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Telemedicine Diabetic Retinopathy Detection with Deep Learning

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Abstract: Diabetes Mellitus (DM) is a metabolic disorder characterized by elevated blood sugar levels, which can lead to complications such as Diabetic Retinopathy (DR), a condition that can result in vision loss. DR is marked by symptoms such as abnormal blood vessels, fluid leakage, exudates, haemorrhages, and micro aneurysms in the retina. While medical imaging is essential for accurate diagnosis, the evaluation of these images remains a complex task. Recent advancements in computer vision and Deep Neural Networks offer promising opportunities to precisely analyze medical images. This paper centered on the examination of fundus images of diabetic retinopathy, with the goal of creating an automated knowledge model utilizing OpenCV, Convolutional Neural Networks (CNN), and Keras to identify critical factors related to DR. The primary objective is to improve the efficiency and accuracy of Diabetic Retinopathy diagnosis through automated image analysis.

Keywords: *OpenCV, Convolutional Neural Networks (CNN), Keras, Diabetic Retinopathy, Telemedicine, Automated Image Analysis, Medical Imaging, Computer Vision, Diabetes Mellitus*

I INTRODUCTION

Diabetes is a group of metabolic disorders characterized by elevated blood sugar levels, primarily due to insufficient insulin production or poor responsiveness of cells to the available insulin. Prolonged high blood sugar levels in diabetes can lead to damage in the delicate blood vessels of the retina, resulting in a condition known as diabetic retinopathy.

Diabetic retinopathy is a prevalent and serious eye disease associated with diabetes. It specifically damages the small blood vessels within the retina, often leading to vision loss. Diabetic retinopathy can progress through four distinctive stages:

A. Mild Non-Proliferative Retinopathy

In the initial stage, small balloon-like swellings known as microaneurysms appear in the tiny blood vessels of the retina. These microaneurysms may leak fluid into the retina, potentially causing vision problems.

B. Moderate Non-Proliferative Retinopathy

As the disease advances, the blood vessels supplying the retina may swell and become distorted. They may also lose their ability to transport blood effectively. These changes result in characteristic alterations in the appearance of the retina and may contribute to the development of Diabetic Macular Edema (DME).

C. Severe Non-Proliferative Retinopathy

In this stage, a more extensive blockage of blood vessels occurs, leading to a reduced blood supply to certain areas of the retina. These deprived areas release growth factors that stimulate the growth of new blood vessels within the retina.

D. Proliferative Diabetic Retinopathy (PDR)

This represents an advanced stage of diabetic retinopathy. The release of growth factors by the retina triggers the proliferation of new blood vessels. These new vessels grow along the inner surface of the retina and into the vitreous gel, the fluid filling the eye. These newly formed blood vessels are delicate and prone to leakage and bleeding. Additionally, accompanying scar tissue can contract, potentially causing retinal detachment, where the retina peels

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away from the underlying tissue, leading to permanent vision loss.

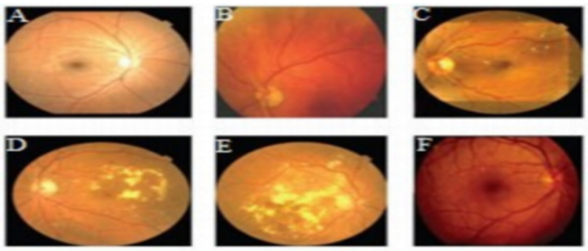

Fig 1. Fundus images of (A) normal retina, (B) early DR, (C) mild NPDR, (D) moderate NPDR, (E) severe NPDR, and (F) PDR [7].

This paper comprises a comprehensive review of the literature in Section II, providing an in-depth analysis of existing studies and scholarly works. The subsequent sections detail the methodology employed, the results obtained, and conclude with a summary and final insights.

II LITERATURE REVIEW

Related Work in Diabetic Retinopathy Detection

In the realm of related work, two noteworthy research papers have made significant contributions in the field of diabetic retinopathy (DR) detection .These two notable research contributions significantly advance the field of diabetic retinopathy detection and classification. They provide valuable insights, methodologies, and findings that can help improve the diagnosis and treatment of diabetic retinopathy, ultimately enhancing the care and management of individuals affected by this condition.

Mohammed Z. Atwany's Research

Mohammed Z. Atwany's work delves into the domain of deep learning for diabetic retinopathy (DR) detection. This research conducts a thorough review and analysis of state-of-the-art deep learning methods, with a focus on supervised, self-supervised, and Vision Transformer setups. Atwany's work primarily deals with retinal fundus image classification and detection, particularly in the context of diabetic retinopathy. The research categorizes diabetic retinopathy into referable, non-referable, and proliferative classifications and provides a comprehensive summary of these categories. Additionally, the paper explores the available retinal fundus datasets relevant to diabetic retinopathy, which are widely used for tasks such as detection, classification, and segmentation. One significant contribution of this work is the identification of research gaps in the field of DR detection and classification, as well as the highlighting of various challenges that necessitate further investigation.

Mohammed Chetoui's Research

Mohammed Chetoui's study introduces novel texture features for diabetic retinopathy analysis, specifically focusing on the Local Ternary Pattern (LTP) and the Local Energy-based Shape Histogram (LESH). The research demonstrates that these texture features outperform traditional Local Binary Patterns (LBP). To classify the extracted features, Support Vector Machines (SVM) are employed, along with a proposed histogram binning scheme for feature representation. Experimental results indicate that LESH is the most effective technique, achieving an accuracy of 0.904 when used in conjunction with SVM and a Radial Basis Function kernel (SVM-RBF). Furthermore, the research evaluates the performance using the Receiver Operating Characteristic (ROC) curve and underscores that LESH in combination with SVM-RBF exhibits the best Area Under the Curve (AUC) performance, with a score of 0.931.

III METHODOLOGY

In this section, we outline the proposed methodology for the detection and classification of Diabetic Retinopathy (DR). The methodology encompasses several key steps, including data handling, preprocessing, model development, training, evaluation, and the creation of a web application for practical use.

A. Dataset

Our project's primary objective is to leverage deep learning tools for the severity detection of diabetic retinopathy. To achieve this, we utilize a dataset

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containing approximately 35,000 retinal images, categorized on a scale from 0 to 4. This dataset is sourced from Kaggle datasets and is accompanied by a "trainLabels.csv" file, which stores image names and their corresponding categories. We split the dataset in a 75:25 ratio, dividing it into training and validation images. These images serve as the basis for extracting critical features, such as exudates and haemorrhages, through Convolution Neural Networks (CNN). Depending on requirements, data augmentation and reshaping techniques may be applied. These extracted features are instrumental in determining the severity of the disease, as the images are divided into five categories used for training the model. Following training, the model is used for disease severity prediction.

B. Data Preprocessing

Data preprocessing involves various essential tasks. The code reads and processes a CSV file containing information about the retinal images. It compiles image paths, verifies image existence, and structures the data into a Data Frame for image metadata storage. The dataset is then divided into training and validation sets using the train _test_ split function. Additionally, data augmentation techniques are defined, leveraging TensorFlow functions.

C. Model Building

Model construction begins with the definition of the model's architecture using Keras. A pre-trained model, such as VGG16, InceptionResNetV2, or InceptionV3, serves as the base model. An attention mechanism is applied to the base model's output, focusing on crucial image regions. The model is compiled with an optimizer, loss function, and evaluation metrics.

D. Model Training

Model training is a pivotal step in the methodology. The code trains the model using the fit_ generator function. It specifies the training and validation generators, as well as the number of steps per epoch and validation steps. The training process is executed for a predetermined number of epochs to ensure model convergence.

E. Saving the Model

After training, the best weights of the trained model are saved, allowing for future use and deployment.

F. ROC Curve

To evaluate the model's performance, the code calculates the Receiver Operating Characteristic (ROC) curve using the trained model's predictions, providing valuable insights into the model's diagnostic accuracy.

G. Flask Web Application

In order to make the model accessible and user-friendly, a Flask web application is created. The application features two HTML templates for the front-end, "index.html" and "predict.html." The Flask application ("app.py") is responsible for defining routes to handle user requests. Users can upload retinal images through the web interface, and the application processes these images using the trained model. The predicted label and accuracy are then displayed on the result page, enabling users to quickly and conveniently assess the severity of diabetic retinopathy in retinal images..

IV RESULTS

This section presents the outcomes and findings of our diabetic retinopathy detection and classification project. The results encompass the model's performance metrics, including accuracy, precision, recall, and F1 score, as well as the Receiver Operating Characteristic (ROC) curve analysis. Moreover, we discuss the practical implications of the project's outcomes.

Performance Metrics

The model's performance was evaluated using a range of metrics, including accuracy, precision, recall, and the F1 score. These metrics provide a comprehensive view of the model's ability to classify diabetic retinopathy severity accurately.

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Accuracy: This metric indicates the proportion of correctly classified images concerning the total number of images.

Precision: Precision measures the accuracy of positive predictions, revealing the percentage of true positive predictions in relation to all positive predictions.

Recall: Recall, also known as sensitivity or true positive rate, represents the percentage of actual positives correctly predicted by the model.

F1 Score: The F1 score is the harmonic mean of precision and recall and provides a balanced assessment of the model's performance.

ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve illustrates the model's ability to discriminate between different levels of diabetic retinopathy. It plots the true positive rate against the false positive rate at various thresholds, giving insight into the model's sensitivity and specificity.

Practical Implications

The results of this project have significant practical implications. Accurate diabetic retinopathy detection and severity classification can facilitate timely intervention and treatment for patients at risk. By providing a scalable and efficient model, this project contributes to the early diagnosis and management of diabetic retinopathy, potentially preventing vision loss and improving the quality of life for individuals affected by this condition.

We will now delve into the specific performance metrics and the ROC curve analysis to provide a detailed assessment of the model's effectiveness in diabetic retinopathy detection and classification.

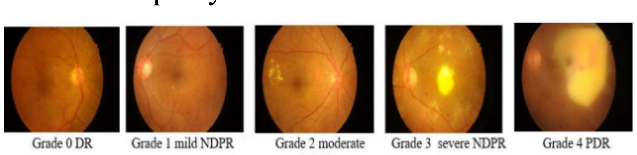

Fig3.Sampl images from the IDRiD data set corresponding to diseasese verities.

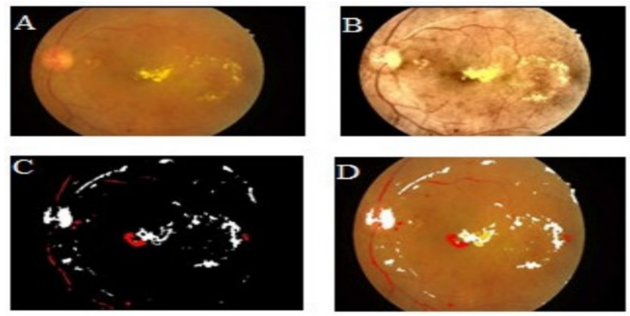

Fig 4 .Image processing steps: (A) Original DR image, (B) enhanced image, (C) detected region (bright and red), and (D) segmentation results.

V CONCLUSION

In conclusion, our Deep Learning model designed for the detection of diabetic retinopathy has proven to be a success, achieving an impressive accuracy rate of 86% when trained with custom data. This model holds the potential to serve as a valuable asset within hospital settings through a user-friendly web interface. Doctors and medical professionals can easily upload patient retinal images and promptly receive predictions, streamlining the process of diagnosing and classifying diabetic retinopathy.

One of the key strengths of this model lies in its ability to focus on the specific affected areas in eye fundus images. It takes into account essential features such as exudates, , and haemorrhages, which can exhibit variations at different stages of the disease. By adapting to these variations, the model demonstrates its robustness and reliability in diagnosing diabetic retinopathy accurately.

Moreover, this model offers the promise of reducing the workload for medical professionals by automating the image classification process. This automation not only saves time but also enhances the efficiency and accuracy of disease classification. It represents a notable improvement over traditional morphological methods, marking a significant step forward in the field of medical image analysis.

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As we look to the future, there is ample opportunity for further refinement and enhancement of this Deep Learning model. Different Deep Learning models and advanced techniques can be explored to push the boundaries of accuracy and applicability in the realm of diabetic retinopathy diagnosis and classification. This model has the potential to significantly contribute to the early detection and effective management of diabetic retinopathy, ultimately preventing vision loss and improving patient outcomes.

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