CNN BASED SCHEME FOR DETECTING RETINOPATHY IN VARIOUS DIRECTIONS

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Abstract

A diabetic condition called Diabetic Retinopathy (DR) destroys blood vessels in the retina, causing vision loss. Symptoms may not present themselves at first or may fluctuate. When it reaches a certain point of severity, it begins to impact both eyes, leading to blurred or lost vision. Most often happens when blood sugar levels become uncontrollable. That's why a diabetic has an extremely elevated chance of developing any number of complications. Complete and permanent blindness may be avoided if the condition is diagnosed in its early stages. Hence, it is necessary to have a reliable screening procedure in place. In this study, a deep learning approach called a Densely Connected Convolutional Neural Network (CNN) is taken into account and used to diagnose diabetic retinopathy in its earliest stages. Most data was checked repeatedly for analysing the image in depth and give the exact data. Data collection, pre-processing, augmentation, and modelling are all parts of the suggested technique. We found that our suggested model was 94% accurate. Additionally, a CNN based regression scheme was took, yielding an 89% value. The primary objective of this study is to design a reliable method of automated DR detection..

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1. Introduction

DR is an eye disease brought on by untreated diabetes that may lead to complete blindness. Therefore, the need of early diagnosis and medical treatment for diabetic retinopathy to avoid its harmful consequences cannot be overstated. Having an ophthalmologist examine your eyes manually takes longer and may be rather painful. Recently, machine learning has emerged as one of the most prominent methods for enhancing productivity across many fields; this includes the analysis and categorization of medical images [1]. This means that an automated method may help physicians identify diabetic retinopathy in its earliest stages. This study presents a novel method for the extraction and categorization of exudates, haemorrhages, and micro-aneurysms using machine learning based on a network of neural networks [2].

Throughout the globe, the number of people diagnosed with diabetes continues to rise. Diabetes is linked to abnormal insulin production and excessive blood sugar, which may lead to metabolic abnormalities and problems such as cardiovascular disease, renal failure, neurological issues, and diabetic retinopathy (vision loss). Diabetic retinopathy is a serious eye disease that may lead to irreversible vision loss if left untreated. Whether one has type 1 or type 2 diabetes, the likelihood of developing the condition rises with age, and this is especially true for persons with a family history of diabetes. The World Health Organization (WHO) has called DR a "extreme eye illness" that demands immediate worldwide consideration. With an estimated 17,000 ophthalmologists [3] and 50,000,000 diabetics suffering from sight problems, India has a severe shortage of eye care professionals. Due primarily to the fact that most individuals are unaware that they are suffering from this ailment, the prevalence of this illness is alarmingly high. They also exhibit callousness and a lack of caution in dealing with this ailment. Because it often has no symptoms or very minor ones in the early stages, this illness often goes undetected until it has progressed to the point where the patient can no longer see well. Thus, early detection of DR is critical to avoiding the complexity of this illness. Experts having access to cutting-edge diagnostic tools and methods are essential for determining this disease's prognosis.

Eye disease known as diabetic retinopathy is a direct result of elevated blood sugar levels, or hyperglycaemia. Loss of eyesight is possible, as is complete blindness. Early indications of diabetic retinopathy include blurred vision, black spots in the field of vision, hazy eyes, and a lack of colour perception. Total blindness caused by diabetes may be avoided with early diagnosis and treatment of retinopathy. About 35% of the 285 million [4] diabetics worldwide develop diabetic retinopathy. It is projected that by 2030, 191 million people worldwide would have diabetic retinopathy, up from 126.6 million in 2010. So considering all this situations, Proposed system is used to create CNN based detection scheme.

2. Related Works

One of the major problems that has the attention of the whole globe is diabetic retinopathy. attracting the interest of scientists who want to develop better methods for detecting the condition at an early stage and so halting the onset of visual changes. The goal of many past and ongoing research is to make the lives of both physicians and patients easier. Many studies on diabetic retinopathy are summarised here [5] – [8]. LBP was employed for feature extraction, while Machine Learning, in particular Support Vector Machines and Random Forests, were utilised for classification, to identify diabetic retinopathy in this study. With an accuracy of 97.46%, the random forest results were superior than those of the SVM. However, only 71 photos were included in the dataset for this research. The identification of DR in earlier research relied on different computer-based approaches, however this was done manually via feature extraction. Employed characteristics such as blood vessels, microaneurysms, exudates, and haemorrhages from 331 fundus pictures [9] to train an SVM with an accuracy of above 85%. Using an SVM classifier [10] – [13] to identify exudates in fundus pictures, an automated technique for identifying DR was proposed. Some of these projects include the detection of red lesions in the retina of the eye, and they use CNN with hand-crafted features for feature extraction.

Advantages and drawbacks of applying Data Mining and machine learning techniques for predicting diabetes-related disorders were weighed in published works. Despite the abundance of studies and works on detecting diabetic retinopathy by machine learning and data mining, a new, alternative method has emerged in recent years. Apply a quantitative method to the problem of finding additional factors for the diagnosis of proliferative diabetic retinopathy. Predictions of Retinopathy are thought to be enhanced by include information about the location, number, and extent of any lesions present [14]. Topics and imaging data were collected and analysed. We compared lesions by counting how many there were, measuring how big they were, how far they were from the ONH's epicentre [15], and by doing a regression analysis to see how the two sets of data compared. The study provided here reviews the numerous methods for diagnosing diabetic retinopathy, including the detection of haemorrhages, microaneurysms, exudates, and blood vessels, and then conducts an experimental analysis of the resulting data..

3. Methodology

Several steps were taken before the photos were sent to the network for analysis. In this study. While the regression model did a decent job, our suggested approach did better. The purpose of the proposed action is to spare just the foreground of the original image while eliminating the background. Returning to the original image for further modification is often required. In the original photo, however, there is frequently distracting or irrelevant scenery. This method is used when taking a photograph out of its original setting is a need. In Figure 1 we see how the proposed method generally works. In figure 1, we can see the workflow of the process

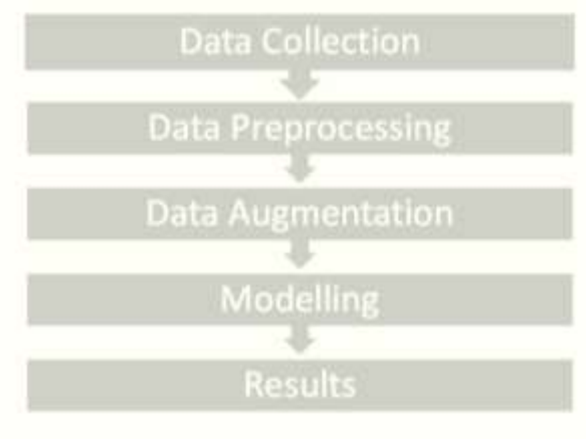

Figure 1. Proposed Scheme Flow

3.1. CNN – Convolutional Neural Network

CNN is used in both classification and regression tasks. However, its primary use is in Machine Learning, namely for Classification problems. The SVM method looks for the best line or decision boundary that splits the space into n different classes so that subsequent data points may be classified effectively. The boundary of the best possible option is a hyperplane. When constructing the hyperplane, CNN is used to choose the most extreme points and vectors. Support vectors are a specialised subset of extreme cases, and the associated method is termed a Support Vector Machine. Have a look at the diagram below, which depicts a decision boundary used in a classification issue with two groups.

3.2. Feature Extracted in particular Area

In order to locate exudate, it is necessary to first transform the picture from the dataset to an HSV image, a step performed during image preparation. In order to see a picture in a different colour space, colour space conversion must be performed. In the shown picture, the hue is channelized from saturation and value into red, blue, and green channels. Yellow exudate extracted from an RGB picture is helpful when converting to HSV. We then do median filtering and edge zero padding. In Figure 2, we see the raw picture. Feature reduction also simplifies data visualisation for humans, particularly when the data is reduced to two or three

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dimensions that are more amenable to being displayed graphically. When there are so many facets to a problem, reliable information is hard to come by, as in the cases described above. Show Figure 2 to see how feature reduction may reduce the number of dimensions in data, making it less sparse and more statistically significant for use in machine learning.

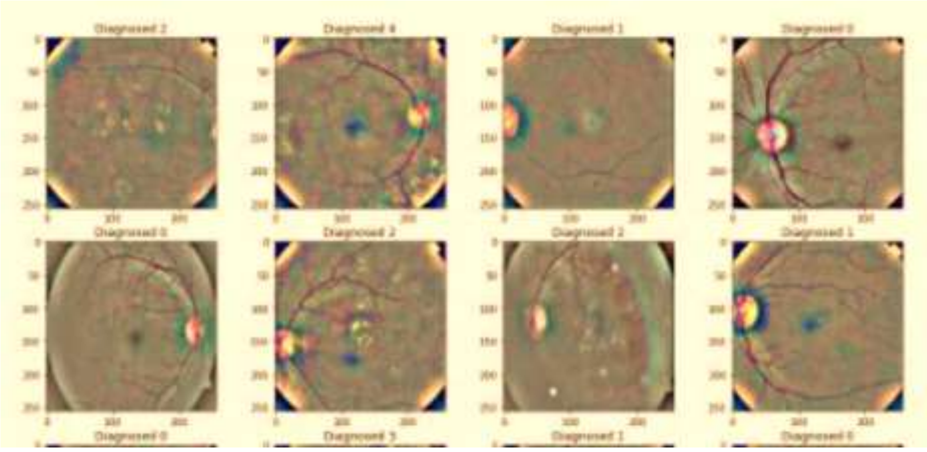

Figure 2. Feature Selection

3.3. Data Source and Pre-processing

Both sets include thousands of retinal photos captured in a variety of settings. Each person has left and right eye pictures provided. Because of the wide variety of cameras, models, etc., used to capture these photographs. It seems to be riddled with noise that must be eliminated, which calls for extensive pre-processing. Each image's diabetic retinopathy has been assigned a severity rating from 0 to 4. There can be no changes to the picture without first pre-processing the data. Prepositions, articles, and pronouns are unlikely to aid in the extraction of significant information from an image and should thus be omitted from the text before it is processed by image mining software. Stemming, also known as lemmatization, is a technique for simplifying words by emphasising their etymological origins. Numerous English words and phrases, for instance, may be understood in more than one way. That is to say, we now know exactly what these expressions signify. After the data has been cleaned up by removing stop words and applying stemming, a vector space model is created. Data in numerical form makes this sort of analysis much easier to do. In the field of image mining, dimensionality reduction is crucial.

Algorithm:

Input: 1600 images of Retina Images

Set: Dataset is injected randomly

CNN Performance

If Test is OK then

Analysis starts from the beginning

else

Test again till the last dataset

elif Area sorted Value

end if

Performing the segmented Retina

Output: Detected Retina Images as Expected

3.4. Data Augmentation

Over the last decade, several new approaches have been implemented. New methods are presented in this study for assessing the health of a Retina picture. We used the wavelet transform to prepare the photos for feature extraction. When it comes to making decisions, visual representation methods like element abstraction may be quite helpful since they filter raw data to extract meaningful information from a picture by doing things like seeing various patterns. Texture, intensity, form, and depth may all be combined with the help of Retina pictures. Depending on how it appears, the CNN system may automatically label neuroimaging data as "normal" or "abnormal." The degree of symmetry between the axial and coronal planes is a potential indicator of whether or not a brain scan is normal. The first step is to get the Retina feature vector. Using a convolutional neural network, the photos are sorted into groups.

4. Performance Evaluation

MATLAB is used to analyse the proposed model; it has built-in support for Hadoop and MDCS for massively parallel computation. Images included in the dataset included a lot of background noise, therefore pre-processing was required. The photos were pre-processed by eliminating the black borders and corners so that the viewer's attention would be only on the fundus image. Next, the photographs were downsized to the industry-standard width and height of 256 pixels by 256 pixels. Finally, the Gaussian noise was taken out of the pictures by blurring them with a Gaussian. After examining the raw data, we found a significant imbalance between the different severity categories. To remedy this problem in the absence of DR, we used data augmentation, which provided us with 7,00 photos across all severity classes and created a more even distribution of data. Images were enhanced and processed before being put into the Dense Net for training. Our model was evaluated, and the results showed a training accuracy of 0.93 and a validation accuracy of 0.90. A value of 0.80 was also determined. Furthermore, when compared to a standard regression model, ours performs better. Table 1 summarises our model's findings. Figure 3 shows the level of retina images and figure 4 shows model representation.

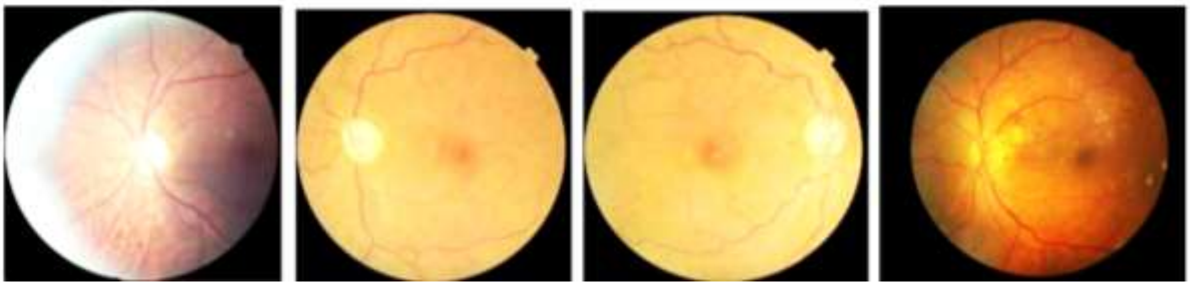

Figure 3. Retina Images from 0 level to 1

Layer (type)	Output Shape	Param #
densenet169 (Model)	(None, 8, 8, 1664)	12642880
global_average_pooling2d_1 (	(None, 1664)	0
dropout_1 (Dropout)	(None, 1664)	0

Figure 4. Layered types

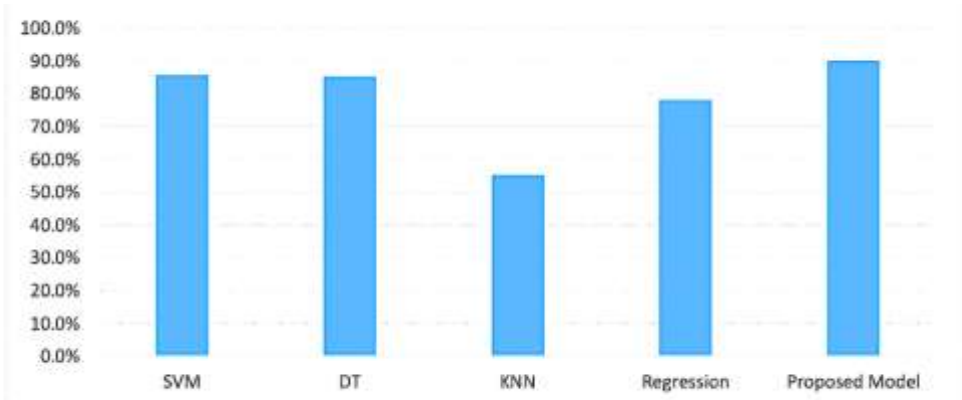

Figure 5. Accuracy Comparison

It's clear that the grouping was spot-on. Figure 5 contrasts the performance of several multimodal classifiers with that of the aforementioned model. The comparison table shows that the suggested method is the most precise. The graphic depicts the improved sensitivity of the proposed classification model over existing methods. The proposed model successfully classifies brain tumours, as shown by the validation findings. Table 1 shows the sensitivity of the proposed model to be 98.3 percent. It shows how specific the proposed classification model is. Given that the proposed model is shown to have a specificity of 99.3 percent, it is clearly better to the alternatives. To validate the segmentation technique, its performance is compared to existing methods.

Table 1. Proposed Values

Achievement	CNN

Accuracy	94%
Prediction Speed	3800obs/sec
Training Time	3.3 sec

5. Conclusion

Due to the large volume of photos that must be pre-processed and enhanced, as well as the inherent risk that certain image attributes would be lost in the process, procedures should be used that not only successfully pre-process the images but also maintain all the minute but crucial details. In addition, rather of providing just two photographs per patient, it would be preferable to supply many images so that more information can be acquired and the likelihood of accurate classification is increased. With the development of new neural networks made possible by enhanced pooling techniques, the scope for adjusting hyper-parameters keeps expanding. In light of this, such strategies may be taken into account for potential future research into ways to improve performance in this domain. Thanks to your elaborate hierarchy of concepts, brain tumours are now easily distinguishable. Because of its flexibility, it may be used in a wide variety of image processing settings. Numerous researchers have proposed investigating numerous medical imaging issues..

References

[1]. Parthasharathi, G. U., Premnivas, R., & Jasmine, K. (2022). Diabetic Retinopathy Detection Using Machine Learning. *Journal of Innovative Image Processing*, *4*(1), 26-33.

[2]. Gothane, S., Raju, K. S., Bhaskar, N., & Divya, G. (2022). Diabetic Retinopathy Detection Using Deep Learning. In *Data Engineering and Intelligent Computing* (pp. 387-393). Springer, Singapore.

[3]. Panwar, A., Semwal, G., Goel, S., & Gupta, S. (2022). Stratification of the lesions in color fundus images of diabetic retinopathy patients using deep learning models and machine learning classifiers. In *Edge Analytics* (pp. 653-666). Springer, Singapore.

[4]. Kanakaprabha, S., Radha, D., & Santhanalakshmi, S. (2022). Diabetic Retinopathy Detection Using Deep Learning Models. In *International Conference on Ubiquitous Computing and Intelligent Information Systems* (pp. 75-90). Springer, Singapore.

[5]. Özbay, E. (2022). An active deep learning method for diabetic retinopathy detection in segmented fundus images using artificial bee colony algorithm. *Artificial Intelligence Review*, 1-28.

[6]. Murugappan, M., Prakash, N. B., Jeya, R., Mohanarathinam, A., Hemalakshmi, G. R., & Mahmud, M. (2022). A novel few-shot classification framework for diabetic retinopathy detection and grading. *Measurement*, *200*, 111485.

[7]. Saini, M., & Susan, S. (2022). Diabetic retinopathy screening using deep learning for multi-class imbalanced datasets. *Computers in Biology and Medicine*, 105989.

[8]. Mane, D., Londhe, N., Patil, N., Patil, O., & Vidhate, P. (2022). A Survey on Diabetic Retinopathy Detection Using Deep Learning. In *Data Engineering for Smart Systems* (pp. 621-637). Springer, Singapore.

[9]. Ghaskadvi, M., Khochare, S., Gonsalves, R., & Dhamanskar, P. (2022). Pneumonia and Diabetic Retinopathy Detection Using Deep Learning Algorithm. In *Sentimental*

Analysis and Deep Learning (pp. 155-175). Springer, Singapore.

[10]. Zhang, G., Lin, J. W., Wang, J., Ji, J., Cen, L. P., Chen, W., ... & Zhang, M. (2022). Automated multidimensional deep learning platform for referable diabetic retinopathy detection: a multicentre, retrospective study. *BMJ open*, *12*(7), e060155.

[11]. Nderitu, P., Nunez do Rio, J. M., Webster, M. L., Mann, S. S., Hopkins, D., Cardoso, M. J., ... & Jackson, T. L. (2022). Automated image curation in diabetic retinopathy screening using deep learning. *Scientific reports*, *12*(1), 1-12.

[12]. Pinedo-Diaz, G., Ortega-Cisneros, S., Moya-Sanchez, E. U., Rivera, J., Mejia-Alvarez, P., Rodriguez-Navarrete, F. J., & Sanchez, A. (2022). Suitability Classification of Retinal Fundus Images for Diabetic Retinopathy Using Deep Learning. *Electronics*, *11*(16), 2564.

[13]. Mohanarathinam, A., Manikandababu, C. S., Prakash, N. B., Hemalakshmi, G. R., & Subramaniam, K. (2022). Diabetic Retinopathy Detection and Classification using Hybrid Multiclass SVM classifier and Deeplearning techniques. *Mathematical Statistician and Engineering Applications*, *71*(3), 891-903.

[14]. Farooq, M. S., Arooj, A., Alroobaea, R., Baqasah, A. M., Jabarulla, M. Y., Singh, D., & Sardar, R. (2022). Untangling computer-aided diagnostic system for screening diabetic retinopathy based on deep learning techniques. *Sensors*, *22*(5), 1803.

[15]. BERBAR, M. A. (2022). Diabetic Retinopathy Detection and Grading using Deep learning. *Menoufia Journal of Electronic Engineering Research*, 11-20.

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