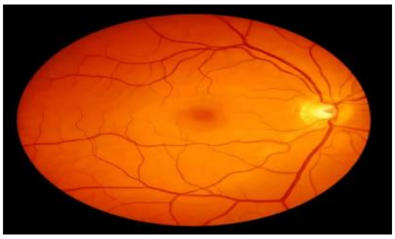


Fig . NO DR

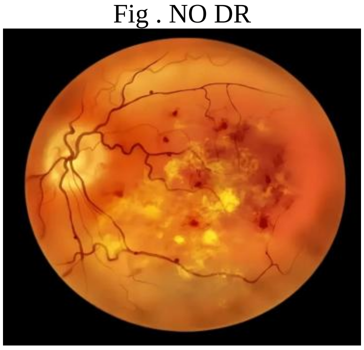


Fig. DR

- **DR** : The image is classified as abnormal if it contains one or more signs of diabetic retinopathy, such as exudates, hemorrhages, microaneurysms, or vascular changes. The severity of the abnormality can also be assessed, categorizing the retinopathy as mild, moderate, severe, or proliferative.

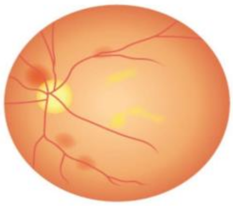


Fig . Severe DR

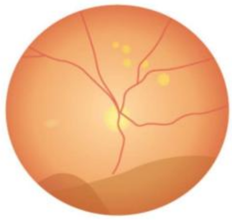


Fig .Proliferative DR

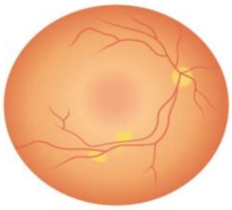


Fig . Moderate DR

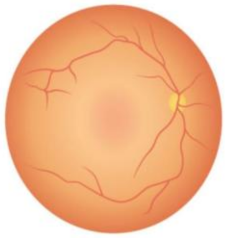
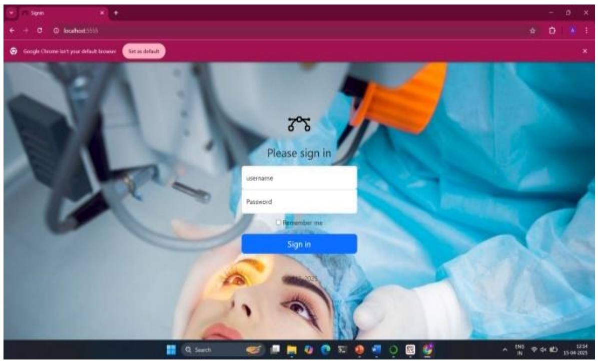
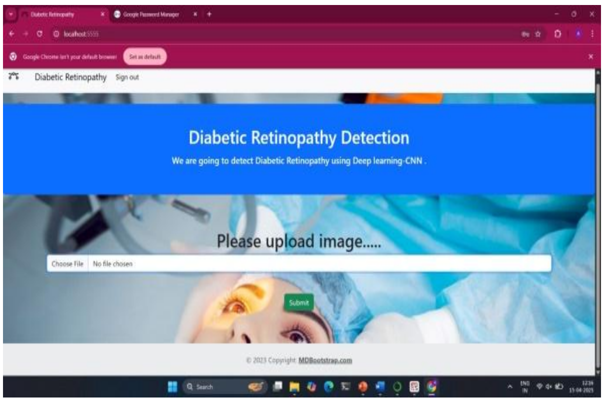
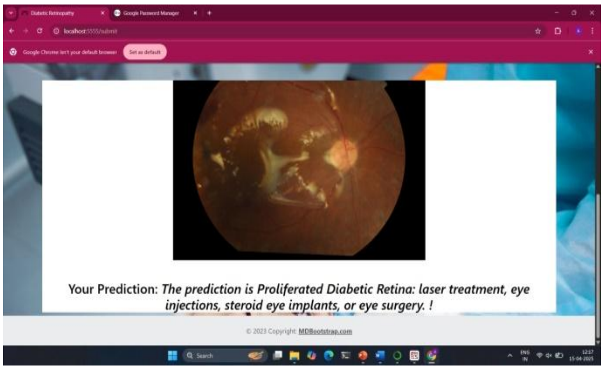


Fig . Mild DR

IV. RESULT







V. CONCLUSION

This research presents an effective approach for the identification and classification of diabetic retinopathy (DR) using deep learning techniques, particularly Convolutional Neural Networks (CNNs) and a pre-trained MobileNet model. The project was carried out in two stages: an initial binary classification to differentiate between DR and non-DR cases, followed by a detailed multiclass classification to determine the specific stage of DR—namely Mild, Moderate, Severe, and Proliferative DR. The use of MobileNet, a lightweight and efficient deep neural network, significantly improved model performance while maintaining computational efficiency, making it suitable for real-time and scalable diagnostic applications. The results demonstrate that deep learning models can accurately detect not only the presence of diabetic retinopathy but also classify its severity, thus providing a valuable tool for early detection and effective disease management. Future work may focus on enhancing model interpretability, reducing bias, and integrating the system into clinical workflows to support automated, accessible, and reliable ophthalmic screening.

VI. REFERENCE

[1]. Chaki, J., Thillai Ganesh, S., Cidham, S.K., Ananda Theertan, S.: Machine learning and art ificial intelligence based Diabetes Mellitus detect ion and self-management: a systematic review. J. King Saud Univ. Comp. Info. Sci. (2020).

[2]. Handayani Tjandrasa, Ricky Eka Putra Arya Yudhi Wijaya, Isye Arieshanti, Classification of Non-Proliferative Diabetic Retinopathy based on Hard Exudates using Soft Margin SVM, IEEE International Conference on Control System, Computing and Engineering, November 2013.

[3]. Surbhi Sangwan, Vishal Sharma , Misha Kakkar , Identification of Different Stages of Diabetic Retinopathy International Conference on Computer and Computational Sciences, 2015.

[4]. Farrikh Alzami, Abdussalam, Rama Arya Megantara and Ahmad Zainul Fanani, Diabetic Retinopathy Grade Classification based on Fractal Analysis and Random Forest, International Seminar on Application for Technology of Information and Communication, 2019.

[5]. Caicho, J. et al., “ Diabetic Ret inopathy: Detection and Classification Using AlexNet , GoogleNet and ResNet50 Convolut ional Neural Networks” Smart T echnologies, Systems and Applications, Communications in Computer and Information Science, vol 1532, 2022.

[6]. Revathy R, Nithya BS, Reshma JJ, Ragendhu SS, Sumithra MD (2020) Diabetic retinopathydetection using machine learning. IJERT 9.

[7]. Lit jens, Geert , et al. "A survey on deep learning in medical image analysis." Medical image analysis 42 (2017): 60-88.

[8]. M. M. U. Islam and M. Indiramma, "Retinal Vessel Segmentation using Deep Learning – A Study," 2020 Internat ional Conference on Smart Elect ronics and Communicat ion (ICOSEC), pp. 176-182, 2020.

[9]. M. Venkata Subbarao,J. T S Sindhu, N N S Harshitha,“Detection of Retinal Degeneration via High-Resolution Fundus Images using Deep Neural Networks”, 2023 Second International Conference on Electronics and Renewable Systems (ICEARS) | 979-8-3503-4664-0/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICEARS56392.2023.10085273

[10]. S. K. M, M. A. V and S. M, "Retinal Image Processing using Neural Network with Deep Leaning," 2022 6th Internat ional Conference on Intelligent Computing and Control Systems (ICICCS), pp. 1030-1036, 2022.

[11]. P at el, J., Umar, S.A., “ Detection of Imagery Vowel Speech Using Deep Learning, Advances in Energy Technology, vol 766, pp. 237–247, 2022.

[12]. P. Kollapudi, S. Alghamdi, N. Veeraiah, Y. Alotaibi, S. Thotakura et al., "A new method for scene classificat ion from the remote sensing images," Computers, Materials & Cont inua, vol. 72, no.1, pp. 1339– 1355, 2022.