An ELEMENTARY MODEL FOR THE DETECTION OF DIABETIC RETINOPATHY USING DEEP LEARNING

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Abstract:

To prevent further vision loss and to aid ophthalmologists in mass screening, automated diabetic retinopathy (DR) detection, screening, and diagnosis is essential. The goal of DR screening is to catch the illness at an early stage, before it worsens, so that treatment can begin. To alleviate the exorbitant expense of human calculation, modern DR analysis systems use digital fundus pictures for diagnosis. In an effort to lessen the burden of subjective interpretation on ophthalmologists, researchers are persistently pursuing automated screening technologies. The steps involved in the proposed system are as follows: preprocessing, feature set formation, classification, and potential lesion extraction. The preprocessing step of digital retinal imaging involves removing pixels from the background and extracting the optic disc and blood vessels. With a processing time of 1 minute and 23 seconds, the CNN model suggested in this study achieves an accuracy of 87.5% and a cross entropy loss of 0.6370. The suggested strategy outperforms the leading approaches in fundus image categorization by a maximum of thirteen percent.

Keywords – computer-aided diagnosis; convolutional neural networks; deep learning; diabetic retinopathy; diabetic retinopathy classification; diabetic retinopathy lesions localization.

I. Introduction

There are varying degrees of vision loss caused by diabetic retinopathy (DR), a condition that develops over time. Ignoring this condition for an extended period of time might result in sudden blindness. In DR, there are two main stages: NPDR, which is marked by vitreous bleeding, and PDR, which is marked by neovascularization. Three sub-stages of NPDR may be identified: mild, moderate, and severe. Regular screening is necessary for people with mild NPDR, whereas patients with moderate to severe NPDR and those in the PDR stage need the right laser therapy. In the NPDR stage, abnormalities such as microaneurysms (MAs), hemorrhages (HMs), hard exudates (EXs), and cotton wool spots (CWs) are caused by damaged retinal blood vessels that leak blood and fluid onto the retinal surface. By recognizing the illness at an early stage, automated DR screening tools hope to begin treatment sooner rather than later.

As an alternative to time-consuming and expensive manual picture grading, digital imaging of the retina is used in DR screening programs. Automated screening methods that lessen ophthalmologists' subjective interpretation and screening burdens are a persistent goal of researchers. For DR severity rating, there are a lot of algorithms in the literature that rely on classical machine learning. A segmentation method was used to pinpoint twelve separate retinal layers that integrate shape, intensity, and spatial data. The normal and DR ratings, as well as the mild and moderate DR grades, were trained into a deep fusion classification network. For various DR lesions such as MAs, HMs, EXs, and CWs, the study suggested a three-stage DR detection and categorization approach. After using filter banks for lesion extraction, the next step is to classify the lesions based on the features retrieved from each potential lesion. Comparing the data with grading from ophthalmology professionals validates the process. DR categorization necessitates a more refined method of interpretation because to its significant diagnostic importance. Parameter tuning and class imbalance are two holes that still hinder their practical deployment, despite the considerable contributions of CNN based techniques in DR diagnosis. For the purpose of DR categorization utilizing fundus pictures, this research proposes four distinct CNN architectures that are based on deep learning. The suggested method gets around the issue of class imbalance by adjusting the

2. ARCHITECTURE

Architecture diagram explains the design of the project. It acts as a Blue Print for the project. It gives a brief idea of the project overview..

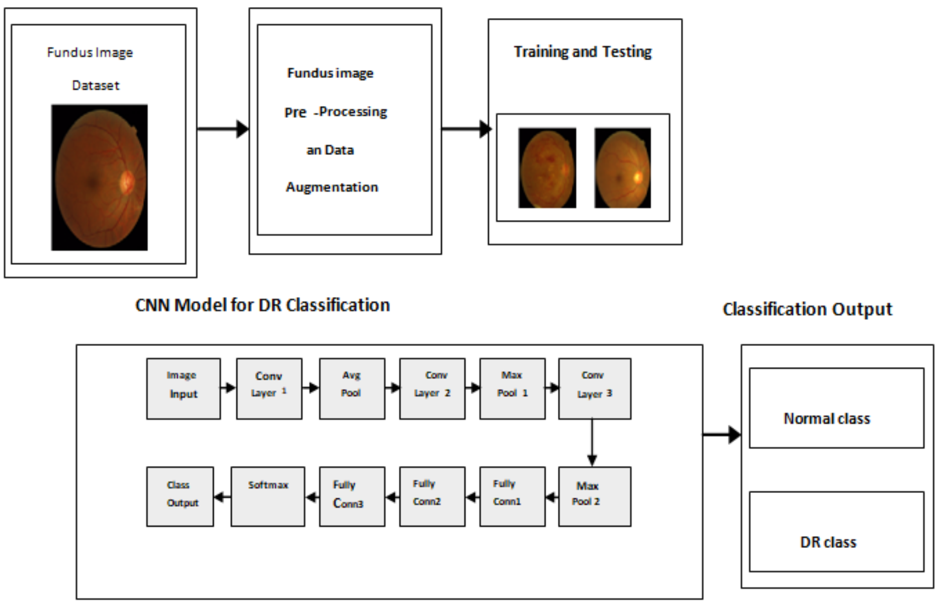


Fig1: Architecture of Diabetic Retinopathy Detection from Eye Fundus Images Using CNN

To develop a model, a Machine Learning algorithm is trained using a training data set. The ML algorithm makes a prediction based on the model when new input data is introduced. The accuracy of the forecast is assessed, and if it is
acceptable, the Machine Learning method is used. If the accuracy isn't good enough, the Machine Learning algorithm is retrained with a new batch of training data. Building a Predictive model that can be used to discover a solution to a Problem Statement is part of the Machine Learning process. Assume you've been given an issue to address using Machine Learning to better understand the process. The below steps are followed in a Machine Learning process:

Step1: Define the goal of the problem statement.

We must now establish precisely what needs to be projected. The purpose of this scenario is to evaluate the possibility of rain using weather parameters. It's also a good idea to make mental notes on what kind,of data you'll need to solve the problem and how you'll get there at this point.

Step2: Data Collection

- What type of data is required to tackle this problem?
- Is the data readily available?
- How do I obtain the information?

After you've figured out what kind of data you'll need, you'll need to figure out how to get it. Data can be collected manually or by web scraping. If you're a newbie trying to learn Machine Learning, though, you won't have to worry about acquiring data. There are plenty of data resources on the internet; simply download the data set and get started.

Returning to the issue at hand, the data required for weather forecasting comprises factors such as humidity, temperature, pressure, location, whether you reside in a hill station, and so on. Such information must be gathered and preserved in order to be analyzed.

Step3: Data Preparation
Almost never is the information you acquire in the appropriate format. Missing values, redundant variables, duplicate values, and other errors will be found across the data set. It's critical to eliminate such inconsistencies because they can lead to inaccurate calculations and predictions. As a result, you search the data set for discrepancies at this point and correct them immediately.

Step4: Exploratory Data Analysis
The initial stage of Machine Learning is Exploratory Data Analysis, or EDA. The purpose of data exploration is to discover patterns and trends in the data. At this point, all of the valuable insights have been gleaned, and the correlations between the variables have been identified. For example, we discovered that many characteristics had a strong correlation between some variables in the dataset utilized in this work, Kaggle dataset (train labels.csv), and that this linked data can be deleted for better data processing. Such connections must be understood and mapped at this point.

Step5: Building a Machine Learning Model
The Machine Learning Model is built using all of the insights and patterns discovered during Data Exploration. The data set is always separated into two parts, training data and testing data, at this stage. The model will be built and analyzed using the training data. The model's logic is based on the Machine Learning Algorithm that is currently in use. The type of problem you're trying to answer, the data set, and the problem's complexity all influence whatever algorithm you use. In the next sections, we'll go over the various types of problems that Machine Learning can address.

Step6: Model Evaluation& Optimization
Once the model has been developed using the training data set, it's time to put it to the test. The testing data set is used to determine the model's effectiveness and ability to accurately anticipate outcomes. After the accuracy has been calculated, any additional model enhancements can be made. You can use techniques like parameter tweaking and
cross-validation to improve the model's performance.

Step7: Predictions
Once the model is evaluated and improved, it is finally used to make predictions. The final output can be a Categorical variable (eg. True or False) or it can be a Continuous Quantity (eg. the predicted value of a stock).

II.LITERATURE SURVEY

"Detection and classification of retinal lesions for grading of diabetic retinopathy,"

Diabetic Retinopathy (DR) is an eye abnormality in which the human retina is affected due to an increasing amount of insulin in blood. The early detection and diagnosis of DR is vital to save the vision of diabetes patients. The early signs of DR which appear on the surface of the retina are micro aneurysms, hemorrhages, and exudates. In this paper, we propose a system consisting of a novel hybrid classifier for the detection of retinal lesions. The proposed system consists of preprocessing, extraction of candidate lesions, feature set formulation, and classification. In preprocessing, the system eliminates background pixels and extracts the blood vessels and optic disc from the digital retinal image. The candidate lesion detection phase extracts, using filter banks, all regions which may possibly have any type of lesion. A feature set based on different descriptors, such as shape, intensity, and statistics, is formulated for each possible candidate region: this further helps in classifying that region. This paper presents an extension of the m-Medoids based modeling approach, and combines it with a Gaussian Mixture Model in an ensemble to form a hybrid classifier to improve the accuracy of the classification. The proposed system is assessed using standard fundus image databases with the help of performance parameters, such as, sensitivity, specificity, accuracy, and the Receiver Operating Characteristics curves for statistical analysis.

"Automated micro aneurysm detection using local contrast normalization and local vessel detection,"
Screening programs using retinal photography for the detection of diabetic eye disease are being introduced in the U.K. and elsewhere. Automatic grading of the images is being considered by health boards so that the human grading task is reduced. Micro aneurysms (MAs) are the earliest sign of this disease and so are very important for classifying whether images show

signs of retinopathy. This paper describes automatic methods for MA detection and shows how image contrast normalization can improve the ability to distinguish between MAs and other dots that occur on the retina. Various methods for contrast normalization are compared. Best results were obtained with a method that uses the watershed transform to derive a region that contains no vessels or other lesions. Dots within vessels are handled successfully using a local vessel detection technique. Results are presented for detection of individual MAs and for detection of images containing MAs. Images containing MAs are detected with sensitivity 85.4% and specificity 83.1%.

III.SYSTEM ANALYSIS

1.1. EXISTING SYSTEM

Automated Diabetic Retinopathy (DR) detection, screening and diagnosis are critical to save vision loss of patients and assist the ophthalmologists in mass screening. DR screening aims at early treatment of the disease by detecting it before the stage progresses. Present DR analysis systems use digital fundus images for diagnosis reducing the high cost of manual computation. Researchers are continuously persisting for automated screening systems which can reduce the subjective interpretation and screening burdens for ophthalmologists.

Disadvantages of Existing System:

1.Less Prediction

1.2. PROPOSED SYSTEM

This paper proposes different Convolutional Neural Network (CNN) architectures with parameter tuning for DR classification. The proposed approach overcomes the class imbalance problem by fine tuning the network parameters. Different filter size variations are considered in the design and their altering response are analyzed at the classification output layer on a benchmark retinal image dataset. CNN model proposed in this paper provides an accuracy of 87.5% with cross entropy loss of 0.6370 with processing time of 1 minute and 23 seconds. Maximum accuracy improvement of 13% is achieved by the proposed approach over state-of-the-art methods demonstrating its preeminence in fundus image classification.

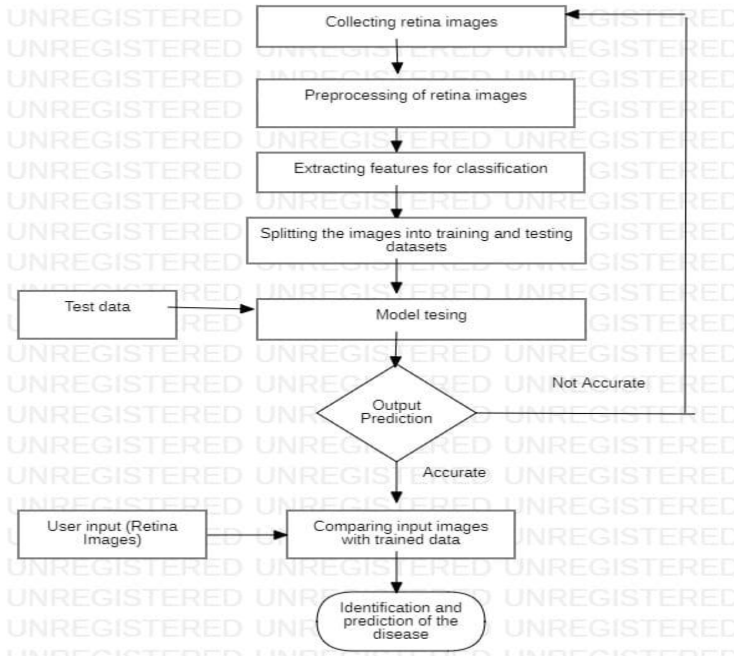
Advantages of Proposed System:

1. More Prediction.

Below diagram depicts the whole system architecture of the most trending articles every year using NLP technique.

IV.SYSTEM DESIGN

4.1 SYSTEM ARCHITECTURE



V..SYSTEM IMPLEMENTATION

5.1.MODULES

- Upload Fundus dataset
- Load GAN Model
- Load Diabetic Retinopathy Prediction Model
- Generate GAN Image & Predict Severity

Module description:

Upload Fundus dataset:

Upload Fundus Dataset module is used to upload dataset which contains FUNDUS images of 5 categories.

Load GAN Model:

Load GAN Model Module is used to load GAN model and generate some synthesis images. we can see GAN images and in the above screen text area we can see GAN generated 200 images with size 32 X 32 and 3 means the images are in color format not gray.

Load Diabetic Retinopathy Prediction Model:

Load Diabetic Retinopathy Prediction Model module is used to generate and load prediction model to predict severity in GAN images we got a message as to see black console to view model summary. CNN creates multi layers and each layer has different image shape features.

Generate GAN Image & Predict Severity:

Generate GAN Image & Predict Severity module to generate some images and predict severity of those images. Here GAN generates 200 images but it’s difficult to display all 200 images so I am displaying 10 random images from 200 GAN images. CNN predicted severity from images generated by the GAN model. From 200 images I am displaying only 10 images. And we can see moderate class predictions also

. VI.CONCLUSION AND FUTURE WORK

“A Generic model for predicting the Diabetic retinopathy using Deep Learning” presents four different CNN based architectures for DR classification so as to reduce the clinician’s burden of manual retinopathy screening. The trained model provides instant diagnosis of the diseased or non-diseased fundus using a single image per eye. Class imbalance situation by fine tuning the network parameters is addressed in this paper. The proposed approach provides maximum 13% improvement over state-of-the-art techniques. In the further part of this research, the CNN network will be trained to distinguish between the mild, moderate and severe cases of DR. Moreover, the experimentation will be done on a larger dataset for more subtle feature learning from fundus images. Thus, this work reveals that CNN can be trained to identify DR features for better classification of abnormalities..

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