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Automated Diabetic Retinopathy Detection

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Abstract - *Diabetic Retinopathy is a disease that can lead to partial or complete blindness, if not diagnosed early but in most of the cases it is diagnosed at the later stage. Research shows that it contributes around 5 percent of the total cases of blindness. Usually it takes about two weeks for the diagnosis of the disease, time and money both are wasted. The proposed system aims to eradicate the above problem. Convolutional neural network (CNNs) are widely used in pattern- and image-recognition problems as they have a number of advantages compared to other techniques. Though it require huge computation power to train a CNN but while testing the results are generated rapidly . A model is presented for classification of DR stages based on the severity using color fundus images. Aim of the project is to provide an automated, suitable and sophisticated approach using Convolutional Neural Network(CNN) so that DR can be detected at early levels easily and damage to retina can be minimized. The model classifies the images into five categories depending upon the severity of the disease of the patient.*

Key Words: **Deep Learning, DL, CNN, Convolution, image processing, diabetic retinopathy, Keras, python**

1. INTRODUCTION

Diabetes mellitus is one of the challenges in the world for the 21st century and it's a chronic and complex disease that affects a large number of people. Diabetes mellitus can affect the body's main organs and leads to heart disease, stroke, amputation, kidney failure, blindness and early death. Diabetic retinopathy is one of diabetes complication that affects the eye and occurs as a result of damage to the blood vessels of light-sensitive tissues in the back of retina. The hyperglycemia continuous causes to a blockage in the tiny blood vessels that nourish the retina. Thus, the eye tries to create new blood vessels, but these vessels do not grow properly and can bleeding easily. Diabetic retinopathy in its early stages does not cause any changes in vision, but with the development of the disease, the level of vision worsens significantly may lead to blindness. Diabetic Retinopathy is one of the main causes of poor vision and blindness. It has been shown that periodic screening of DR and timely treatment reduces the risk of blindness. Automated detection of diabetic retinopathy is essential to address these challenges as well as to detect the disease at early stage to prevent blindness with appropriate treatment using advances in technical medical developments.

1.1 Deep Learning

Deep learning is an emerging area of machine learning (ML) research. It comprises multiple hidden layers of artificial neural networks. The deep learning methodology applies nonlinear transformations and model abstractions of high level in large databases. The recent advancements in deep learning architectures within numerous fields have already provided significant contributions in artificial intelligence. The Deep Learning (DL) concept appeared for the first time in 2006 as a new field of research within machine learning. It was first known as hierarchical learning and it usually involved many research fields related to pattern recognition. Deep learning mainly considers two key factors: nonlinear processing in multiple layers or stages and supervised or unsupervised learning. Nonlinear processing in multiple layers refers to an algorithm where the current layer takes the output of the previous layer as an input. Hierarchy is established among layers to organize the importance of the data to be considered as useful or not. On the other hand, supervised and unsupervised learning is related with the class target label, its availability means a supervised system, whereas its absence means an unsupervised system. Deep learning implies an abstract layer analysis and hierarchical methods. However, it can be utilized in numerous real life applications. As an example, within digital image processing; gray scale image coloring from a picture used to be done manually by users who had to choose each color based on their own judgment. Applying a deep learning algorithm, coloring can be performed automatically by a computer. Today, several deep learning based computer vision applications are performing even better than human i.e. identifying indicators for cancer in blood and tumors in MRI scans. It is improvement of artificial neural network that consist of more hidden layer that permits higher level of abstraction and improved image analysis. It becomes extensively applied method due to its recent unparalleled result for several applications i.e. object detection, speech recognition, face recognition and medical imaging.

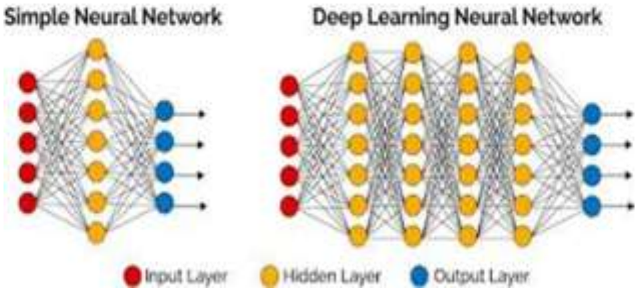

Fig -1: Deep Learning Neural Network

1.2 Convolutional Neural Network

CNN algorithm can take in an input image and assign importance to different objects in the image to be able to distinguish one from the others. ConvNet is specializing in processing data that uses multiple layers such as convolutional layers, pooling layers and fully connected layer. The core building block of the CNN is convolution layers which filter inputs to extract useful data for certain tasks. Whereas, pooling layers are used to maintain the process of efficiently training of the model by replacing the output of the network at definite locations for extracting dominant features for limited rotation and positional invariance. Furthermore, pooling layers decreases the memory consumption and the spatial size of the convolved feature and therefore permit more convolutional layers for usage.

Image classification can be done by supervised and unsupervised. In supervised learning, a training model will be made by analysing the features of training data. Based on this training model, the new data will be classified. CNN is an algorithm for classification in supervised learning method. CNN is a type of feed-forward ANN which inspired by the neurons and brain. It is a variation of multilayer perceptron which needs only less pre-processing techniques and it is easier to train.

1.2.1 Convolutional Layer

The core building block of CNN is convolutional layer. The layer contains a set of learn able filters and these filters have small receptive fields. In each forward pass, it will produce a two-dimensional map of corresponding filter by computing the dot product between input and entries of filter. By this, the network will learn about the filters which are activated when specific feature at specific spatial position occurs. The depth dimension with activation maps of each filter will form the full output volume of convolutional layer

1.2.2 Pooling layers

Pooling is a non-linear down sampling. To implement the pooling layer, the most common non-linear function. The max pooling layer partitions the input image into congregation of non-overlapping rectangles and the layer will output the maximum for each sub region. If a feature is identified, then this helps in finding the rough location relative to other features. The intermediate representation's dimensionality will be reduced by max pooling. Pooling layers are inserted in between convolutional layers.

1.2.3 Fully Connected Layer

The fully connected layers do the high-level reasoning of a neural network. This layer connects all the neurons of the previous layers (convolutional or pooling or connected). The activations can be computed by a matrix multiplication, and then a bias offset will be added. Image classification using CNN is used for the task of classification of DR images in this work. Fundus retina images are used as the dataset. As we are using supervised learning, we need both training and test dataset. In training phase, we need to do some preprocessing steps.

1.2.4 Training Phase

In training phase, the input of the CNN algorithm will be the preprocessed training data. As the input goes iteratively through each layer (convolutional, pooling, and fully connected), it will identify the features in the images. The layers in the algorithm will find the best features which are needed for classification using feature maps. There must be at least six layers in the algorithm to get a model. When the number of layers are increasing, the training model will be more and more efficient. About nine convolutional layers, eight max pooling layers and two fully connected layers are the combination of layers we would like to use in the present work. This combination will make the algorithm to work more accurately and efficiently. We can easily classify the image with the number of layers.

1.2.5 Testing Phase

During testing, the model will find the features of images and classifies according to it. In DR detection, the training model has 5 classes. The first one is severity 0 which state that patient does not have the disease. The other classes are mild NPDR, moderate NPDR, severe NPDR, and NPDR. NPDR is the most severe condition of the disease where the patient loses his/her vision. The algorithm will first classify whether the patient is suffering from disease or not. If the patient is suffering from the disease, then it will check the severity level of his disease. The output for this will be the patient's severity level.

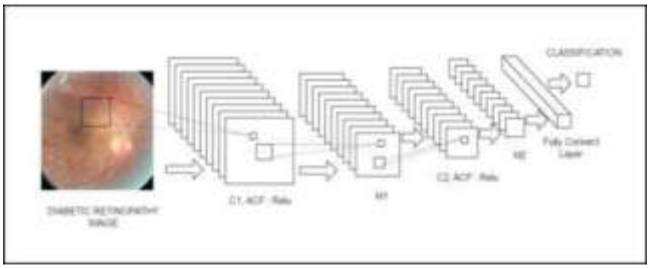

Fig -2: CNN Architecture

1.3 Objective

Regardless of the type of diabetes, all individuals diagnosed with DM need regular and repetitive annual retinal screening for timely detection and apt treatment of diabetic retinopathy (DR). Conventionally, retinopathy screening is done by fundus examination by ophthalmologists or with the help of color fundus photography using conventional fundus cameras (mydriatic or non-mydriatic) by trained eye technicians or optometrists. The primary issue is the grading of the retinal images by ophthalmologists (retinal specialists) or trained persons, whose numbers are very scarce compared to the load of patients requiring screening. Second, some of these patients are based in rural areas and can't visit an eye care provider. Thirdly, as such follow ups are required for years together, the attitude, and/or behavioral aspects negatively impact the patients practice despite knowledge of consequences. These issues can be solved with provision of an automated imaging system within easy reach of the patient. Hence, there has been an increasing interest in the development of automated analysis software using computer machine learning/artificial intelligence (AI) for analysis of retinal images in people with diabetes thus solving at least some part of the problem.

1.4 Scope

Till now we have not tested the computer test data, therefore our first target would be to achieve the same. Our main focus would be to design such a detection system which is highly accurate and precise. Our network architecture with dropout techniques yielded significant classification accuracy. This architecture has some setbacks such as an additional stage classification are needed for the images taken from a different camera with a different field of view. Also our network architecture is complex and computation intensive requiring high level graphics processing unit to process the high resolution images where the level of layers stacked more. We can also implement our whole model as an application on mobile phones , so as to make diabetic retinopathy detection easier and time saving.

2. EXISTING SYSTEM

It provides a provision for only manual consultation. Patient has to travel longer distance to consult the doctor. It poses greater risks as the traveling may even make the situation of the patient even more adverse. Patient has to wait for hours for the dilation of eyes so as to widen the pupil. After dilation the doctor has to check for abnormal blood vessels, swelling, retinal detachment, test your vision & cataracts.

3. PROPOSED SYSTEM

A model is proposed which uses CNN for the automated detection of DR. DR can be classified into several stages

such as normal, mild NPDR- small areas of balloon like swellings in the retinal blood vessels, moderate NPDR- swelling & distortion of blood vessels, severe NPDR- blood vessels are blocked & causes abnormal growth factor secretion, PDR- growth factors induce proliferation of new blood vessels in the inner retina. Colored fundus images is the input to the CNN model. CNN removes aberrant noise to recognize features like micro-aneurysms & exudates from the fundus images. The model achieves an accuracy of around 95% for a 2 class classification that is the model detects the presence of DR or not & an accuracy of 85% for a 5 class classification that is if DR is present then it's severity is also determined. DR stage classification has been regarded as a critical step in the evaluation & management of DR. Lack of effective treatment can lead to vision impairment or even irreversible blindness. This disease can be diagnosed by examining the fundus images. Deep CNN reduces the complexity of the neural network & so it is widely used in deep learning. Training set of images in the training database is passed to the model for training the CNN model. Here the CNN model used is 2-D CNN sequential model also called keras CNN. The convolution layer of CNN will extract features from the source image. The extracted features are down-sampled to reduce the dimensionality of the extracted features so as to get more important features by the pooling layer. These features are flattened by the flatten layer into a vector that forms the input to the fully connected layer. Fully connected layer joins all other layers in the model & activation of features is done. This is very essential for the efficiency of stage wise classification.

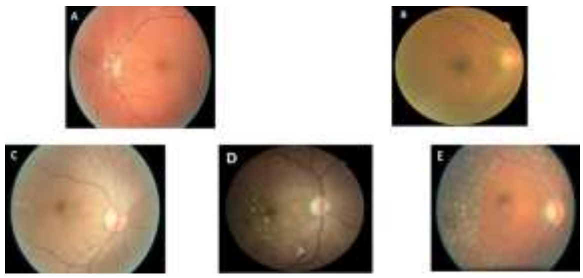

Fig -3: Stages of DR

4. CNN ALGORITHM

First reshapes the input images into a for suitable for the CNN model. The model is built using sequential.add() .A pooling layer followed by a flatten layer is added to the CNN model which acts as a vector fully connected layer. Add one or more fully connected layers for increased efficiency. The layers are all compiled and finally trained. The trained CNN model is fed with testing set of images & stage wise DR detection is performed.

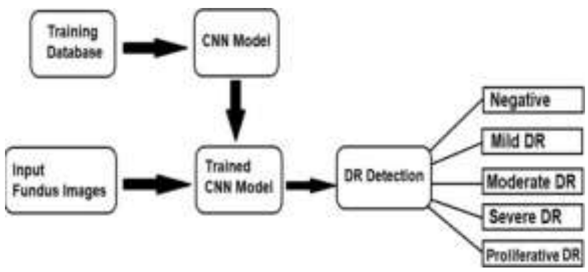

Fig -4: CNN Training & Testing

5. CONCLUSION

This Automated Diabetic Retinopathy Detector is a desktop application that provides essential and easy way to detect the image of person affected with diabetic retinopathy. The image dataset which are collected from various sites and places and their features are extracted and train them with various classification algorithm and add different labels. The deep learning techniques which is also used for classifying the various images to detect which type or which stage of diabetic retinopathy .The application focus mainly to detect diabetic or not and collect the records and details. This will help Doctors to done their work very easily and also they can save more time.

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