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RETINAL IMAGE ANALYSIS FOR DIABETES BASED EYE DISEASE DETECTION USING DEEP LEARNING TECHNIQUE

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ABSTRACT:

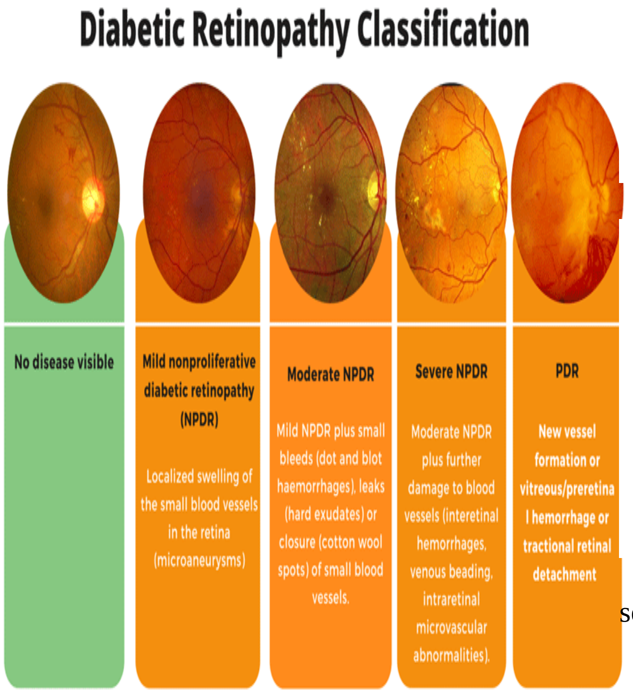
Diagnosing diabetic retinopathy (DR) in the beginning stages of treatment is essential because it is a frequent consequence of diabetes mellitus (DM). Deep learning techniques have had considerable success in the area of medical image processing thanks to the quick development of convolutional neural networks in the field of image processing. To find fundus lesions, a number of medical lesion detection techniques have been proposed. Currently, the diabetic retinopathy image classification process ignores the fine-grained characteristics of the diseased image, and the majority of the retinopathy image data sets have serious uneven distribution issues, which severely restricts the network's ability to predict the classification of lesions. A new non-homologous bilinear pooling convolutional neural network model is what we suggest, and To help the network extract specific features from the image, integrate it with the attention mechanism. The experimental results demonstrate that the network model we presented can significantly increase the prediction accuracy of the network while preserving computational efficiency, as compared to the most widely used fundus picture categorization algorithms.

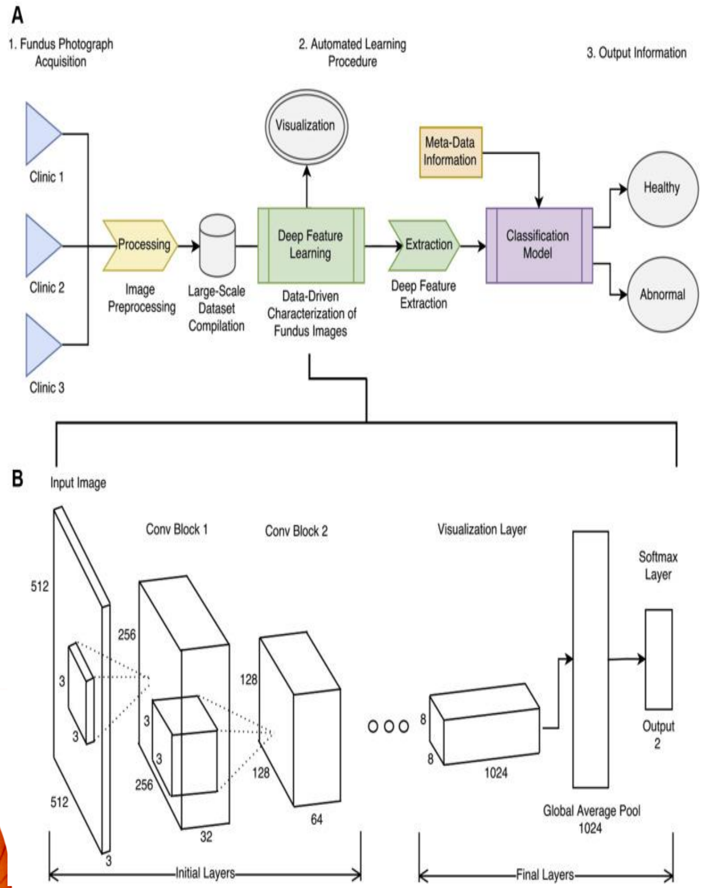
INTRODUCTION:

Among diabetic patients, diabetic retinal fundus disease is a prevalent ophthalmological condition. According to the severity of the fundus lesions, images can be categorised into five categories: normal, mild, moderate, severe, and hyperplasia [1]. The five stages of diabetic fundus lesions are depicted in Figure 1. A new development in non-invasive medical imaging is optical coherence tomography (OCT). OCT produces high-resolution images that can be classified by medical professionals based on the features of the lesion they can see. Fundus photographs of individuals with diabetic retinopathy must be taken using specialised equipment, and the clinical diagnosis must then be made by the physician. The time it takes to wait for findings is typically several days, which makes it harder for patients and doctors to communicate and even makes the condition worse. It is frequently inaccurate and challenging to manually classify lesions due to the variety of lesions and the difficulties in measuring the classification conditions. The majority of DR classification duties are still now carried out by doctors, which unquestionably results in significant personnel and material resource waste.

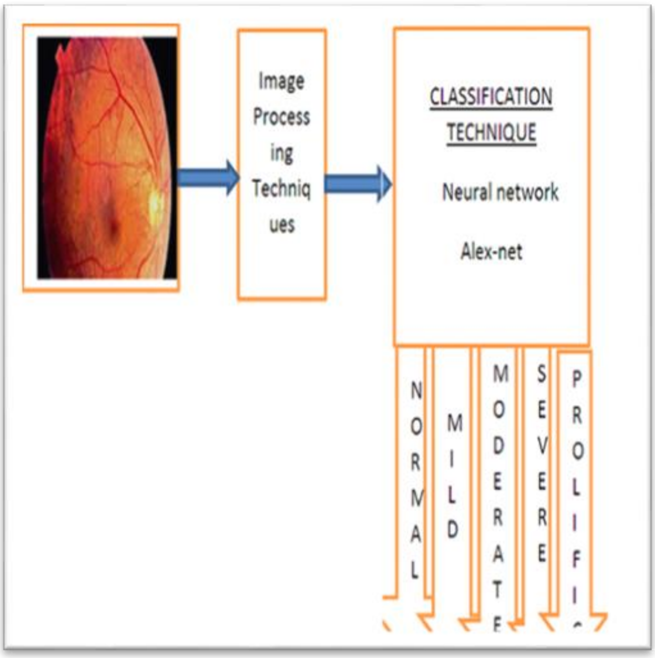
The creation of a computer-aided diagnosis system that uses a common measurement standard to assess the severity of lesions is required to address the aforementioned issues. As computer technology and artificial intelligence have advanced in recent years, it has been increasingly interwoven with other fields of study. Numerous interdisciplinary fields have benefited from the growth of computer technology. One of these multidisciplinary topics between medicine and computer science is medical image processing [2]. The topic of diabetic retinopathy retinal image classification has seen extensive adoption of numerous deep learning-based medical image classification techniques. Additionally, Kaggle started a number of competitions on the automatic diagnosis of diabetic retinopathy. The classification of diabetic retinal fundus images is distinct from the classification of other images. The diabetic fundus disease data set's visual features are remarkably comparable, with the exception of a few abnormalities like bleeding sites or aneurysms. The same diabetic retinal fundus lesions may result in several degrees of lesions, which causes the images of various grades of lesions to look similar. Therefore, it is possible to think of the picture classification of diabetic retinal fundus lesions as a fine-grained classification issue. The difference between categories is the main focus of conventional picture classification. On data sets with significant variances between categories (like cats and dogs, snakes and frogs), it can produce good results. The network model is necessary to successfully extract the distinctiveness of the data set since fine-grained picture classification further splits images belonging to the same category.

In order to get more distinct picture features for the classification of diabetic retinal fundus illness and the fine-grained classification, we integrated an attention mechanism with a compact bilinear pooling network model. A frequently employed network model in the area of fine-grained categorization is the compact bilinear pooling model. To extract image features, it employs two feature extractors. The bilinear network model is able to extract additional image features thanks to the bilinear pooling operation that combines the image features obtained by the two feature extractors. In order for the network to pay more attention to helpful information and weaken irrelevant information, the attention mechanism is primarily utilised to identify the critical areas in the data set image. The classification precision of the network model can be increased yet further by incorporating the attention mechanism with the bilinear pooling network model. Experiments demonstrate that the issue of traditional networks' inability to accurately categorise images of diabetic retinopathy can be resolved by the combination of bilinear pooling operation and attention mechanism.





“ Original fundus image(left),image with vessel segmented(center),vessel free fundus image(right)”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RELATED WORKS:

The classification of diabetic retinal fundus disease aims to categorise individuals based on the severity of the illness from an image of the patient's fundus. In order to undertake the next stage of treatment for the patient in accordance with the patient's lesion type and severity, this research can assist doctors swiftly confirm the patient's lesion grade and the location of the lesion area. Methods based on machine learning and methods based on deep learning can be used to categorise the existing research on the classification of diabetic retinal fundus lesions. Researchers with medical backgrounds are required to manually extract the image features from the diabetic retinal fundus disease data set using the machine learning method. The image merely has to be classified using the extracted features by the classification model. Nguyen et al. [5] suggested using a multi-layer feedforward network in 1996 to categorise the severity of diabetic retinopathy. To categorise lesion characteristics, Zhang et al. [6] employed the fuzzy C-means clustering technique and support vector machines. In order to understand the features of bleeding spots and to identify the disease according to those characteristics, they subsequently suggested another method that combined dimensionality reduction with support vector machines [7,8]. Barriga et al.'s [9] analysis of the retinal region in the image's centre made use of least squares and support vector machines for classification as well as amplitude modulation-frequency modulation for feature extraction.

The attention mechanism is frequently utilised in the field of fine-grained image categorization because it can identify regions of interest using self-learning techniques without the need for extra manual labelling information. By creating a network model, the technique based on fine-grained feature learning extracts better features. This technique combines various features collected by the two networks to jointly complete the goal of image classification. It does this by using a bilinear neural network structure to extract more precise specialised information from the image.

We propose a new non-homologous bilinear pooling network model that builds on the aforementioned approaches by employing two convolutional neural networks with distinct structural properties to improve the model's ability to extract features from images and to add an attention mechanism module that weakens the image's pointless features. In order to alleviate the impact of the imbalanced distribution of the data set on the predictive capacity of the network model, we additionally incorporated a supplement cross entropy loss function to the network model. Complement cross entropy can be used to train a reliable classification model with an uneven category distribution using inaccurate category information. The findings of the experiments indicate that, in the same experimental setting, our method has an accuracy rate that is between one and three percentage points higher than that of other methods.

EXPERIMENT AND METHODS:

In the past few years, a lot of researchers working in the field of image processing have used machine learning to aid in the classification of images. The main goal of our suggested technique was to categorise the disease severity in the fundus images. The classification of DR in the suggested model in order to use deep learning to get the most accurate data possible from the image collection.

A. Dataset : In our study, fundus photos with various viewpoints, differences, blur, variations, and image sizes were captured using various cameras and taken from the Kaggle database. In this investigation, a total of 35,015 retinal pictures in various sizes and formats were used. There are a total of 48 and 90 fundus photos utilised for testing and training.

B. Preprocessing : The methodology for preparing fundus photos in the suggested method is shown in the above image. Data cleaning, instance selection, normalisation, transformation, feature extraction, and selection are all completed in this step[8]–[9]. The green portion of the original fundus image is subtracted from the retinal image after scaling it down to a resolution of 120 * 120. Equation (1) uses red (R), green (G), and blue (B) components of photos to calculate the colour retinal fundus, which is then converted to a grey image using luminance conversion.

Gray image = 0.298 * R + 0.588 * G + 0.115 * B

the result obtained after training of dataset is done in training applied input images are classified into two dataset that is diabetic retinopathy image and normal retinal image which is shown by “YES” and “NO” label respectively. Validation is sum up of testing and learning. And efficiency of training a system is directly proportional to the validation. YES: Diabetic Retinopathy Image NO: Normal Retinal Image. Following equations

C. Extract Feature Layer [Inception V3 DNN Architecture] Model Feature extraction is a technique that combines variables to get around the problem while still describing the data with accuracy. The whole network works in 4 layers. The first layer is the input layer from which the input is given followed by the convoluted and average pooling layers and then the soft max layer is connected to the output layer. The output layers are for extracting certain features. After removing certain features, a 2-layer hidden neural-network is used for classification [10] The Inception-V3 model is classified into two parts for image recognition. The first part features feature extraction with a convoluted neural network. Fully connected and assorted parts with Softmax layers. Each pixel value of the image was reduced by the weight of the adjacent pixel values and added to 55% grayscale. This operation is similar with the procedure of various photo editor software, which creates images of the wound space in the blood vessels as well as the fundus clearer. Then, to eliminate the effect of the boundary caused by the last operation, the fundus area in the reflection will be cut to 90% of the original size by wrapping the mask with a transparent circle in the center.

D. Inception v3 model In this section, funds are embedded in Siamese-like blocks of the network after the removal of the final layer of Inception V3 to extract high-dimensional features of images. In Inception-v3, the transfer learning method is used. The parameters of the previous layer were kept, then the last layer was removed and the new last layer was re -trained to input the dataset, changing the number of output nodes used only 45 different images. The output layer has been trained using the back propagation algorithm and cross entropy function has been used to adjust the weight parameters of network to evaluate the errors in output and label vector of the sample range. The resolution of input image in the Inception-V3 was fixed at 299 × 299; however, the image resolution of standard dataset was 224 × 224. The image size was not changed to 299 × 299 during the training and testing of the Inception-V3 model [16]. In this process the number of channels was fixed but the size of the generated feature map was changed to get better result

CONCLUSION

Experimental analysis shows that the proposed method of detecting normal and abnormal diabetic retinopathy with high accuracy. The high accuracy of the classification proves that the proposed system is reliable as well as its implementation can resolve the issues in existing system. However, in some studies, where the image was out of focus and some algorithms failed to detect features in the DR. Therefore, in the future, the algorithm has been improved to solve the effect of unstable image

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