Diabetic Retinopathy Detection: Classifying Proliferative and Non-Proliferative Forms Using CNN and VGG-16

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Abstract_ The paper proposes a convolutional neural network (CNN) approach to diagnosing diabetic retinopathy (DR) from digital fundus images. The authors describe how traditional methods of diagnosing DR require experienced clinicians to identify small features and use a complex grading system, making it difficult and time-consuming. The proposed CNN approach can identify intricate features such as micro-aneurysms, exudate, and hemorrhages on the retina, providing an automatic diagnosis without user input.

We developed a network with a CNN architecture and data augmentation to train the model. They trained the network using a high-end graphics processing unit (GPU) on the publicly available Kaggle dataset, which consisted of 80,000 images. The results demonstrated impressive accuracy, with a sensitivity of 95%.

Overall, this paper shows the potential for using deep learning approaches to improve the accuracy and efficiency of diagnosing DR from digital fundus images. The proposed CNN approach can provide an automated diagnosis without the need for experienced clinicians, potentially improving patient outcomes and reducing healthcare costs.

Keywords: Diabetic retinopathy (DR), Colour fundus images, Convolutional neural network (CNN), graphics processor unit (GPU), Kaggle dataset.

1.INTRODUCTION

The use of convolutional neural networks (CNNs) for diagnosing diabetic retinopathy (DR) from fundus images has demonstrated superior performance in detection and classification tasks. DR is a major complication of diabetes that can lead to vision loss and blindness. The damage to retina blood vessels caused by increased blood sugar levels can result in various abnormal effects on the retina, including micro aneurysms, exudates, hemorrhages, neovascularization, and macular edema. DR is classified into five stages, ranging from mild non-proliferative DR to proliferative DR and macular edema.

Currently, DR diagnosis is primarily done through dilated eye examination, which is subjective and requires specialized training by a retina specialist. Other methods of diagnosis include fluorescein angiography and optical coherence tomography. However, many diabetic patients may not have adequate access to trained eye-care professionals or tertiary eye-care services, resulting in delayed diagnosis and irreversible pathology.

Therefore, there is a need for an objective and non-invasive diagnostic system that can accurately detect and grade DR at an early stage. CNNs have shown promise in fulfilling this need, as they can identify intricate features on the retina and provide an automated diagnosis without user input. Such a system could potentially improve patient outcomes by enabling earlier detection and reducing healthcare costs by reducing the need for specialized training and expertise

2.LITERATURE SURVEY

The earliest digital retina fundus images were classified by hand by combining empirically obtained parameters with extracted features. Cree et al. presented one of these works. The authors have demonstrated that computer vision methods can accurately detect micro aneurysms. Each candidate's pixel area and total pixel intensity were measured using eight simple morphological and thresholding features in their experiments. It is demonstrated that automated micro aneurysm detection can be used for diagnostic purposes because the proposed method produced results that were comparable to those obtained by medical professionals.

In more recent studies, methods were developed to identify the stage of diabetic retinopathy in addition to micro aneurysms in fundus images. Yun and co. proposed a method for classifying retina fundus images as proliferative, normal, moderate, or severe DR. Using disc and diamond structuring elements, morphological operations were used to preprocess the input images. Six features were then obtained by taking into account the RGB channel perimeter and area of the pixels. A single-layer feed-forward neural network with eight units in the hidden layer was used for classification. Six units were used as input for each of the aforementioned feature values, and four units were used as output, one for each severity of DR. Nayak et al. outlined a strategy for using adaptive histogram equalization in image preprocessing to extract features about blood vessels through morphological operations and texture analysis. A multi-facet perceptron handled the extricated highlights. The blood vessel area and perimeter, the exudate area, and texture were the four inputs that made up the architecture. Before the two units that were used to classify the inputs for the proliferative DR, the nonproliferative DR, and the normal retina—labeled "01"—were processed by two hidden layers with eight units each. Rosas and co. preprocessed the image using computer vision techniques to propose the recognition of a micro aneurysm. The no uniform brightening, first and foremost, was decreased, and the grayscale forces were standardized to get two elements. The primary elements utilized head part examination to segregate the round-molded up-and-comers' area, and the subsequent one utilized radon highlights to count the number arrangement of discrete point values. After that, those features were sent to a pair of perceptron classifiers in a hierarchical system to learn the threshold needed to tell if the area had a micro aneurysm or not.

Hand-created extricated highlights require particular information and observational outcomes to accomplish exact miniature aneurysm discovery in computerized pictures. In such manner, late picture handling propels were robotized the component obtaining stage from crude pictures to helpful data utilizing convolutional brain organizations. Numerous grouping undertakings utilize profound learning techniques with a huge pile of convolutional layers to obtain highlights from the organization's feedback. Gargeya et al. presented a first strategy. where the DR screening is automated by the authors. Using a 5-fold cross-validation strategy, the validation results produced an AUC of 0.95 in the Messidor dataset. Dutta et al. also proposed additional work. used extracted statistical features like average, median, standard deviation, maximum, and minimum to demonstrate that a multilayer perceptron outperformed a convolutional neural network by 83.6 percent. Mansour proposed a computer-aided DR diagnosis system that would remove the background from the image and then process it with the AlexNet model to get features. A 10-fold cross-validation method is used by a super vector machine (SVM) algorithm to process these features. The findings demonstrated that using feature reduction prior to SVM processing yields improved results with a validation accuracy of 97.93 percent. Qummar and co. proposed a five-deep learning model ensemble approach that was successful with unbalanced data and achieved 70% validation accuracy. One late methodology was introduced by Gadekallu et al. who presented a deep learning model with an accuracy of 96% that was optimized through intelligent computing and PCA. One more work by Majumder et al. proposed a lightweight and effective real-time algorithm for smartphones with an accuracy of 87.4 percent.

The difficulty of distinguishing between the four DR stages was encountered with the previous methods. When some works compare their proposals as binary classifications of a healthy and unhealthy eye, this difficulty becomes apparent.

3.PROPOSED SYSTEM

Deep learning method analysis was performed in this study with the goal of achieving high accuracy in identifying diabetic retinopathy disease using retinal fundus images. The accuracy of identifying diabetic retinopathy disease will be improved in this study by using image processing techniques that aim to perform vascular extraction first before entering the deep learning method process.

3.1 ALGORTHM USED

Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a type of Deep Learning algorithm that are widely used in image analysis tasks, such as image recognition, object detection, and segmentation. CNNs are particularly effective in analyzing two-dimensional images because they can develop an internal representation of the image that includes information about position and scale.

The layers of a CNN typically include an input layer, an output layer, and multiple hidden layers. The hidden layers of a CNN include convolutional layers, which apply filters to the input image to extract features, pooling layers, which downsample the output of the convolutional layers, and fully connected layers, which use the extracted features to classify the input image. Normalization layers may also be included to improve the stability and performance of the model.

The advantage of using CNNs is their ability to automatically learn features from the input data, rather than relying on manual feature extraction. This makes CNNs particularly effective in tasks where the features of interest may not be known in advance or are difficult to describe. Additionally, CNNs can handle large amounts of data and are computationally efficient, making them well-suited for use in real-time applications

VGG16:

VGG-16 is a convolutional neural network that is 16 layers deep. You can load a pre-trained version of the network trained on more than a million images from the ImageNet database [1]. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. VGG16 is a convolutional neural network(CNN) model. “ VGG1-16 is one of the most successful vision model architecture. This model accomplishes 92.7% top-5 test precision on ImageNet dataset (Dataset having 15 million images of various different categories) which contains 14 million pictures having a place with 1000 classes.

4.RESULTS AND DISCUSSION

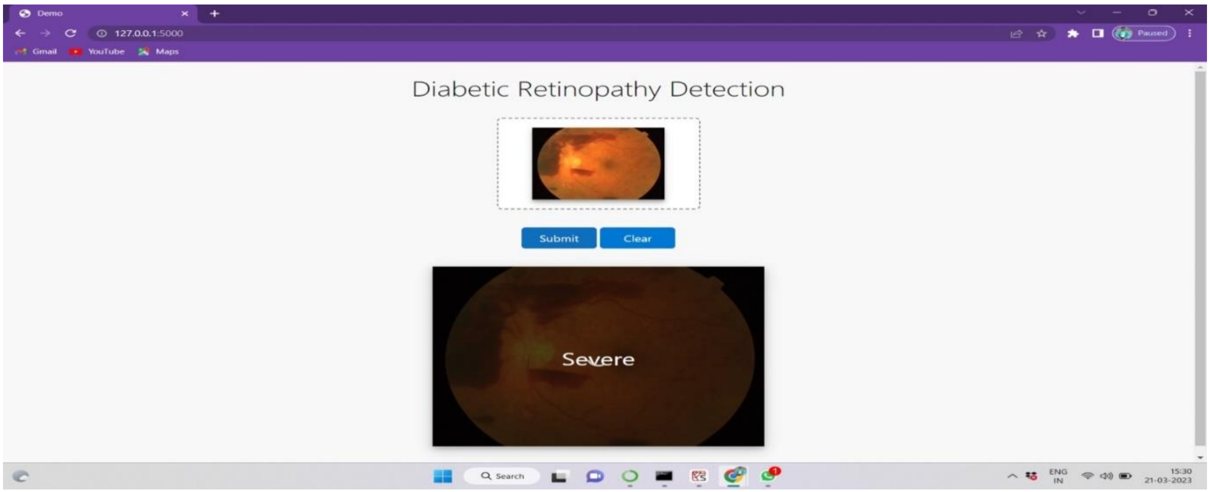
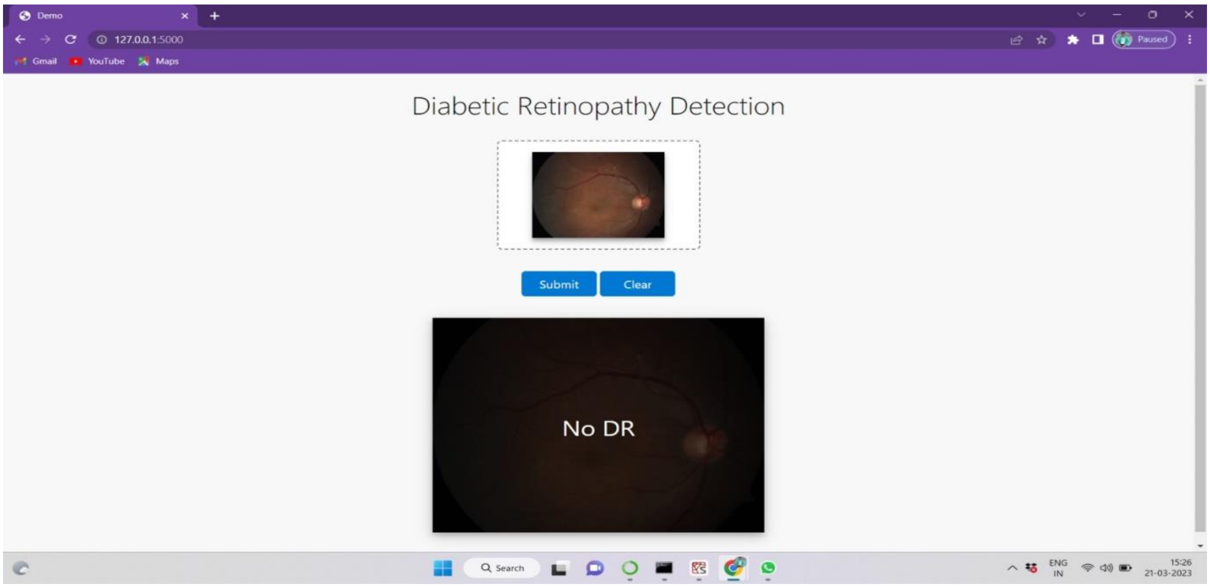


Fig 1: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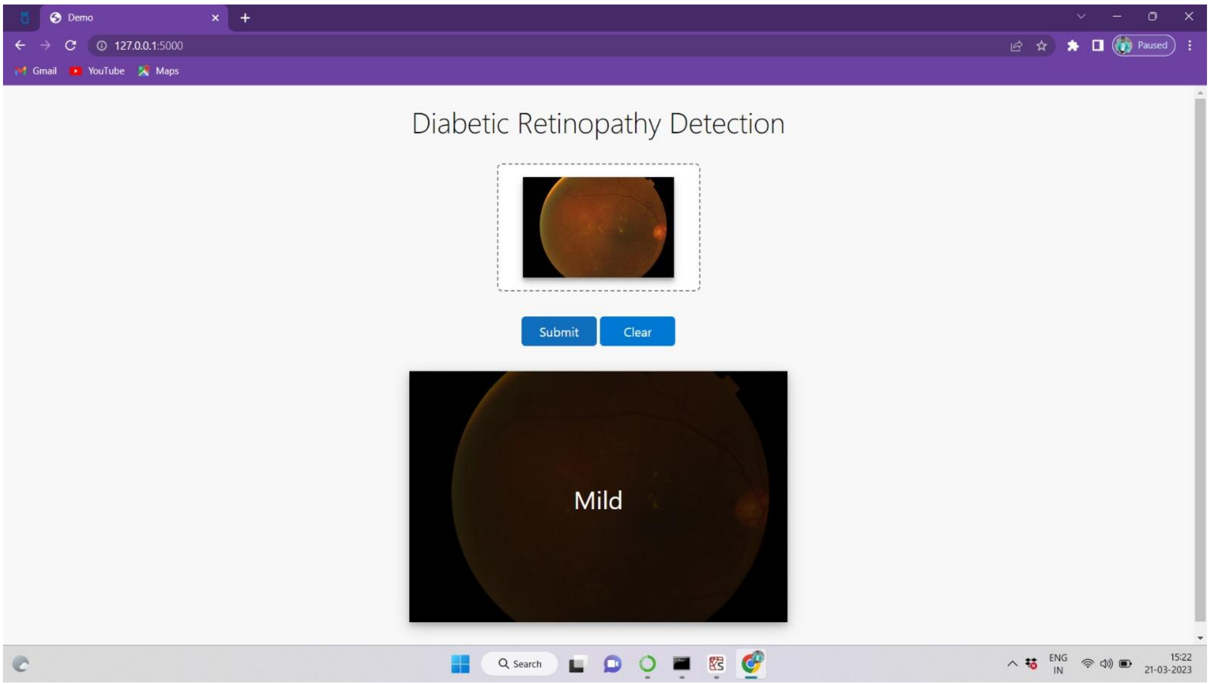
21-03-2023

Fig 2: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Search
ENG
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15:22
21-03-2023

Fig 3:

5.CONCLUSION

A diabetic patient has a 30% chance of developing Diabetic Retinopathy, according to multiple studies. (DR). If the disease is not detected early, it can cause floaters, blurred vision, and, eventually, blindness. Manual diagnosis of these images is time-consuming and complex, necessitating the services of highly qualified specialists. We have successfully developed a Convolutional Neural Networks model that detects Diabetes using a pre-trained VGG-16 framework. This model may aid doctors in making faster diagnoses of this disease..

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