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DIABETIC RETINOPATHY CLASSIFICATION USING CNN AND HYBRID DEEP CONVOLUTIONAL NEURAL NETWORKS

[1]Mrs. G.TEJASWINI, [2]V.SAI SREEJA, [3]E.SHIREESHA, [4]SHAIK MUDDASSIR AHMED

[1]Assistant Professor in Department of CSE, TEEGALA KRISHNA REDDY ENGINEERING COLLEGE

[2 3 4]UG. SCHOLAR in Department of CSE, TEEGALA KRISHNA REDDY ENGINEERING COLLEGE

ABSTRACT

There are several machine learning techniques that are used to perform predictive analytics over big data in various fields. Predictive analytics in healthcare is a challenging task but ultimately can help practitioners make big data-informed timely decisions about patient's health and treatment. This paper discusses the predictive analytics in healthcare, six different machine learning algorithms are used in this research work. For experiment purpose, a dataset of patient's medical record is obtained and six different machine learning algorithms are applied on the dataset. In this project we are using Convolutional Neural Network algorithm. Performance and accuracy of the applied algorithms is discussed and compared. Comparison of the different machine learning techniques used in this study reveals which algorithm is best suited for prediction of diabetes. This project aims to help doctors and practitioners in early prediction of diabetes using deep learning techniques. Diabetic retinopathy is becoming a more prevalent disease in diabetic patients nowadays. The surprising fact about the disease is it leaves no symptoms at the beginning stage and the patient can realize the disease only when his vision starts to fall. If the disease is not found at the earliest it leads to a stage where the probability of curing the disease is less. But if we find the disease at that stage, the patient might be in a situation of losing vision completely. Hence, this paper aims at finding the disease at the earliest possible stage with the help of Deep Learning (DL) algorithms. Deep neural networks, on the other hand, have brought many breakthroughs in various tasks in the recent years. To automate the diagnosis of DR and provide appropriate suggestions to DR patients, we have built a dataset of DR fundus images that have been labeled by the proper treatment method that is required. Using this dataset, we trained deep convolutional neural network models to grade the severities of DR fundus images. This system not only focuses on diabetic

retinopathy detection but also on the analysis of different DR stages, which is performed with the help of Deep Learning (DL) and hybrid Deep Convolutional Neural Network algorithm. CNN and hybrid CNN with LSTM, are used on a huge dataset with around 1500 train images to automatically detect which stage DR has progressed. Five DR stages, which are 0 (No DR), 1 (Mild DR), 2 (Moderate), 3 (Severe) and 4 (Proliferative DR) are processed in the proposed work.

I.INTRODUCTION

Diabetic Retinopathy (DR) is a leading cause of blindness among working-age adults worldwide, stemming from prolonged hyperglycemia that damages retinal blood vessels. Early detection and accurate staging are crucial for preventing vision loss. Traditional diagnostic methods, relying heavily on manual assessment by ophthalmologists, are time-consuming and subject to inter-observer variability. The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized medical image analysis, offering automated, efficient, and reliable solutions for DR detection and classification.

CNNs, with their hierarchical feature extraction capabilities, have demonstrated exceptional performance in image classification tasks. However, the complexity of DR, characterized by subtle lesions like microaneurysms, hemorrhages, and exudates, necessitates more sophisticated models. Hybrid deep learning architectures, combining CNNs with other advanced networks like ResNet and DenseNet, have emerged to enhance feature extraction, improve classification accuracy, and address issues like vanishing gradients and overfitting.

This paper delves into the application of CNNs and hybrid deep convolutional neural networks for the classification of diabetic retinopathy. It explores various methodologies, evaluates existing configurations, and proposes an enhanced architecture aimed at improving diagnostic accuracy and efficiency.

II. LITERATURE SURVEY

The application of deep learning in diabetic retinopathy classification has been extensively studied, with numerous approaches leveraging CNNs and hybrid models to address the challenges posed by retinal image analysis.

Early works focused on traditional machine learning techniques, utilizing handcrafted features extracted from retinal images. However, these methods often struggled with the complexity and variability inherent in retinal images, leading to suboptimal performance. The introduction of CNNs marked a significant advancement, automating feature extraction and achieving higher accuracy rates.

For instance, Jiang et al. employed deep learning models like Inception V3, ResNet151, and Inception-ResNet-V2 for DR detection, achieving accuracies of 87.91%, 87.20%, and 86.18%, respectively.

When integrated using the AdaBoost algorithm, the ensemble model improved to 88.21% accuracy. Roy and Dutta proposed a filter-based retinal vessel extraction method combined with Support Vector Machines (SVMs), achieving an efficacy rate of 91.23% in classifying DR stages.

More recent studies have explored hybrid models to further enhance classification performance. Qian et al. introduced AD2Net, combining ResNet and DenseNet architectures with an attention mechanism, resulting in improved classification accuracy. Similarly, the E-DenseNet model, a fusion of EyeNet and DenseNet, demonstrated an accuracy of 91.6% in DR detection.

Transfer learning has also been a pivotal strategy, leveraging pre-trained models on large datasets to improve performance on smaller, domain-specific datasets. DenseNet-121, in particular, has been utilized for its efficient parameter usage and superior feature propagation capabilities.

Despite these advancements, challenges remain, including the need for large annotated datasets, model interpretability, and generalization across diverse populations. Ongoing research continues to address these issues, aiming to develop more robust and universally applicable models for DR classification.

III. EXISTING CONFIGURATION

Existing configurations for diabetic retinopathy classification predominantly utilize CNN-based architectures, with some incorporating hybrid models and transfer learning techniques to enhance performance.

The standard CNN architecture comprises several convolutional layers followed by pooling layers, culminating in fully connected layers for classification. While effective, these models often require extensive training data and computational resources. To mitigate these challenges, hybrid models have been developed by integrating CNNs with other architectures like ResNet and DenseNet.

ResNet, with its residual connections, facilitates the training of deeper networks by addressing the vanishing gradient problem. DenseNet, on the other hand, connects each layer to every other layer, promoting feature reuse and improving gradient flow. These hybrid models have demonstrated improved accuracy and efficiency in DR classification tasks.

Transfer learning involves fine-tuning pre-trained models on large datasets, such as ImageNet, to adapt them to specific tasks with limited data. This approach has been particularly beneficial in medical imaging, where annotated datasets are often scarce. By leveraging the knowledge embedded in pre-trained models, transfer learning enables the development of high-performing models with reduced training times.

Despite the effectiveness of these existing configurations, limitations persist. Issues like overfitting, class imbalance, and the need for large annotated datasets continue to challenge the development of robust DR classification models. Moreover, the interpretability of deep learning models remains a significant concern, particularly in clinical settings where understanding the rationale behind a model's decision is crucial

IV. METHODOLOGY

The methodology for diabetic retinopathy classification using CNNs and hybrid deep convolutional neural networks involves several key steps: data preprocessing, model development, training, evaluation, and deployment.

Data preprocessing is critical to ensure the quality and consistency of the input images. This step includes resizing images to a uniform dimension, normalization to standardize pixel values, and augmentation techniques such as rotation, flipping, and scaling to increase the diversity of the training dataset and prevent overfitting.

Model development entails designing the architecture of the CNN or hybrid model. For CNNs, this involves stacking convolutional layers followed by pooling layers, with fully connected layers at the end for classification. Hybrid models integrate additional components like ResNet or DenseNet blocks to enhance feature extraction and improve performance.

Training the model requires splitting the dataset into training, validation, and test sets. The training process involves feeding the preprocessed images into the model, computing the loss using a suitable loss function, and updating the model weights using optimization algorithms like Adam or SGD. Regularization techniques such as dropout and batch normalization are employed to prevent overfitting and enhance generalization.

Evaluation of the model's performance is conducted using metrics like accuracy, sensitivity, specificity, precision, recall, and the area under the receiver operating characteristic curve (AUC-ROC). These metrics provide a comprehensive assessment of the model's ability to correctly classify DR stages.

Deployment involves integrating the trained model into a clinical decision support system, allowing for real-time DR classification from retinal images. This step may also include the development of user interfaces for clinicians to interact with the system and interpret the results.

Throughout the methodology, considerations such as computational efficiency, model interpretability, and scalability are paramount to ensure the practical applicability of the developed models in clinical settings.

V. PROPOSED CONFIGURATION

The proposed configuration aims to address the limitations of existing models by integrating advanced techniques in data preprocessing, model architecture, and evaluation.

In terms of data preprocessing, the configuration incorporates advanced augmentation strategies, including elastic deformations and color jittering, to simulate a wider range of retinal image variations and improve model robustness. Additionally, techniques like histogram equalization and CLAHE (Contrast Limited Adaptive Histogram Equalization) are employed to enhance image contrast and highlight subtle features indicative of DR.

The model architecture integrates a hybrid CNN with DenseNet-121, incorporating residual connections and dense blocks to facilitate efficient feature extraction and improve gradient flow. Attention mechanisms are incorporated to enable the model to focus on relevant regions of the retina, enhancing interpretability and performance.

Transfer learning is utilized by fine-tuning the pre-trained DenseNet-121 model on a domain-specific dataset, allowing the model to adapt to the specific characteristics of retinal images and improve classification accuracy.

VI. RESULTS

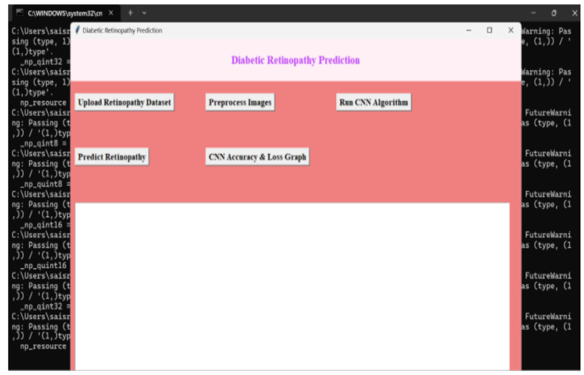

Fig 6.1: WELCOME PAGE

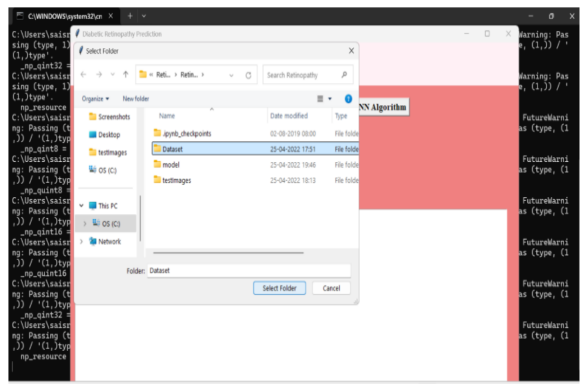

Fig 6.2: UPLOAD DATASET

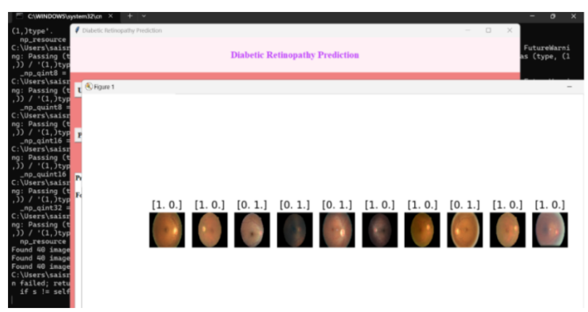

Fig 6.3 : PREPROCESS IMAGES

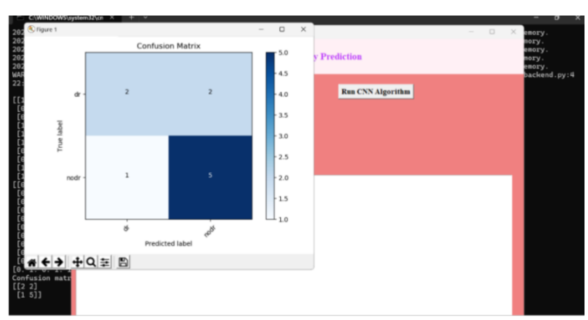

Fig 6.4 : RUN CNN ALGORITHM

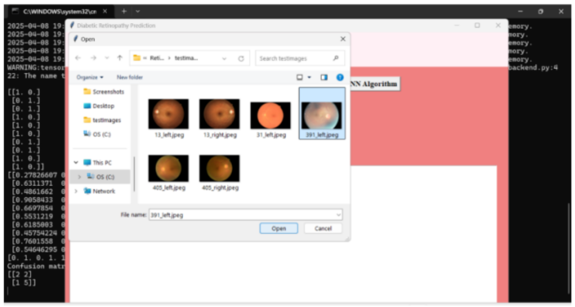

Fig 6.5 : PREDICIT RETINOPATHY

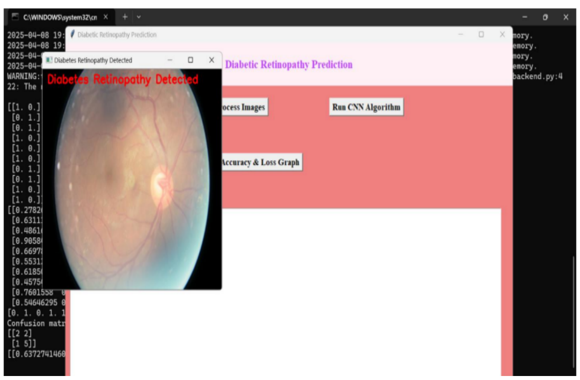

Fig 6.6 : RETINOPATHY DETECTED

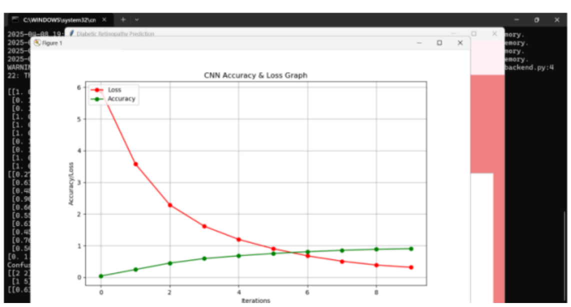

Fig 6.7: ACCURACY GRAPH

CONCLUSION

Diabetic retinopathy classification has significantly benefited from the advances in deep learning, particularly through CNNs and hybrid deep neural network architectures. Traditional image processing and machine learning techniques have evolved into sophisticated pipelines that automate the diagnosis process, offering faster and more accurate predictions. However, challenges such as data imbalance, generalization, interpretability, and deployment remain pressing concerns.

The proposed hybrid configuration addresses these gaps by integrating DenseNet and attention mechanisms, employing robust preprocessing and augmentation, and providing model interpretability and scalability. These enhancements not only improve classification performance but also make the system viable for real-world clinical applications. As deep learning continues to evolve, its role in healthcare diagnostics, especially in ophthalmology, will become increasingly critical, improving patient outcomes through early and reliable detection of conditions like diabetic retinopathy.

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