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IMPLEMENTATION OF TRANS CONVOLUTION NEURAL NETWORKS MODEL IN DIABETIC RETINOPATHY CLASSIFICATION BASED ON DEEP LEARNING

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Abstract

Currently, the numerous people have lost the vision as a result of Diabetic Retinopathy (DR), a condition that is a major global issue. If the disorder is not appropriately managed in the beginning, the disease will become serious. The blood vessels in the retina disruption progressively prevents light from passing via the patient with DR visual nerves, making them blind. Normal, mild, moderate, severe, and PDR are the five phases or grades of DR. The colored fundus images are often examined by highly qualified specialist to identify this dangerous condition. Automated diagnosis of the illness by professionals requires time and is susceptible to inaccuracy. It has been proposed to directly determine the DR and its many phases from retinal images utilizing a number of computer-based visual approaches. However, due to their inability to encode the underlying complicated features, these techniques could only accurately detect DR's numerous phases, particularly for the beginning phases. Therefore, in this paper propose an effective approach for DR detection from human fundus image. The input images are preprocessed by Bilateral filter, intended to minimize distortions and noise. The implementation of Gray Level C-occurrence Matrix (GLCM), the higher order texture features are extracted. Finally, the extracted features fed into Transformer Convolutional Neural Network (TCNN) for DR detection from fundus image data set. The proposed classifier obtain over all accuracy 97%, which is higher than other methods. The overall proposed system implemented in python platform to validate its performance

Keywords—DR, Bilateral filter, GLCM, TCNN

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I. INTRODUCTION

Among the most dangerous side effects of diabetes is diabetic retinopathy (DR) that damages the retina and results in vision loss. It harms the retinal tissue's blood vessels, causing them to leak fluid and blur vision. According to statistics from the US, UK, and Singapore, DR is one of the most common illnesses, and with conditions that might lead to vision loss, like glaucoma and cataracts [1-3]. Proliferative Diabetic Retinopathy (PDR) and Non-Proliferative Diabetic Retinopathy (NPDR) are the 2 types of DR. Initial DRs are referred to as NPDRs and are further broken down into moderate, mild and severe stages. One Micro-Aneurysm (MA), a tiny red dot at the end of blood arteries, is present in the mild stage. A me-shaped haemorrhage forms in the retina at the moderate stage when the MAs rupture into different levels. In each of the 4 categories, there are more than 20 intraretinal haemorrhages at the severe stage, along with obvious venous bleeding and noticeable intraretinal microvascular anomalies [4, 5].

Numerous research have demonstrated for diabetic retinopathy detection from human fundus image. Modern Machine Learning (ML) techniques like deep learning have demonstrated promising diagnostic results in the areas of speech & picture recognition, and natural language processing [6].

It is commonly used in a variety of fields, such as social media, telephony, cybersecurity, and health. By 2025, there are projected to be 594 million DR sufferers worldwide, up over 392 million today. According to a research [7] carried out in the Pakistani province of Khyber Pakhtunkhwa (KPK), 5.7% of diabetic peoples diagnosed with DR became blind. In contrast, modest NPDR gradually develops into PDR if it is not controlled in the early stages. 135 patients with DR symptoms were observed in Sindh, Pakistan, for a separate article [8]. PDR was diagnosed in 26.7% of the persons who were examined, accounting for 24.5% of all DR patients

The sufferers have no symptoms in the beginning phases of the illness, yet in the later stages, it causes cataract, vision problems, abnormalities, and gradual reduction in visual sharpness. As a result, it is difficult yet essential to recognize the DR in its beginning stages in order to avoid the negative impacts of subsequent stages [9. 10]. As stated in the section above, DR is detected using colour fundus images. Since only highly skilled domain specialists are able to do the manual analysis, it takes time and money. In order to help doctors and radiologist, it is essential that you utilize machine vision techniques to automatically evaluate the fundus images.

The conventional methodologies employed by the hands-on analytical techniques, including HoG [11], Gabor filters [14], SIFT [12], LBP [13] and others, to extract features do not successfully encode fluctuations in illumination, rotation and scale. End-to-end learning effortlessly picks up on the rich, hidden aspects, improving classification. There are numerous manual construction and attempting to learn end-to-end methods [15] utilized to identify the DR in input dataset, however not one of them could identify the Mild stage. The early control of this lethal disease depends on the discovery of the mild stage. This research employed end-to-end deep ensemble networks to recognize all phases of DR, even the moderate stage.

This paper emphasis the TCNN classifier to identify the DR from the human fundus image. The initial stage of preprocessing done by bilateral filter the noises from input image. By using GLCM method, the high ranked features are extracted. At last, the proposed TCNN achieves 97% accuracy and highly efficient in contrasted other techniques.

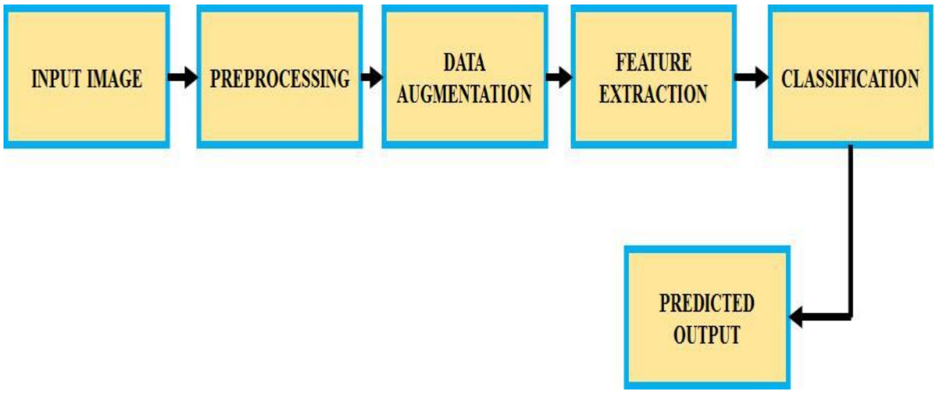

Fig.1. Proposed system

Figure 1 illustrates the schematic diagram representation of suggested diabetic retinopathy detection system.

II. PROPOSED METHODOLGY

This suggested system employs machine learning based TCNN for the diagnosing of DR. The input image is preprocessed using Bilateral filter. While handling with noisy images, the adaptive histogram with limited contrast Equalization Bilateral filter is employed in order to evaluate whether visible the distortion appears. This dataset is passed into the data augmentation block after pre-processing, then the data augmentation process increase the amount of data by adding modified existing data. The feature extraction block is then exposed to the image. For GLCM, a feature extraction block is utilized. The GLCM extraction technique is used to produce a suitable threshold value. The selected attributes are fed into the TCNN classifier for machine learning data classification. Finally, for improved accuracy, TCNN's classification method is employed. Ultimately, the required output outcome is attained.

A. Preprocessing

Here the Bilateral filter methods is used to pre-process the image. By using a nonlinear set of parameters from neighboring images, bilateral filtration softens the images while maintaining the borders. Bilateral filtering is intended to accomplish across an image's ranges exactly typical filters do in its area. A pixel could be comparable to the other by occupying an identical position information, or it can be same to another pixel by having values that are related to one another, perhaps in a perceptually significant way. Nearness and familiarity both refer to proximity in the domain and the range, respectively. Conventional filtering, which promotes closeness by evaluating number of pixels with coefficients which decrease with range, is a domain filtering. By averaging image data with weights that decrease with differentiation, range filtering averaged image values. Due to the fact that variety filters' parameters change based on the hue or brightness of the image, these are nonlinear. They are analytically never more difficult than typical non-separable filters. Bilateral filtering is the word employed to describe the combination of domain and range filtering.

$$h(\ ) = {}^{-1}(\ ) \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} (\ )\ (\ ,\ ) \qquad (1)$$

Where, the geometrical proximity among a nearby point and the neighborhood centre is measured by the expression

(,), the reality that output and input images may be multiband is highlighted by the bold typeface used for the letters and h. If the low-pass data is to be preserved via low pass filtering, the following equation is derived by,

$$( ) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (,) \qquad (2)$$

If thefiltering is shift-invariant,is constant, and (,)only depends on the vector differential (−). As a result, the nearness function currently runs in the domain of , while the similarity function continues to operate in the range of . equation. (2) Normalizing constant is changed by

$$( ) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (( ), ( ) \qquad (3)$$

The normalization function depends on the imagef, as opposed to the closeness function . if the mutual information function s only varies based on the difference ( ), ( ), and then it is impartial ( ). Bilateral filtering is the term used to describe the coupled domain and range filtering that ensures simultaneously geometric and photometric localization. The following is a description of combined filtering:

$$h( ) = \frac{1}{( )} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} ( ) (,) (( ), ( )) \qquad (4)$$

With the normalization,

$$( ) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (,) (( ), ( )) \qquad (5)$$

B. Data Augmentation

- Since the size of the initial data set is limited, data augment is necessary to address the problem of data imbalance.

- Data augment is the process of creating big training data samples by repeatedly deforming the data in the training dataset.

- Data augmentation's fundamental tenet is to ensure that the labels of additional data produced by performing deformations to previously labelled data remain unaltered.

- A number of ways to add information to an image, including rotating it in different directions—horizontally and vertically—adding noise, and changing the color of the image.

Algorithm 1 Data Augmentation Algorithm

```
Input: sp: Spectrogram
 Sr: Sample Rate
 bg: Background Noise
 tm: Time Shifting,
 bgnr: Background Noise Range
 tsh: Time shifting rate
Algorithm:
Initialize and assign input parameters (sp, bg, tm, bgnr, tsh)
sp = read_folder ('folder name/'+Filename');
    for i: = 1 to length (sp) do
        data = Read Spectrogram File (sp, Name);
        bg = add.random.bgnoise (data, bgnr);
        tm = Time. Shifting (data, sr * tsh);
        Write spectrogram (bg_noise.jpg.bg);
        Write spectrogram (time_shifting.jpg. tm);
    end for
```

The pseudo-code for the data augmentation technique is presented in Algorithm 1.

C. Feature Extraction

Color and texture are the two factors used to derive image features. Computing the mean is used for colour feature extraction.

The colour intensities standard deviation for each of the Blue (B) ,Green (G) and Red (R) colourr elements. Both the training and test image are used in the feature extraction procedure. For such verification process on the training sample, the value of the extracting features would be gathered in the database. For the test image, feature extraction results are compared with the similarity computation procedure. The Figure 2 illustrates the basic structure of GLCM.

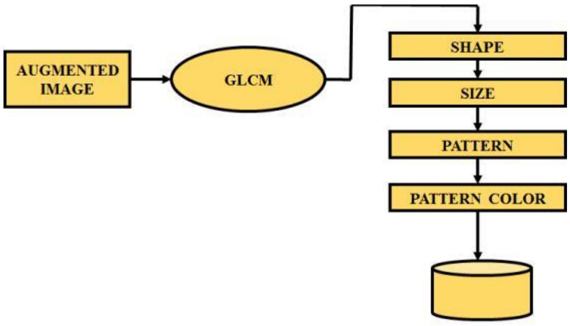

Fig.2. Structure of GLCM

A. GLCM

Among the second-order statistical techniques deployed to examine the textures in an image is called GLCM. The computation across linked two-pixel pairs from the source images makes up the second order in issue. GLCM is one alternative way to combine various grayscale values in a picture. Contrast, homogeneity, energy, correlation and entropy are some of the GLCM features that were used in this investigation. An integrated grayscale image with pixels spaced 1 with a modest angle of 0°, 45°, 90°, and 135° is calculated using GLCM. The GLCM extracting feature estimation formula is as follows:

1) Contrast

It is a measurement of the extent to which the image's pixel grey levels vary. A formula for calculating contrast is found in equation 6.

$$= \sum_{=1} \sum_{=1} [\;-\;]^2 \times \;(\;,\;) \qquad (6)$$

2) Correlation

It measures the linear relationship among the values of the grey levels of an image. The correlation calculation formula is equation 7.

$$= \sum_{=1} \sum_{=1} \frac{(\;-\;)(\;-\;)(\;(\;,\;))}{} \qquad (7)$$

Where,

μ = mean

σ = Standard Deviation

$$\mu i = \sum_{i=1}^{L} \sum_{j=1}^{L} i * GLCM(i,j)$$

$$\mu j = \sum_{i=1}^{L} \sum_{j=1}^{L} j * GLCM(i,j)$$

$$\sigma i = \sqrt{\sum_{i}^{L} \sum_{j}^{L} (i - \mu_i)^2 \; GLCM_{i,j}}$$

$$\sigma j = \sqrt{\sum_{i}^{L} \sum_{j}^{L} (i - \mu_j)^2 \; GLCM_{i,j}}$$

3) Energy

Is the total amount of colour consistency in an image, energy can be calculated using equation 8.

$$Energy = \sum_{i=1}^{L} \sum_{j=1}^{L} GLCM(i,j)^2 \qquad (8)$$

4) Homogeneity

$= {}^{1}\Sigma^{L}i=1\ \Sigma^{L}j=1$

It is the depending on GLCM

2) Standard Deviation closeness variation in

Utilized establish whether an image's colors are distributed. The formula employed for determining

the image. The homogeneity can be calculated using equation 9.

$$= \sum_{i=1}^{L} \sum_{j=1}^{L} \frac{(\ ,\ )}{1+|\ -\ |} \quad (9)$$

5) Entropy

Represent size of the grey level inconsistency in an image using GLCM's variable elements. Entropy can be calculated using equation 10.

$$= -\sum_{i=1}^{L} \sum_{j=1}^{L} (\ ,\ ) \log (\ ,\ ) \quad (10)$$

B. Feature Extraction of Color

The significant aspect of an image is its colour. The RGB colour space is used for most colour images. These three distinct colors that make up the image. The intensity of the pixels can be used to compute the colour features present in an image. The standard deviation and average colour of intensity on every colour elements were the colour attributes that were targeted in this investigation.

1) Mean Color ( )

Often used determine an image's colour depth range.

The equation to calculate the colour mean is equation 11.

$$= \sqrt{\frac{1}{1} \sum_{i=1}^{L} \sum_{j=1}^{L} (\ ,\ -\ )^{2}}$$

- Average depth of color.

D. TCNN Classification

TCNN is also known as by the name TransConvNet. It is a deep learning method that uses an input image and gives each entity in the image a value, allowing it to explore and identify more. Even TCNN are developed using neurons found in the human brain while bearing in mind the presence of the visual cortex in humans.. The figure 3 indicates the

(12) architecture diagram for suggested system. For the following reasons, TCNNs are preferred to other neural network architectures

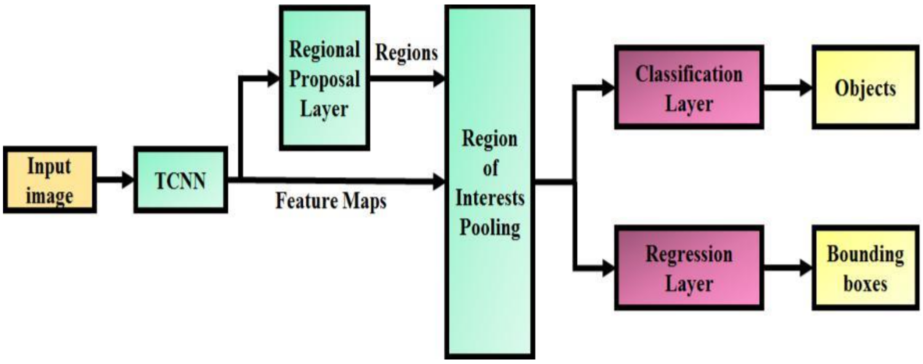

Fig.3. Architecture of TCNN

- Especially contrasted to other neural networks, TCNN need significantly less preprocessing.

- TCNNs are effective in extracting both spatial and temporal information from images.

- TCNNs' network can be modified to perceive the image's key elements. The proposed TCNN is demonstrated in figure 4.

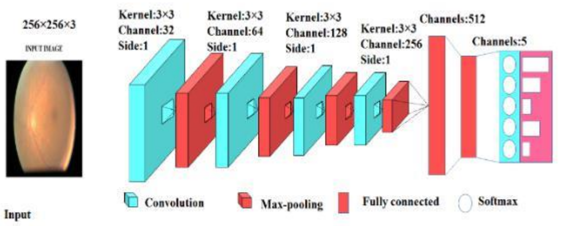

Fig.4. Proposed TCNN

The sophisticated features of deep learning methods used in the TCNN model's construction enable the platform to concentrate on its intended function without being adversely affected by imbalanced datasets. Since each neuron is coupled to every previous layer neuron, the TNN model fixes the input size receptive field volume size. This makes it nearly difficult to handle inputs with such high dimensions. Each neuron has a volume size of 5*5*3, which equates to 75 weights and 2 bias parameter. In TNN, variable sharing is taken into consideration to lower the overall amount of variables.

The categorization probability and corresponding labels are predicted using a TCNN approach. Targets for vessel identification are challenging to distinguish from the surroundings. With this concept, end-to-end real-time targets identification may be achieved by predicting the coordinates of the targets and classifying the objects simultaneously in moment in order to increase detection performance.

The following classes are included in the related ground reality segmentation images:

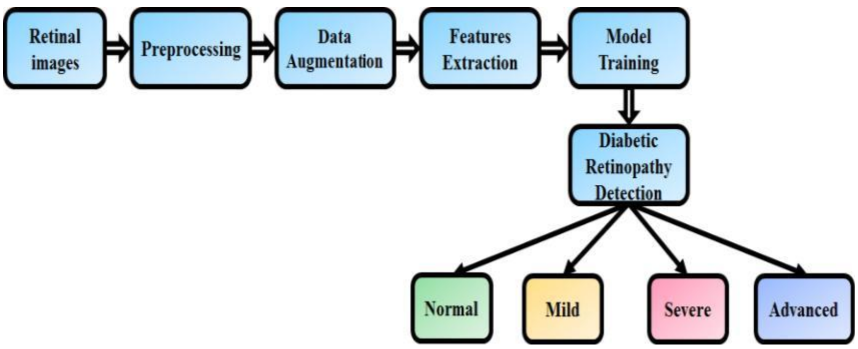

Fig.5. DR diagnosing network

By taking into account inputs from the Feature Network

and Regional Proposal Network, this diagnosing network aims at building the final bounding box. It has four completely connected layers, and the classification and bounding box regression layers are coupled to each other to provide the final detection of DR. Which is illustrated in figure 5.

III. RESULTS AND DISCUSSION

The suggested system implemented by using MATLAB platform to verify its performance.

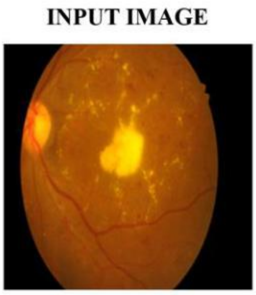

Fig.6. Image of Input

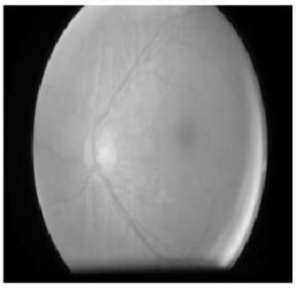

Fig.7. Gray Scale Image

Figure 6 shows the fundus input image. Likewise, figure 7 demonstrates that a collection of 256 ×256 8-bit grayscale images is utilized as the cover image for an augmented image.

Fig.8. Noise Reduced Data

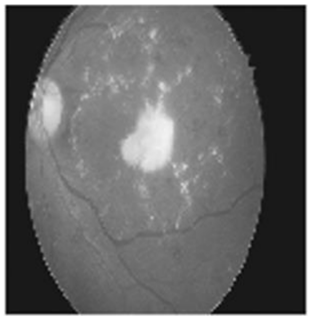

Fig.9. Filtered Image

With help of Bilateral filter, the amount of noise removed from the input image, which is indicated in figure

8, similarly, the figure 9 illustrates filtered image of suggested system.

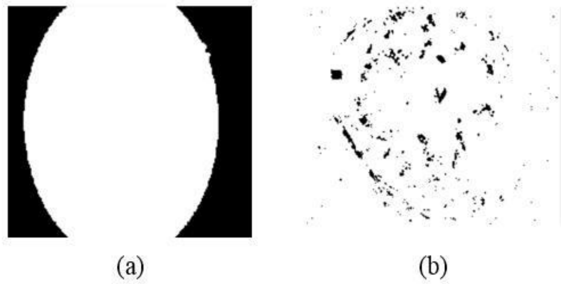

Fig.10. (a) Binary image and (b) Pattern

The figure 10 denotes the simulations results with binary image and binary pattern.

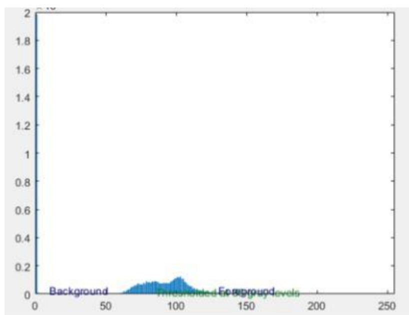

Fig.11. Histogram of original image

Figure 11 displays the image's grayscale histogram and the accumulated distribution function.

Table .1. Feature Extraction

Contrast	0.9736
Homogeneity	0.8805
Energy	0.4557
Correlation	0.9499
Entropy	3.2422

From the table representation, it is noted that the contrast, homogeneity, energy, correlation and entropy features are extracted by using GLCM method. The corresponding attained values are denoted in Table 1.

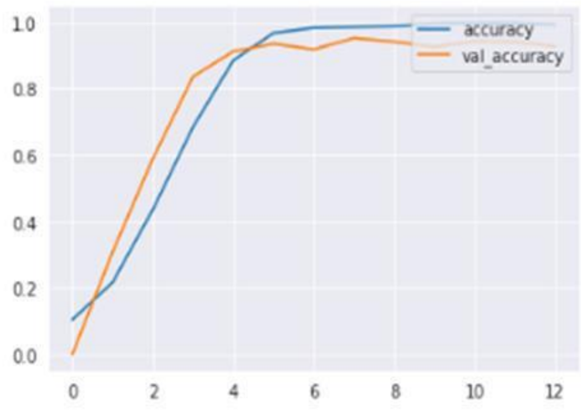

Fig.12. Accuracy of TCNN classifier

The TCNN classifier obtained highest accuracy of 97% that is illustrated in figure 12.

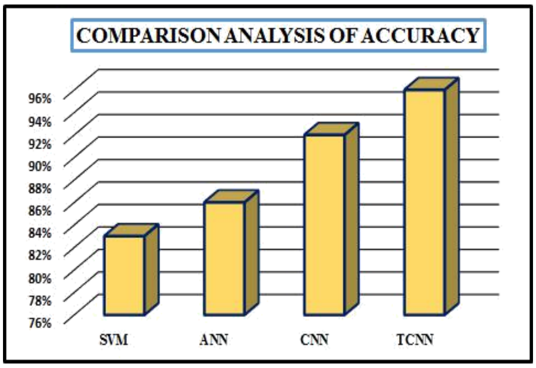

Fig.13. Comparison analysis

According to the graph representation, the proposed system outperforms in terms of accuracy 96%.Based on comparison with conventional approaches such as SVM, ANN, CNN, the proposed TCNN classifier produces the best results.

V. CONCLUSION

The most dangerous side effect of diabetes is diabetic retinopathy, which damages the retina and causes vision loss. The rear of the eye is damaged by excessive blood sugar levels, which is the causes of diabetic retinopathy (retina). As a result, fluid leaks from the retinal tissue's blood vessels, causing vision to be blurry. The main objective of this paper is to identify DR from human fundus images using the TCNN classification method. Bilateral filtering is done to reduce noise in the input image at the earliest stage of preprocessing. It is possible to extract the high ranked features using the GLCM method. Finally, the proposed TCNN can achieve 97% accuracy and is highly efficient compared to other methods.

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