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Research Paper

DETECTING DIABETIC RETINOPATHY USING HWT AND CONVOLUTIONAL LENET

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ABSTRACT

A common side effect of diabetes mellitus is diabetic retinopathy (DR), which results in retinal lesions that impair vision. Blindness may result if it is not identified in time. Unfortunately, treatment for DR only maintains vision; it is not a reversible process. The risk of vision loss can be considerably decreased with early detection and treatment of DR. In contrast to computer-aided diagnosis systems, ophthalmologists' manual diagnosis of DR retina fundus images is time-consuming, labour-intensive, expensive, and prone to misdiagnosis. Deep learning has recently emerged as one of the most popular methods that has improved performance in many fields, particularly in the analysis and classification of medical images. In medical image analysis, convolutional neural networks are increasingly utilised as a deep learning technique and are extremely.

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I. INTRODUCTION

In the medical field, early disease detection increases the effectiveness of treatment. Diabetes is a condition in which there is insufficient insulin, which raises blood glucose levels. Globally, 425 million adults are impacted. Diabetes has an impact on the kidneys, heart, nerves, and retina.

One consequence of diabetes is diabetic retinopathy (DR), which results in swelling and blood and fluid leakage from the retina's blood vessels. If DR is in an advanced stage, it may result in blindness. DR accounts for 2.6% of blindness globally. Diabetes patients who have had the condition for a long time are more likely to have DR. Diagnosing and treating diabetes patients requires routine retinal screening.

1.1 MOTIVATION

Diabetic Retinopathy (DR) is a serious eye condition that can lead to blindness if not caught early. It's a common complication of diabetes and often progresses without noticeable symptoms until the damage is already done. That's why early detection is so important — it can make a huge difference in preserving someone's vision.

Unfortunately, diagnosing DR isn't always easy. It typically involves trained specialists manually examining retinal images, which can be slow, expensive, and prone to human error. In many parts of the world, especially rural or under-resourced areas, access to expert eye care is limited. This makes early diagnosis even more difficult and increases the risk of people going untreated.

With recent advances in artificial intelligence, especially in the fields of deep learning and image processing, we now have the opportunity to change that. This project explores how we can use the Hilbert Wavelet Transform (HWT) to extract meaningful features from retinal images and pair it with a Convolutional LeNet model to automatically detect signs of DR.

The goal is to build an intelligent system that can help doctors make faster, more accurate diagnoses — or even assist in areas where specialists aren't available. By doing this, we hope to improve early detection rates, reduce

the burden on healthcare workers, and ultimately help prevent blindness caused by diabetic retinopathy.

1.2 PROBLEM STATEMENT

Diabetic Retinopathy (DR) is a serious eye condition and one of the main causes of preventable blindness, especially in adults of working age. It happens when high blood sugar levels from diabetes start damaging the tiny blood vessels in the retina. What makes DR particularly dangerous is that it often develops without noticeable symptoms in the early stages — and by the time it's detected, some vision may already be lost.

Right now, detecting DR typically involves trained specialists manually examining retinal images. While this method can be effective, it's also slow, labor- intensive, and can vary from one expert to another. Plus, in many rural or under- resourced areas, there just aren't enough specialists or medical facilities available to screen everyone who needs it.

Because of these challenges, there's a growing need for an automated system that can help identify DR earlier and more consistently. Some existing computer-based methods have made progress, but many still fall short — especially when it comes to picking up subtle signs in the early stages of the disease.

This project aims to tackle those limitations by combining two powerful techniques: Hilbert Wavelet Transform (HWT) for extracting detailed features from retinal images, and Convolutional LeNet, a deep learning model designed for image classification. Together, they can create a smart, efficient system that not only improves detection accuracy but can also be scaled and used in real-world clinics — even where expert resources are limited.

1.3 SCOPE AND OBJECTIVE

Most of the related works classifies the disease with two classifiers, i.e. whether he/she has a healthy eye or has a diabetic retinopathy defective eye. The scope in our research is to split this classes into defective and non defective stages of diabetic retinopathy. An eye can be classified into 4 classes. Besides, extracting hand crafted features from raw images after different processing is one of the best scopes we have worked in this research. The objective of using this method is to get some features which are specifically responsible for the diabetic retinopathy.

II. LITERATURE SURVEY

This section reviews the studies in which the DR dataset was classified into many classes. The work by V. Gulshan et al. [60] introduced a method to detect DR and diabetic macular edema (DME) using CNN model. They used Messidor-2 [31] and eyepacs-1 datasets which contain 1748 images and 9963 images, respectively to test the model. These images were first normalized, and the diameter was resized to 299 pixels wide before feeding them to the CNN. They trained 10 CNNs with the pretrained Inception-v3 [20] architecture with a various number of images, and the final result was computed by a linear average function. The images were classified into referable diabetic macular edema, moderate or worse DR, severe or worse DR, or fully gradable. They obtained a specificity of 93% in both datasets and 96.1% and 97.5% in sensitivity for the Messidor-2 and eyepacs-1 datasets, respectively; however, they did not explicitly detect non-DR or the five DR stage images.

M. Abramoff et al. [61] integrated a CNN with an IDX-DR device to detect and to classify DR images. They applied data augmentation to the Messidor-2 [31] dataset, which contains 1748 images. Their various CNNs were integrated using a Random Forest classifier to detect DR lesions as well as retina normal anatomy. The images in this work were classified as no DR, referable DR, or vision threatening DR. They reported an area under the curve of 0.980, a sensitivity of 96.8%, and a specificity of 87.0%. Unfortunately, they considered images of the mild DR stage as no DR, and the five DR stages were not considered.

H. Pratt et al. [42] proposed a method based on a CNN to classify images from the Kaggle dataset [26] into five DR stages. In the preprocessing stage, color normalization and image resizing to 512 × 512 pixels were

performed. Their custom CNN architecture contained 10 CONV layers, eight max-pooling layers, and three FC layers. The SoftMax function was used as a classifier for 80,000 test images. L2 regularization and dropout methods was used in CNN to reduce overfitting. Their results had a specificity of 95%, an accuracy of 75% and a sensitivity of 30%. Unfortunately, CNN does not detect the lesions in the images, and only one dataset was used to evaluate their CNN.

EXISTING SYSTEM

In order to detect diabetic retinopathy, a retinography is performed, which entails in capturing the structures within the eye (retina) by either dilating the pupil or without dilation. Typically, the ophthalmologists diagnose diabetic retinopathy based on features such as the blood vessels, exudates, haemorrhages, micro aneurysms and texture. Colour fundus photography captures the retina of the eye with exclusively designed cameras, which is treated as a standard means of detecting premature signs of diabetic retinopathy. The fundus imaging has an essential starring role in diabetes monitoring since the events of retinal abnormalities are common and their consequences are severe. Since the eye fundus is sensitive to vascular abnormalities, the fundus imaging is additionally considered as a contender for non-invasive screening. The achievement of this kind of screening methodology relies upon the precise fundus image capture, and particularly on exact and consistent image processing algorithms for identifying the abnormalities.

In most developing nations, there are limited numbers of specialists to examine diabetic retinopathy in screening programs. It is also prone to misdiagnosis and requires more effort than automatic methods. Hence, there is an immediate need for developing an automated screening system for diabetic retinopathy diagnosis.

PROPOSED SYSTEM

Our First phase is data collection. There are many publicly available datasets for the retina to detect DR and to detect the vessels. The dataset contains features extracted from image set to predict whether an image have signs of diabetic retinopathy or not. Then features and labels of the dataset are identified. After that the dataset is divided into two sets, one for training where most of the data is used and the other one is testing. In training set four different classification algorithms can be fitted for the analysis performance of the model. The algorithms like kNearest Neighbor, random forest, support vector machine and neural networks can be used. After the system has done learning from training datasets, newer data is provided without outputs. The final model generates the results for predicting diabetic retinopathy using the knowledge it gained from the data on which it was trained.

III. MODULE DESCRIPTION

Gathering Data:

Data Gathering is the first step of the machine learning life cycle. The goal of this step is to identify and obtain all data-related problems. In this step, we need to identify the different data sources, as data can be collected from kaggle . It is one of the most important steps of the life cycle. The quantity and quality of the collected data will determine the efficiency of the output. The more will be the data, the more accurate will be the prediction.

This step includes the below tasks:

- Identify various data sources
- Collect data
- Integrate the data obtained from different sources

By performing the above task, we get a coherent set of data, also called as a dataset. It will be used in further steps.

Data Preparation:

After collecting the data, we need to prepare it for further steps. Data preparation is a step where we put our data into a suitable place and prepare it to use in our machine learning training.

In this step, first, we put all data together, and then randomize the ordering of data. This step can be further divided into two processes:

Data exploration:

It is used to understand the nature of data that

we have to work with. We need to understand the characteristics, format, and quality of data.
A better understanding of data leads to an effective outcome. In this, we find Correlations, general trends, and outliers.

Data Wrangling

Data wrangling is the process of cleaning and converting raw data into a useable format. It is the process of cleaning the data, selecting the variable to use, and transforming the data in a proper format to make it more suitable for analysis in the next step. It is one of the most important steps of the complete process. Cleaning of data is required to address the quality issues.

- Missing Values
- Duplicate data
- Invalid data
- Noise

So, we use various filtering techniques to clean the data.
It is mandatory to detect and remove the above issues because it can negatively affect the quality of the outcome.

Data Analysis

Now the cleaned and prepared data is passed on to the analysis step. This step involves:

- Selection of analytical techniques
- Building models
- Review the result

The aim of this step is to build a machine learning model to analyze the data using various analytical techniques and review the outcome. It starts with the determination of the type of the problems, where we select the machine learning techniques such as Classification, Regression, Cluster analysis; Association, etc. then build the model using prepared data, and evaluate the model.

Train Model

Now the next step is to train the model, in this step we train our model to improve its performance for better outcome of the problem.
We use datasets to train the model using various machine learning algorithms. Training a model is required so that it can understand the various patterns, rules, and, features.

Test Model

Once our machine learning model has been trained on a given dataset, then we test the model. In this step, we check for the accuracy of our model by providing a test dataset to it.
Testing the model determines the percentage accuracy of the model as per the requirement of project or problem.

Deployment

The last step of machine learning life cycle is deployment, where we deploy the model in the real-world system.
If the above-prepared model is producing an accurate result as per our requirement with acceptable speed, then we deploy the model in the real system. But before deploying the project, we will check whether it is improving its performance using available data or not. The deployment phase is similar to making the final report for a project.

IV. SYSTEM DESIGN

SYSTEM ARCHITECTURE

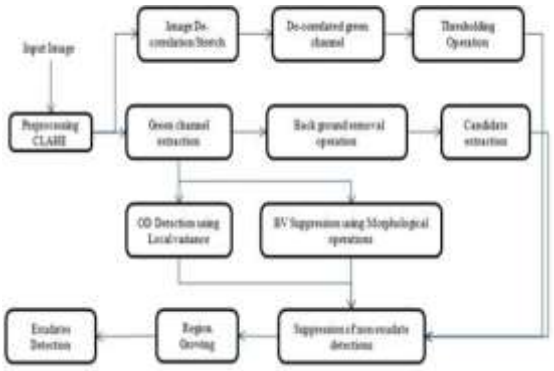

Fig. System Architecture

V. OUTPUT SCREENS

CHECKING FOR DIABETIC RETINOPATHY

FIG: Home Page

FIG: Select DR Label

FIG: Selecting input image

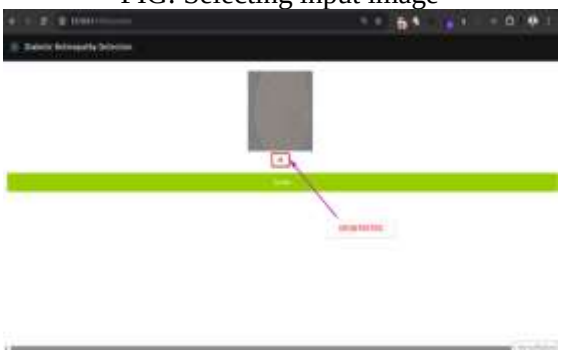

FIG: DR Detected

CHECKING FOR NO DIABETIC RETINOPATHY

FIG: HOME PAGE

FIG: SELECT NO DR LABEL

FIG: SELECT ANY INPUT IMAGE

FIG: NO DR Detected

VI. CONCLUSION

Automated screening systems significantly reduce the time required to determine diagnoses, saving effort and costs for ophthalmologists and result in the timely treatment of patients. Automated systems for DR detection play an important role in detecting DR at an early stage. The DR stages are based on the type of lesions that appear on the retina. This article has reviewed the most recent automated systems of diabetic retinopathy detection and classification that used deep learning techniques. The common fundus DR datasets that are publicly available have been described, and deep-learning techniques have been briefly explained. Most researchers have used the CNN for the classification and the detection of the DR images due to its efficiency. This review has also discussed the useful techniques that can be utilized to detect and to classify DR using DL.

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