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Prediction of Diabetic Retinopathy using Deep Learning

Aswini Devi B[1], Harini S[1], Keerthana M[1], Samyuktha C[1], Sangeethapriya J[2]

Student, Information Technology, Saranathan College of Engineering, Trichy, India[1]

Assistant Professor, Information Technology, Saranathan College of Engineering, Trichy, India[2]

Abstract: *Diabetic retinopathy (DR) is a serious eye disease originating from diabetes mellitus and the most common cause of blindness in the developed countries. Early treatment can prevent patients from getting affected due to this condition or at least the progression of DR can be slowed down. The key to the early detection is to recognize micro-aneurysms (MAs) in the fundus of the eye in time. Thus, mass screening of diabetic patients is highly desired, but manual grading is slow and resource demanding. Micro-aneurysms (MAs) are early signs of DR, so the detection of these lesions is essential in an efficient screening program to meet clinical protocols. Early micro aneurysm detection can help reduce the incidence of blindness and micro-aneurysm detection is the first step in automated screening of diabetic retinopathy. A reliable screening system for the detection of MAs on digital fundus images can provide great assistance to ophthalmologists in difficult diagnoses. This project presents image processing techniques such as dark object detection to analyze the condition or enhance the input image in order to make it suitable for further processing and improve the visibility of micro-aneurysm in color fundus images. The correlation coefficient between each processed profile and a typical micro-aneurysm profile is measured and used as a scale factor to adjust the shape of the candidate profile. Each candidate is then classified based on Customized Sequential Convolutional neural network algorithm. We implement this retinal imaging in real time environments.*

Keywords: *Diabetic retinopathy*.

I. INTRODUCTION

Diabetic retinopathy is a condition that affects the eyes as a complication of diabetes. It is caused by damage to the blood vessels in the retina due to high blood sugar levels. The condition is a leading cause of blindness in adults aged 20-74 years in the United States. In the early stages of diabetic retinopathy, there may be no symptoms, but as the condition progresses, symptoms may include blurred vision, floaters, and loss of vision. It is diagnosed through a comprehensive eye exam that includes a visual acuity test, dilated eye exam, and retinal photography. Treatment options depend on the stage of the disease and may include

lifestyle modifications, medications, laser therapy, intraocular injections, and vitrectomy surgery. Prevention involves managing blood sugar levels, blood pressure, and cholesterol, as well as regular eye exams for early detection and treatment. Overall, early detection and treatment are essential for preserving vision and preventing complications. Diabetic retinopathy is a progressive condition that can lead to significant vision loss if left untreated. The condition develops slowly over time and may not show any symptoms in the early stages. It is essential for individuals with diabetes to undergo regular eye exams to detect diabetic retinopathy as early as possible, even if they do not experience any symptoms. The treatment options for diabetic retinopathy depend on the stage of the disease. In the early stages, managing blood sugar levels, blood pressure, and cholesterol can slow down the progression of the condition. Medications, including anti-VEGF drugs and steroids, may also be prescribed to control swelling in the retina. In more advanced stages, laser therapy is a common treatment option that is used to prevent or reduce the risk of vision loss. Laser therapy is a non-invasive procedure that uses a laser to seal off leaking blood vessels and stop the growth of abnormal blood vessels. In some cases, intraocular injections may also be prescribed to reduce swelling in the retina. Vitrectomy surgery is another option for individuals with advanced diabetic retinopathy, in which the vitreous gel in the eye is removed and replaced with a clear solution. Preventing diabetic retinopathy is essential for preserving vision and

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reducing the risk of complications. This can be achieved through lifestyle modifications such as regular exercise, a healthy diet, and avoiding smoking. Additionally, it is essential for individuals with diabetes to monitor and control their blood sugar levels, blood pressure, and cholesterol.

II. EXISTING SYSTEM

They provide a completely convolutional architecture in this research that can do structured prediction for the task of segmenting retinal vessels. On the DRIVE database, we showed that our suggested design performed at the cutting edge of technology. Computer-assisted detection of retinal illnesses relies heavily on the automatic segmentation of retinal blood vessels from fundus images. they formulate the segmentation task as a multi-label inference task and utilize the implicit advantages of the combination of convolutional neural networks and structured prediction. The proposed technique only analyse the retinal vessel.[1].

In this paper, a new methodology based on the multiple instance learning (MIL) framework is developed in order to overcome this necessity by leveraging the implicit information present on annotations made at the image level. Contrary to previous MIL-based DR detection systems, the main contribution of the proposed technique are the joint optimization of the instance encoding and the image classification stages.The proposed technique achieves comparable or better results than other recently proposed methods, with 90% area under the receiver operating characteristic curve (AUC) on Messidor, 93% AUC on DR1, and 96% AUC on DR2, while improving the interpretability of the produced decisions.Need experts in disease predictions.[2]

In this paper, we focus on recent advances in deep learning methods for retinal image analysis. A large diversity of deep learning techniques has been tested on the retinal fundus images.It clearly shows that the performance of the existing methods drops due to low contrast of tiny vessels which are not extracted easily. The major drawback of this paper is the disease can't be predicted[3].

This proposed model can predict DR in three different stages: normal, non-proliferative diabetic retinopathy (NPDR), and proliferative diabetic retinopathy (PDR) based on the features that are present in an input retinal fundus image using support vector machine (SVM). Deep learning models require a large amount of annotated data to be trained effectively. However, obtaining such data can be challenging,especially in the medical domain. It may produce false positives, leading to incorrect diagnosis and treatment [4].

The process of DR detection in the proposed approach was fully autonomous. Thus, it could serve as an important role in making automated screening for early DR based on retinal fundus photographs. Interpretable: RBF-SVM produces a decision boundary that can be easily interpreted, making it easier to understand how the model makes its predictions. RBF-SVM may not scale well to very large datasets, as it requires the storage of a large kernel matrix[5].

The proposed work aims to implement an automated system that can perform binary classification as well as multiclass classification of DR from retinal fundus images for better disease diagnosis. In order to achieve the goal, a new combined feature extraction technique is implemented using Heraldic and ADTCWT methods. Accurate detection can improve the diagnosis and treatment of diabetic retinopathy, leading to better outcomes for patients. Deep learning algorithms require a large amount of annotated data to be trained effectively. However, obtaining such data can be challenging, especially in the medical domain[6].

The proposed method using Haralick and multi- resolution features has been shown to achieve high accuracy in binary and multiclass classification of diabetic retinopathy. The method may not perform well when the dataset is small, as the model may overfit to the training data[7].

In this paper, we proposed an effective high-resolution DR image generation model which is conditioned on the grading and lesion information. The synthesized data can be used for data augmentation, particularly for those abnormal images with severe DR levels, to improve the performance of grading models.The grading labels of the EyePACS dataset are not absolutely correct, particularly for those DR images with low-level grades (e.g. grade-0 and grade-1)[8].

III. PROPOSED SYSTEM

We propose a system for Diabetic Retinopathy prediction from fundus image using Customized Sequential Convolutional Neural Network. The aim of the project for diabetic prediction using deep learning is to develop a model that can accurately predict the likelihood of an individual developing diabetes based on their demographic, lifestyle, and health-related data.

The step-by-step process of the project are as follows:

- To collect and pre-process relevant data on demographic, lifestyle, and health-related factors from a variety of sources.
- To select appropriate deep learning algorithms for developing the diabetic prediction model.
- To train and test the model using the collected data to evaluate its performance and accuracy.
- To optimize the model by fine-tuning the hyper- parameters and feature selection to improve its predictive capabilities.
- To deploy the model for practical use in clinical settings to aid in the early detection and prevention of diabetes.

Overall, the project aims to leverage the power of deep learning to create a predictive model that can help healthcare professionals identify individuals at risk of developing diabetes, leading to earlier intervention and improved health outcomes.

IV. ARCHITECTURE DIAGRAM

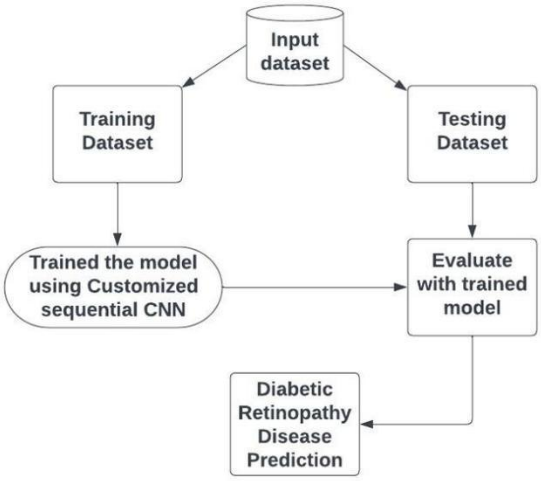

Fig 4.1 Architecture Diagram

In our project we collect the retinal image datasets from Kaggle sources. Datasets includes Type 1 and Type 2 diabetic images. We split the datasets in the ratio of 80:20 for training and testing respectively.Then perform preprocessing steps such as image resizing and noise filtering approach to provide the structured datasets. In noise filtering using median filter to remove noises in images. Perform the model building using CNN algorithm with Type 1 and Type 2 diabetics images. Use a sequential CNN as a starting point for the model by loading its weights and freezing its layers. This will enable the model to leverage the pre-trained features and reduce the amount of training required. Perform classification algorithm to predict the disease from uploaded retinal images. Perform preprocessing steps to remove noises from image and extract the features. Finally classify the retinal image to predict the disease and to provide the diagnosis details

Modules Description

- IMAGE ACQUISITION - In this, module is used to acquire a digital image. Retinal images of humans play an important role in the detection and diagnosis of cardiovascular diseases that including stroke, diabetes, arterio sclerosis, cardiovascular diseases and hypertension. Vascular diseases are often life critical for individuals, and present a challenging public health problem for society. The detection for retinal images is necessary and among them the detection of blood vessels is most important. The alterations about blood vessels such as length, width and branching pattern, can not only provide information on pathological changes but can also help to grade diseases severity or automatically diagnose the diseases. The fundus of the eye is the interior

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surface of the eye, opposite the lens, and includes the retina, optic disc, macula and fovea, and posterior pole. The fundus can be examined by ophthalmoscope or fundus photography. The retina is a layered structure with several layers of neurons interconnected by synapses. In retina we can identify the vessels. Blood vessels show abnormalities at early stages also blood vessel alterations. Generalized arteriolar and venular narrowing which is related to the higher blood pressure levels, which is generally expressed by the Arteriolar to venular diameter ratio. It constructed a dataset of images for the training and evaluation of our proposed method. This image dataset was acquired from publicly available datasets such as DRIVE and STAR. Each image was captured using 24 bit per pixel (standard RGB) at 760 x 570 pixels. First, tested against normal images which are easier to distinguish. Second, some level of success with abnormal vessel appearances must be established to recommend clinical usage. A normal image consists of blood vessels, optic disc, fovea and the background, but the abnormal image also has multiple artifacts of distinct shapes and colors caused by different diseases.

- PREPROCESSING - To improve the image in ways that increases the chances for success of the other processes. The gray scale conversion operation is to identify black and white illumination. Noise in colored retinal image is normally due to noise pixels and pixels whose color is distorted so implement median filter can be used to enhance and sharpen the vascular pattern for preprocessing and blood vessel segmentation of retinal images performing well in preprocessing, enhancing and segmenting the retinal image and vascular pattern. Human perception is highly sensitive to edges and fine details of an image, and since they are composed primarily by high frequency components, the visual quality of an image can be enormously degraded if the high frequencies are attenuated or completed removed. In contrast, enhancing the high frequency components of an image leads to an improvement in the visual quality. Image sharpening refers to any enhancement technique that highlights edges and fine details in an image. Image sharpening is widely used in printing and photographic industries for increasing the local contrast and sharpening the images. In principle, image sharpening consists of adding to the original image a signal that is proportional to a high-pass filtered version of the original image. In this filter, the original image is first filtered by a high-pass filter that extracts the high-frequency components, and then a scaled version of the high-pass filter output is added to the original image, thus producing a sharpened image of the original. Note that the homogeneous regions of the signal, i.e., where the signal is constant, remain unchanged.
- SEGMENTATION - Retinal image segmentation using Customized SequentialCNN algorithm involves using deep learning techniques to automatically identify and segment the regions of interest in retinal images. The first step in this process is data collection. A large dataset of retinal images with corresponding diagnosis labels needs to be collected. The dataset should be diverse enough to account for variations in age, sex, and ethnicity to ensure the algorithm can generalize well to different populations. Once the dataset has been collected, it needs to be preprocessed to remove any artifacts and enhance the quality of the images. This can involve techniques such as noise reduction, contrast enhancement, and normalization. The preprocessed images can then be segmented to extract regions of interest, such as the optic nerve head and retinal blood vessels. The Customized Sequential CNN model learns to automatically extract relevant features from the images and segment them based on these features. Once the Customized Sequential CNN model has been trained, it can be evaluated on a separate test dataset to assess its accuracy and generalizability. The model can also be fine-tuned by adjusting its hyper-parameters or by using transfer learning techniques to improve its performance.
- CLASSIFICATION - diabetic or non-diabetic. The first step in this process is data collection. A large dataset of retinal images with corresponding diagnosis labels needs to be collected. The dataset should include both diabetic and non-diabetic retinal images. The dataset should be diverse enough to account for variations in age, sex, and ethnicity to ensure the algorithm can generalize well to different populations. Once the dataset has been collected, it needs to be preprocessed to remove any artifacts and enhance the quality of the imagdies. This can involve techniques such as noise reduction, contrast enhancement, and normalization. The preprocessed images can then be used to train a Customized Sequential CNN model for diabetic classification. The Customized Sequential CNN model can be trained using a combination of labeled retinal images and corresponding diagnosis labels. The Customized Sequential CNN model learns to automatically extract

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relevant features from the images and classify them based on these features. Transfer learning techniques can also be used to fine-tune the Customized Sequential CNN model and improve its performance. Once the Customized Sequential CNN model has been trained, it can be evaluated on a separate test dataset to assess its accuracy and generalizability. The model can also be optimized by adjusting its hyper-parameters or by using techniques such as data augmentation to improve its performance.

- DISEASE DIAGNOSIS - Diabetic retina is a complication of diabetes that affects the retina, which is the light-sensitive layer at the back of the eye. High blood sugar levels in people with diabetes can damage the blood vessels in the retina, causing them to leak fluid or bleed. Over time, this can lead to vision problems and even blindness if left untreated. The deep learning model can be trained using a combination of labeled retinal images and corresponding diagnosis labels. Transfer learning techniques can also be used to fine-tune the deep learning model and improve its performance. Once the deep learning model has been trained, it can be evaluated on a separate test dataset to assess its accuracy and generalizability. The model can also be optimized by adjusting its hyper-parameters or by using techniques such as data augmentation to improve its performance. In this module, we can classify the diseases whether it is diabetic or not and also identify the type 1 and type 2 diabetics. Finally provide the precaution details about predicted diseases.

V. ALGORITHM DETAILS

In a customized sequential convolutional neural network (CNN), the optimizer is a key component of the training process. The optimizer is responsible for adjusting the weights of the network in order to minimize the loss function, which is a measure of the difference between the predicted output and the actual output.

There are several types of optimizers that can be used in Customized Sequential CNNs, each with its own strengths and weaknesses. Here are some commonly used optimizers in customized sequential CNNs:

- Stochastic Gradient Descent (SGD): SGD is one of the most basic optimization algorithms used in CNNs. It updates the weights in the direction of the negative gradient of the loss function. SGD can be slow to converge and can get stuck in local minima, but it is computationally efficient and can work well in practice.
- Adam: Adam is a popular optimizer that combines ideas from both Adagrad and RMSprop. It uses adaptive learning rates to update the weights, which can lead to faster convergence and better performance than SGD.
- Adagrad: Adagrad is an optimizer that adapts the learning rate of each parameter based on its historical gradient. It can be useful for sparse data, but may have difficulty converging in high-dimensional spaces.
- RMSprop: RMSprop is an optimizer that uses a moving average of the squared gradient to adapt the learning rate. It can be more stable than SGD and Adagrad, and can work well for problems with sparse gradients.
- AdaDelta: AdaDelta is an optimizer that uses an adaptive learning rate and a moving average of the gradient to update the weights. It can work well for problems with sparse gradients and can be more stable than other optimizers.

Overall, the choice of optimizer depends on the specific problem being solved and the characteristics of the data. It is important to experiment with different optimizers and learning rates to find the best combination for a given problem.

Training a Customized Sequential CNN (Convolutional Neural Network) for diabetic retinopathy prediction involves several steps. The first step is to collect a large dataset of unlabeled retinal images, where each image is labeled with the type of disease present. This dataset should be diverse and representative of the different types of diabetic retinopathy that can affect retina. The next step is to preprocess the images, which may include tasks such as resizing, normalization, and data augmentation. Resizing ensures that all images have a consistent size, which is necessary for training a Customized Sequential CNN. Normalization helps to standardize the pixel values across images, which can improve the performance of the Customized Sequential CNN. Data augmentation involves generating new images by applying transformations such as rotations, translations, and zooms to the existing images. This can help to increase the size of the dataset and improve the robustness of the Customized Sequential CNN.

The third step is to split the dataset into training, validation, and testing sets. The training set is used to train the customised sequential CNN, while the validation set is used to evaluate its performance during training and make decisions about the model architecture and hyperparameters. The testing set is used to evaluate the performance of the

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final model on new, unseen data. The fourth step is to design the architecture of the customised sequential CNN. This involves selecting the number and type of layers, the size of the filters, the activation functions, and the optimisation algorithm. The architecture of the CNN should be chosen based on the specific task at hand and the characteristics of the dataset.

The fifth step is to train the customised sequential CNN on the training set using back propagation and gradient descent optimisation. The goal is to minimise the loss function, which measures the difference between the predicted output and the true label for each image in the training set. The sixth step is to evaluate the performance of the customised sequential CNN on the validation set. This helps to ensure that the model is not overfitting to the training data and can generalise well to new data. If the performance on the validation set is poor, the model architecture and hyperparameters may need to be adjusted. The seventh step is to test the performance of the final model on the testing set. This provides an estimate of the performance of the model on new, unseen data.

Overall, training a customised sequential CNN for diabetic retinopathy prediction is a complex process that requires careful attention to data preprocessing, model architecture, and hyper-parameter tuning. However, with sufficient data and expertise, customised sequential CNNs can be powerful tools for improving disease prediction. Customised sequential CNN has multiple layers that process and extract important features from the image. There are mainly four steps to how customised sequential CNN works.

Step: 1 Convolution Operation with Relu Activation Function The objective of the convolution operation is to find features in the image using feature detectors to preserve the special relationship between pixels. The Relu activation function is used to break linearity and increase non-linearity because images themselves are highly non-linear.

Step: 2 Pooling is a down-sampling operation that reduces dimensions and computation, reduces over-fitting as there are fewer parameters and the model is tolerant towards variation and distortion

Step: 3 Flattening is used to put pooling output into one dimension matrix before further processing.

Step: 4 A fully connected layer forms when the flattening output is fed into a neural network which further classifies and recognized images. And also implement multiclass classifier; we can predict diseases in leaf images with improved accuracy.

VI. IMPLEMENTATION

For this process, a dataset is needed to be loaded into the system. The customised sequential convolutional neural network algorithm used for developing the disease prediction is done. Based on the collected data, we train and test the model to find out its accuracy and performance. The output of this process will be checking whether the image uploaded is affected by diabetic retinopathy or not and also classifying the type of diabetic.

Experimental Results

After the continuous training of epochs, the output is obtained it is attached. Once the training is completed we can start testing the system.

We had trained upto 50 epoches with an accuracy of 96%. Fig.4 shows the training of dataset and the epochs during training session.

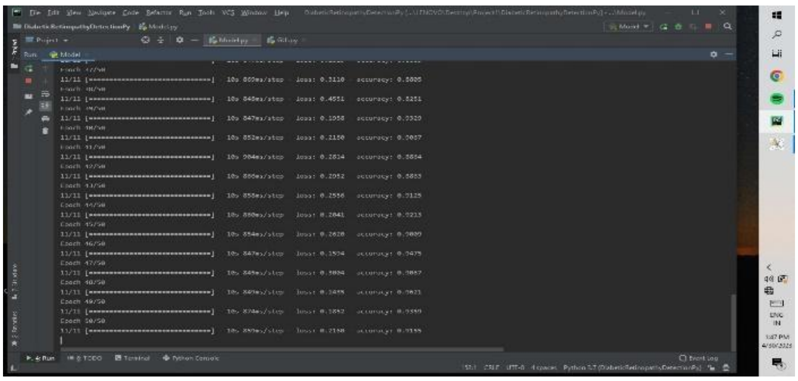

Fig 5.1 Epochs

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VII. CONCLUSION

In conclusion, retinal image analysis using machine learning techniques has shown great potential in the early detection and prediction of several eye diseases, such as diabetic retinopathy and glaucoma. With the increasing prevalence of these diseases worldwide, there is a growing need for more effective and efficient screening methods.

	CSCNN	GATL	CNN	EBL
10	68	48	32	26
20	78	57	46	31
30	86	69	59	45.6
40	93	81	68	59.8
50	96	91.1	82	70.7

Fig 6.1 Accuracy Values

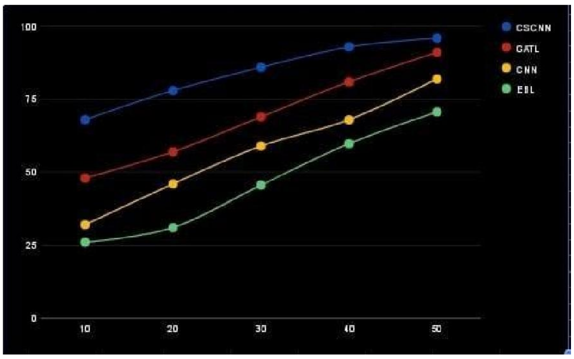

Fig 6.2 Accuracy Comparison

Machine learning-based approaches can not only improve the accuracy and speed of diagnosis but also reduce the burden on healthcare systems and improve patient outcomes. The proposed system using Customized Sequential CNN algorithms for retinal image segmentation, diabetic and glaucoma classification can help healthcare providers to make more informed decisions and provide personalized treatment plans. The combination of deep learning algorithms and retinal imaging has the potential to revolutionize the way we diagnose and manage these diseases, leading to better patient outcomes and a reduction in the overall healthcare burden. With the help of deep learning algorithms, medical professionals can process complex retinal images more efficiently, which can result in faster and more accurate diagnoses. Moreover, these approaches can help overcome the challenges associated with subjective interpretations of medical images. Human error and inter-observer variability can lead to inconsistencies in the interpretation of medical images, which can have a significant impact on patient outcomes. By leveraging machine learning algorithms, we can obtain more objective and standardized results that can help improve the quality of care

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