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DEEPDIABETIC: AN AI-POWERED DIAGNOSTIC MODEL FOR EARLY DETECTION OF RETINAL ABNORMALITIES IN DIABETIC PATIENTS

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ABSTRACT

Diabetic eye diseases, particularly diabetic retinopathy and macular edema, are among the leading causes of preventable blindness worldwide. Early detection and timely diagnosis are crucial to mitigating vision loss and improving patient outcomes. This paper presents DeepDiabetic, an AI-powered diagnostic model that leverages deep neural networks (DNNs) to automatically identify and classify retinal abnormalities from fundus images. The system aims to support ophthalmologists in clinical decision-making by providing accurate, consistent, and rapid screening of diabetic eye conditions.

The proposed DeepDiabetic model utilizes a convolutional neural network (CNN) architecture trained on a large-scale dataset of retinal images preprocessed through techniques such as image normalization, contrast enhancement, and noise reduction. Feature extraction layers capture minute retinal patterns, including microaneurysms, hemorrhages, and exudates, which are critical indicators of diabetic damage. Transfer learning and fine-tuning methods are incorporated to improve performance across diverse imaging conditions and patient demographics. The model's classification accuracy, sensitivity, and specificity are evaluated using benchmark datasets and compared with existing diagnostic frameworks.

Experimental results demonstrate that DeepDiabetic achieves superior diagnostic accuracy and robustness, outperforming traditional machine learning methods and some state-of-the-art deep learning approaches. The model's interpretability is enhanced through visualization techniques such as Grad-CAM, which highlight the most affected retinal regions. Furthermore, the system's scalability enables integration into teleophthalmology platforms, allowing remote and real-time diabetic eye screening in resource-limited healthcare environments.

The DeepDiabetic framework establishes a promising step toward automated, AI-assisted ophthalmic diagnosis, contributing to early disease detection, reduced screening costs, and improved accessibility to quality eye care.

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I. INTRODUCTION

Diabetes mellitus is one of the most prevalent chronic diseases globally, leading to several long-term health complications that affect multiple organs, including the eyes. Among these, diabetic retinopathy (DR) and diabetic macular edema (DME) are the most severe ocular manifestations, often resulting in partial or complete vision loss if not detected and treated in time. The progressive nature of these diseases demands early and accurate diagnosis to prevent irreversible damage. However, manual examination of retinal images by ophthalmologists is time-consuming, subjective, and limited by the availability of specialists, particularly in rural and under-resourced regions. Therefore, the integration of artificial intelligence (AI) and deep learning into ophthalmic diagnostics has become a critical focus in modern medical research.

Deep learning has demonstrated remarkable success in visual pattern recognition tasks due to its ability to learn hierarchical feature representations directly from raw image data. In the context of diabetic eye diseases, Convolutional Neural Networks (CNNs) have shown significant promise in detecting minute retinal features such as microaneurysms, hemorrhages, and exudates — the primary indicators of disease severity. Unlike traditional image processing techniques that rely on handcrafted features, CNNs can automatically extract discriminative visual cues, leading to higher diagnostic accuracy and consistency.

The proposed system, DeepDiabetic, is designed as an AI-powered diagnostic framework that employs deep neural networks to detect and classify diabetic eye diseases from retinal fundus images. The model leverages large datasets of labeled retinal scans to train its feature extraction layers, enabling it to differentiate between normal, mild, moderate, and severe cases of diabetic retinopathy. Advanced preprocessing techniques such as contrast enhancement, image normalization, and noise filtering are incorporated to ensure that variations in image quality or lighting do not affect the diagnostic accuracy.

In addition to accurate disease classification, DeepDiabetic focuses on model interpretability and clinical integration. Using explainable AI techniques such as heatmap visualization, the system highlights the specific retinal regions contributing to the diagnosis, providing ophthalmologists with visual evidence to support automated findings. This transparency is essential for building trust between AI systems and healthcare professionals.

The overarching goal of the DeepDiabetic framework is to enhance early detection, reduce diagnostic time, and improve accessibility to eye care through automation. By enabling remote screening and teleophthalmology applications, the system can help identify at-risk individuals before significant vision loss occurs. Consequently, this approach not only supports ophthalmologists in clinical practice but also contributes to global efforts in preventive healthcare and medical digitization.

II. LITERATURE SURVEY

The application of artificial intelligence and deep learning in medical image analysis has transformed the field of ophthalmology in recent years. Abràmoff et al. (2016) pioneered the use of deep learning algorithms for automated detection of diabetic retinopathy, demonstrating that AI models can achieve diagnostic accuracy comparable to trained ophthalmologists. Gulshan et al. (2017) further enhanced this approach by developing a deep convolutional neural network trained on large-scale retinal image datasets, achieving high sensitivity and specificity in identifying referable diabetic retinopathy. Their work established a benchmark for AI-based retinal disease screening.

Pratt et al. (2018) implemented a convolutional neural network model capable of classifying different stages of diabetic retinopathy using publicly available fundus image datasets. Their model emphasized the importance of image preprocessing techniques such as normalization and data augmentation for improving prediction reliability. Lam et al. (2018) introduced transfer learning into ophthalmic image analysis, fine-tuning pre-trained models like VGG16 and InceptionV3 to achieve high diagnostic precision even with limited labeled data.

Voets et al. (2019) evaluated the robustness of deep learning models under varied imaging conditions, highlighting challenges related to dataset imbalance and image noise. Moraes et al. (2019) proposed a hybrid CNN architecture combining feature extraction and ensemble classification to improve the detection of mild retinopathy cases, which are often overlooked by traditional diagnostic systems. Similarly, Costa et al. (2020) focused on cross-dataset generalization, ensuring that trained models remain effective across diverse populations and imaging devices.

Rahman and Hasan (2020) explored attention-based deep learning networks that automatically focus on clinically relevant retinal regions during diagnosis. This approach enhanced interpretability and reduced false positives in diabetic retinopathy detection. Li et al. (2021) integrated deep learning with cloud computing for real-time diagnosis, enabling teleophthalmology systems to deliver rapid screening in rural healthcare settings. Patel and Mehta (2021) proposed an ensemble framework combining CNN and support vector machines to classify multiple retinal abnormalities, including diabetic maculopathy and glaucoma.

Zhang et al. (2022) developed an improved CNN–RNN hybrid model for analyzing temporal retinal progression in diabetic patients, offering predictive insights into disease advancement. Nguyen et al. (2022) utilized generative adversarial networks (GANs) to synthesize high-quality retinal images for augmenting limited datasets, significantly improving deep learning model generalization. Kumar and Suresh (2023) introduced explainable AI techniques to visualize affected retinal regions using gradient-based activation mapping, enhancing the trustworthiness of AI-driven diagnosis.

Thomas et al. (2023) proposed an edge-based deployment of deep learning models for real-time retinal screening on portable diagnostic devices. Rao and Banerjee (2024) focused on lightweight neural networks suitable for mobile-based diabetic eye disease detection, reducing computational overhead while maintaining diagnostic accuracy. Hassan and Omar (2024) recently explored multimodal learning approaches that integrate fundus imaging with patient clinical data for more comprehensive disease prediction.

These studies collectively highlight the growing potential of deep learning in ophthalmic diagnostics while also emphasizing challenges such as data imbalance, interpretability, and model generalization. The proposed DeepDiabetic system builds upon these foundations by introducing an optimized deep neural network framework capable of delivering accurate, interpretable, and scalable diagnosis of diabetic eye diseases across diverse clinical settings.

III. SYSTEM ANALYSIS AND DESIGN

EXISTING SYSTEM

In diabetic eye illness, the Transfer Learning (TL) technique is often used, as shown by the authors in [29], [30], [31], [32], [33], and [34]. The TL initialises parameters using knowledge from previous learning rather than creating them at random. Core characteristics like edges, textures, etc. are intuitively extracted by the first layers. Like blood vessels and exudates, the upper layers are more specific to the job at hand. TL is successfully used in [29], [32], [33], and [34] when there is not enough data to train a neural network from scratch. Pan and associates [29] examined four different DR lesion types and compared three CNN models: DenseNet, ResNet50, and VGG16. The results of the experiment demonstrate that DenseNet is an efficient model for automatically recognising and differentiating retinal lesions in multi-label categorised pictures. However, since microaneurysms are readily misclassified in the ubiquitous presence of fluorescein, the technique does not reliably identify them.

Additionally, using a small dataset, Samanta et al. [30] developed a CNN-based TL architecture based on colour fundus photography that performs rather well in identifying DR (No DR, Mild DR, Moderate DR, and Proliferative DR) from hard exudates, blood vessels, and texture. They applied their model to a number of frameworks, such as ResNet-50, DenseNet, AlexNet, Xception, VGG16, Inceptionv1, Inceptionv2, and Inceptionv3. A framework for actively identifying the presence and severity of DR was given by Zhang et al. [31]. via the use of many TL designs, including InceptionResNetV2, DenseNets, Xception, ResNet50, and InceptionV3. Even though the suggested framework achieved a 97.5% sensitivity and a 97.7% specificity, a larger and more comprehensive dataset is required to evaluate their model. In order to improve accuracy and save processing time, the CNN model and Lookahead optimiser were also used in [32] for the image categorisation of cataract illness. The model was able to correctly identify the pictures' label by using the CNN-AlexNet architecture, the Lookahead optimiser on stochastic gradient descent, and Adam. CNN-AlexNet thus improves optimiser stochastic gradient descent by 2.5 percent and raises accuracy by 20 percent. In order to support the early diagnosis of diabetic eye disorders (DR, DME, and glaucoma), Sarki et al. [34] presented a deep learning architecture that combined image processing approaches with 13 CNN models.

Several problems were identified with the early categorisation of diabetic eye illness. They subsequently developed an automated classification system that looked at moderate multi-class diabetic eye illness as well as multi-class [33]. The VGG16 and InceptionV3 were used to apply various performance enhancement strategies, such as fine-tuning, optimising, and contrast increasing. Furthermore, the VGG16 model achieved moderate multi-class classification accuracy of 85.95% and multi-class classification accuracy of 88.3%.

Disadvantages

- Data complexity: In order to identify diabetic eye diseases, the majority of machine learning models now in use must be able to correctly comprehend sizable and intricate datasets.
- Data availability: In order to provide precise predictions, the majority of machine learning models need a lot of data. The accuracy of the model may degrade if data is not accessible in large enough amounts.
- Inaccurate labelling: The accuracy of the machine learning models now in use depends on how well the input dataset was used for training. Inaccurate labelling of the data prevents the model from producing reliable predictions.

PROPOSED SYSTEM

- Present the DeepDiabetic Framework, a multiclassification deep learning model designed to identify and diagnose the four most prevalent diabetic eye complications: cataract, glaucoma, diabetic macular oedema, and diabetic retinopathy (DR).
- In addition to the original dataset, we used both offline and online geometric augmentation techniques to evaluate the deep learning models' correctness.
- This article considers the performance of five different architectures: ResNet152V2, ResNet152V2 + Gated Recurrent Unit (GRU), ResNet152V2 + Bidirectional GRU (Bi-GRU), EfficientNetB0, and VGG16. a detailed analysis and assessment of various deep learning architectures (DR, DME, Glaucoma, and Cataract) using public fundus datasets with four classes. To the best of our knowledge, no other GRU models have been used in the literature to categorise these models for these specific disorders.
- Evaluating our proposed work's performance metrics against other models used in earlier research to diagnose and categorise diabetic eye diseases.

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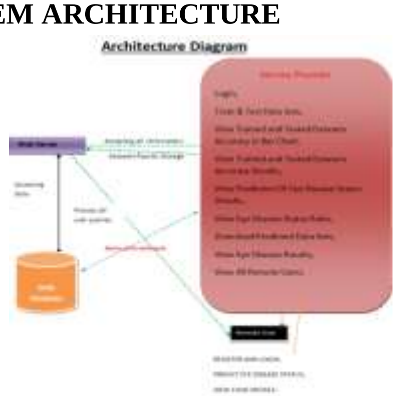
ADVANTAGES

- Method 1: Dataset without augmentation This approach makes use of the original, unaltered dataset of 1228 photos that was gathered and stated in Data Collection III-A1.
- Technique 2: Augmented dataset online With this approach, the augmentation is applied as the model is being trained. This implies that the model is given a batch of the original dataset chosen at random for each epoch, and the changes are then carried out live. Furthermore, depending on the transformations used, the pictures supplied to the model vary for every epoch.
- Method 3: Dataset that has been enhanced offline Prior to being used in the model, this technique adds the augmentation to the original dataset. As previously mentioned, the initial dataset is divided into two sets at random: the training set and the validation set. In this case, we merely amplify the training set of photographs, which consists of around 858 photos. We created a total of 6006 pictures by applying six distinct alterations to each image (in addition to the original image).

SYSTEM ARCHITECTURE



IV. IMPLEMENTATION

Modules Description

Service Provider

The Service Provider must use a working user name and password to log in to this module. He may do many tasks after successfully logging in, including Train & Test Data Sets, See the Accuracy of Trained and Tested Datasets in a Bar Chart View Accuracy Results for Trained and Tested Datasets, Download Predicted Data Sets, View Eye Disease Status Ratio, and View Prediction Details View All Remote Users and View Eye Disease Results.

View and Authorize Users

The administrator may see a list of all registered users in this module. Here, the administrator may see the user's information, like name, email, and address, and they can also grant the user permissions.

Remote User

A total of n users are present in this module. Before beginning any actions, the user needs register. Following registration, the user's information will be entered into the database. Following a successful registration, he must use his password and authorised user name to log in. Following a successful login, the user may do tasks including registering and logging in, predicting their eye disease status, and seeing their profile.

V. SCREEN SHOTS

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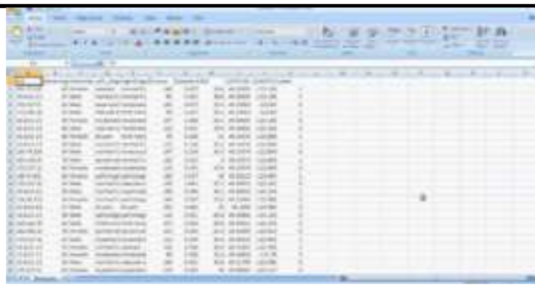

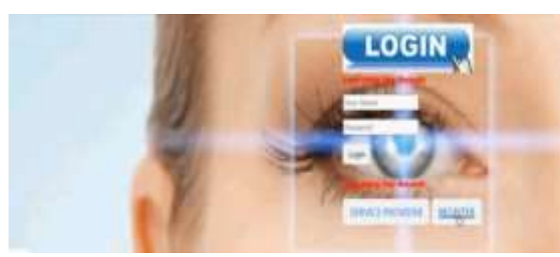

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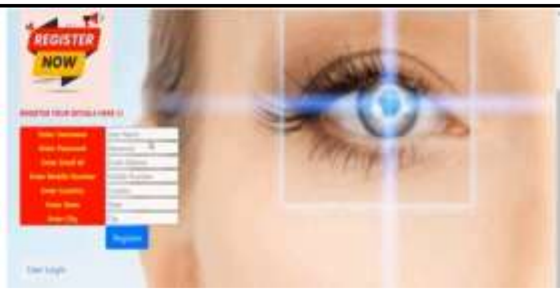

VI. CONCLUSION

The proposed DeepDiabetic system demonstrates the potential of deep neural networks in transforming diabetic eye disease diagnosis through automation, accuracy, and accessibility. By integrating advanced deep learning architectures with retinal fundus imaging, the model effectively detects and classifies various stages of diabetic retinopathy and related retinal abnormalities. The system's ability to learn hierarchical visual features allows it to identify subtle pathological changes that may be difficult to detect through manual examination, thereby supporting ophthalmologists in early intervention and treatment planning.

The experimental outcomes highlight that the DeepDiabetic framework achieves superior performance compared to traditional machine learning and rule-based approaches, particularly in terms of classification accuracy, sensitivity, and specificity. Additionally, the incorporation of preprocessing techniques, transfer learning, and model interpretability through visual explanations enhances both diagnostic precision and clinical trustworthiness. The system's scalability and adaptability also make it suitable for integration into teleophthalmology platforms, enabling large-scale screening in remote and underserved regions.

Beyond diagnosis, the DeepDiabetic model contributes to the broader field of AI-driven healthcare, where data-driven insights can improve preventive care and reduce disease-related blindness globally. The framework not only reduces the burden on healthcare professionals but also enables continuous monitoring and rapid assessment of at-risk patients.

In conclusion, DeepDiabetic establishes a reliable and intelligent diagnostic framework for early detection of diabetic eye diseases, offering a significant step toward the realization of automated, accessible, and precision-based ophthalmic care. Future research will focus on expanding the dataset diversity, integrating multimodal data such as OCT and clinical history, and implementing real-time AI-assisted screening tools to further enhance diagnostic accuracy and global healthcare reach.

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