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Detection diabetic retinopathy with the Binary Convolution Neural Network

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ABSTRACT

Diabetic Retinopathy is a rapidly developing illness it can result in visual loss if not discovered and treated promptly. Early detection is advantageous since it slows the progression of disease and lowers the cost of recovery. Domain specialists play a big role in the current DR detection method. To fight this problem, we offer Binary Convolutional Neural Networks, that dramatically minimize ram use will be reduced, and the implementation will be speed up.In terms of DR classification, our technique is both hardware effective and accommodating.The Kaggle dataset was used in the experiments. Several image processing techniques, feature extraction approaches, and BCNN-based classification are used in our methodology. This design is exceptionally durable and light, and it has the ability to perform admirably in micro real-time applications with little computational capacity, allowing the screening process to be sped up. Our model was put through its paces in five different classes: No DR, Mild DR, Moderate DR, and Severe DR and Proliferative DR. When compared to the standard model, experiments utilizing the Kaggle dataset reduced memory disk consumption by 37% and increased duration by 49%.

Keywords: Diabetic Retinopathy (DR); Deeplearning; image Processing

I.INTRODUCTION

Diabetes is a long-term illness defined by a high blood sugar level amount of sugar in the blood of the patient. The pancreas of the human body produces Insulin, which helps to lower blood glucose levels. Diabetic Retinopathy (DR), vision impairment, heart attacks, renal failure, and stroke are just a few of the health issues associated with diabetes. Diabetes is caused by a reduction or absence of Insulin in the body, or the inability to utilise Insulin.This condition has an impact on people of all ages. According to a poll conducted by the International Diabetes Federation in 2015, almost 410 million individuals worldwide suffer from diabetes. Diabetes claimed the lives of almost 5 million people in 2015. To solve this problem, in recent decades, various people have tried to build automated DR detection systems.

CNNs have been increasingly useful in a variety of situations as annotated data has become more widely available and GPUs have evolved. Though significant numbers of data points are difficult to obtain by in medical datasets (ILSVRC).Since most networks are designed to detect items in the ImageNet dataset, deep learning When training a models with minimal data, underfitting is a severe problem. Oversampling on the lower class in large datasets is common, however oversampling on a short dataset will not assist prevent overfitting.

II.RELATED WORK

Diabetic Retinopathy is the most frequent cause of preventable vision loss, affecting mostly the working-age population of the world. This makes it perfect for developing and testing image processing algorithms for early diagnosis of diabetic retinopathy[1]. We trained an ensemble of deep Convolution Neural Networks using the publicly accessible Kaggle dataset of retina photos in this study.On the same Kaggle dataset, it performs better than state-of-the-art methods[2]. This article uses a convolutional neural network with appropriate Pooling, Softmax, and Rectified Linear Activation Unit (ReLU) layers to identify DR images as per the nature of the disease to obtain a high degree of precision.Classification accuracies of 96.6 percent and 96.2 percent, 95.6 percent and 96.6 percent, respectively, have been achieved in the case of healthy pictures, images of stage 1, stage 2, and stage 3 of diabetic retinopathy[3].The proposed DL models were developed with the intention of predicting future DR progression, which was defined as a 2-step worse on the Initial Treatment Diabetic Retinopathy Scale. The Diabetic Retinopathy Severity Scale measures the severity of diabetic retinopathy. It might aid in the recruitment of patients for DR clinical trials[4].

In this cross-sectional study, fundus images from 213 study participants was exposed to offsite, automatic analysis. For detecting pertaining diabetic retinopathy, the sensitivity and specificity of the analyses were 100.0 percent and 88.4 percent, accordingly, and 85.2 percent and 92.0 percent, respectively, for any diabetic retinopathy[5]. Using these photos, this research creates automated techniques to diagnose Diabetic Retinopathy. Sensitivity, specificity, and accuracy were calculated to be 98.94 percent, 97.87 percent, and 98.15 percent, respectively[6].The features are extracted using deep networks and convolutional neural networks in the suggested research (CNN). The micro aneurysm can be detected in the early stages of the shift from normal to sick condition on mild DR images. This study provides evidence that the proposed framework outperforms other typical detection algorithms in terms of accuracy[7]. A new approach for DR diagnosis based features intensities and textural data extracted from fundus photos was developed using a decision tree-based ensemble learning strategy. The GA's parameters can be changed to obtain a new collection of features and see whether this yields better results[8]. To fight this problem, the suggested Binary Convolutional Neural Networks, which substantially decrease memory usage and speeds up the process. When compared to the base model, memory usage is reduced by 37% and runtime is increased by 49%[9].A CNN architecture based on transfer learning and color fundus photography. Each retinal shot is graded in roughly 0.99 seconds with minimum hardware requirements, resulting in a resilient system. [10]. We proposed a BCNN strategy to classify photos from a small and kagle dataset consisting of 3000 training shot belong to 5 classes and 415 validation images in order to achieve a significantly good result.

III.PROPOSED METHOD

The pre-processing of photographs using Gussian filter methods to improve the image's attributes. Another method explored in this study was extracting statistical features from images. The objective was to extract information from a scaled image of 2000, because high resolution allows for more investigation. The Binary Convolutional Neural Networks (BCNN) were created to reduce this issue, and they significantly reduce memory consumption and speed up the implementation process. The final SoftMax layer for DR-classed pictures has five classes. The photographs are classified as No DR, Mild DR, Moderate DR, Severe DR, and Proliferative DR.

3.1 PRE-PROCESSING

The Gaussian filter is a linear smoothing filter. A low pass filter, the Gaussian blur is. It reduces the amount of noise in the blurred image. Gaussian smoothing is a preprocessing procedure used by computer vision algorithms to organize and enhance visual structure at various sizes. Using mathematics to impart a Gaussian blur to an image is just like convoluting with a Gaussian function. This is also known as a two-dimensional transform. The Fourier conversion of a Gaussian filter removes the frequency component.

3.2 FEATURE EXTRACTION

Morphological non-uniform feature enhancement is a technique that involves a set of stages that must be performed while enhancing an image. The brighter background can be seen here. To make the photograph more interesting, the bright background was omitted it easier to find the features. Noised features can be seen by removing the background illuminated picture from the original image. The image contrast has been adjusted, and the image has been binarized with the necessary threshold noise romitted. This binary image is transformed to RGB, providing you a clear view of all of the properties. Statistic procedure: Some of the statistic words to use as features for training the machine learning model include average, median, standard deviation, skewness, root mean square error, mean absolute deviation, quartiles, minimum, maximum, and threshold level values:

Table.1 Features extracted

Features	The Relationship Between Each Feature and Images
Average	The mean, often known as the average, is a figure that indicates the data's central tendency.
Median	The mean, often known as the average, is a figure that represents the central tendency of data.
Standard deviation	This shows how the values fluctuate over time or depart from the average or mean value.
Root Mean Square Error	It was originally used to calculate the relationship between the price or load conditions of pixels in an image.
Mean Absolute Deviation	It's the average distance between each of the data set's pixel values and the mean or average.
Threshold	The numerical value that is responsible for converting the original image to greyscale.

3.3 BINARY CONVOLUTION NEURAL NETWORK

Instead of regular convolution layers, our suggested method uses binary convolution layers. The max-pooling approach was utilized, as well as binarization of dense layers. The final SoftMax layer for DR-classed pictures has five classes. The input generated by pre-trained networks is higher. Preprocessed signals and bias, that reduce memory usage, are used to solve this.

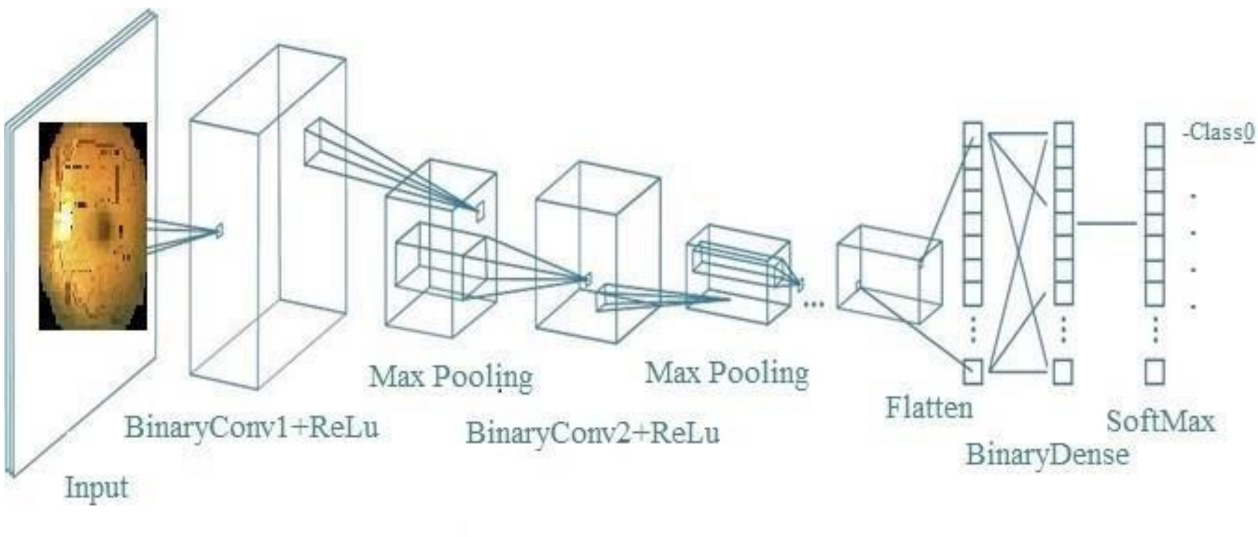

Fig. 1.BCNN Structure for Diabetic Retinopathy

Pre-trained models multiplied on reference frame using various filters as part of convolution.Binarization, on the other hand, replaces these with bitwise procedures such as Binarized Neural Networks (BNN). The key benefit of this model is that it prioritizes all weights. Dropouts are used in most models to minimize overfitting. However, in our method, BCNN functions as a regularizer to prevent overfitting.

IV. RESULT AND DISCUSSION

Our model Binary Convolution Neural Networkperformance with Diabetics retinopathy. The speed of classification improves. TABLE 2 compares the performance of BCNN

Classification	**Memory Consumption(MB)**	**Run time(MB)**	**Accuracy**
AlexNet	116.58	16356.3	68.34
Inception V3	183.27	26145.4	92.23
Resnet50	293.5	26142.2	91.81
DenseNet	316.53	20054.8	93.45
BCNN using Inception V3	**114.53**	**13243.6**	**91.04**

Table 2. Performance Comparison of DR

This examination was carried out using retinal pictures and modal characteristics collected by BCNN. This assessment can be compared to other classification techniques. Figure 2 depicts the stages of diabetic retinopathy identification using a confusion matrix.

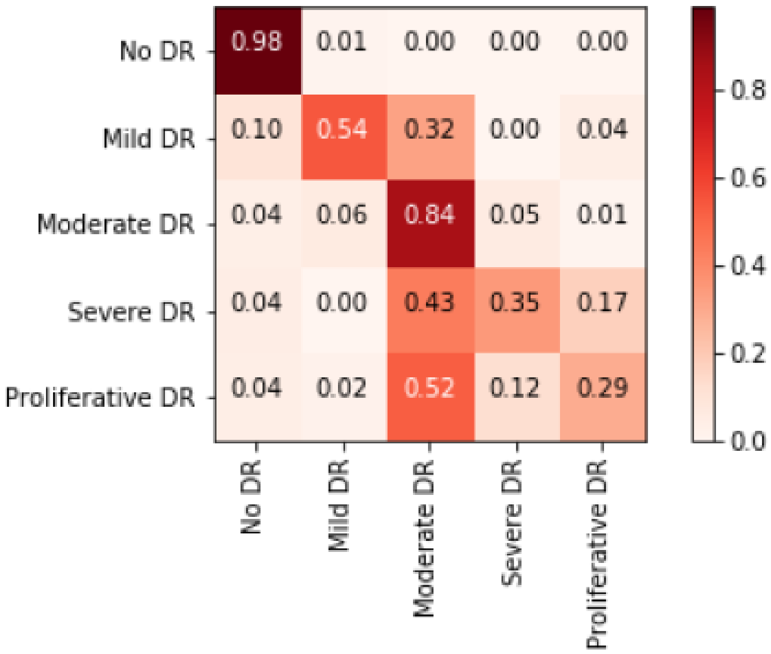

Fig 2. Diabetic Retinopathy Confusion matrix

The MO curve is the farthest from the graph's top-left corner, indicating that the model has the lowest success rate in this class. The curves of the remaining four classes are all quite close to the corner, with AUC scores of around 1.00 apiece. Because the classification's accuracy score is the closest to the average, the provided ROC curve was created from it. TheROC curve of classification performance is shown in Figure 3.

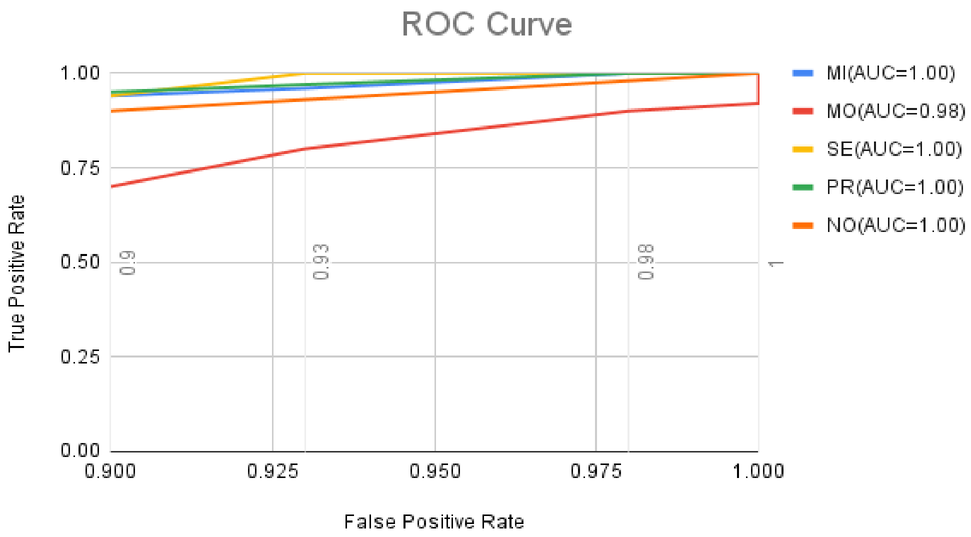

Fig 3. ROC curve of classification performance

CONCLUSION

The BCNN model is suggested in this study, which achieves effective memory classifications is reduced in program execution. By binarizing the strengths and signals, this strategy saves storage space and speeds up the process in a hardware-friendly manner.In memory-constrained situations with huge images, our solution works effectively. Experiments using Kaggle fundus image datasets revealed that the linear function of our algorithm may be enhanced without impacting classification accuracy. This approach reduces memory utilization by 37.50% while increasing runtime by 49.34%.

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