International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Optimized CNN Model for Diabetic Retinopathy Detection and Classification

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Submitted:24/03/2023 **Revised:**27/05/2023 **Accepted:**12/06/2023

Abstract: Nowadays, retinopathy detection and classification is considered as most effective identification approach for many diseases. Moreover, Detection of veins in the retina is a significant perspective in the discovery of disease and is done by isolating the retinal veins concerning the fundus retinal images. Likewise, it yields the irreplaceable realities about the retina expected for the recognition of infections because of expanded glucose levels and pulse levels, which give prior distinguishing proof in retinal vessels. This assists with giving prior treatment to lethal illnesses and forestalls further effects because of diabetes and hypertension. In this paper, an innovative hybrid Strawberry-based Convolution Neural Framework (SbCNF) is designed to detect and classify the retinopathy disease from the retinal images. Different datasets are utilized to section theretinal veins. Here, DRIVE datasets are used as the entire execution. The execution of this research is done on the python platform. Moreover, this study provides the potential improvement in the retinopathy detection application. The implementation outcomes have been validated with the traditional classification models methods in terms of accuracy, precision, recall, F-measure, etc. The analysis demonstrates that the designed algorithm achieved the finest accuracy in retinopathy recognition due to its effective advantages like less computational complexity.

Keywords: *retinopathy detection; retinal veins; DRIVE datasets; Strawberry; accuracy; precision; recall; F-measure.*

1. Introduction

The medical image analysis is the technology for creating visual pictures of an inner body part for medical research and medicinal intervention [1], which has grown more common in the last decade. Many approaches are employed to confirm information regarding the body's function [2]. Many pictures can be taken each year for various diagnostic purposes all around the world. Without enveloping movements, this image analysis generates the visualization of the internal organization of the body [3]. Due to evolution of image processing approaches such as image exploration, image identification, and image augmentation, medical imaging should be developed fast[4]. This image analysis method was utilized to boost the percentage and number of identified images. This image processing was utilized to boost the percentage and number of identified images [5].

The medical image analysis deals with pictures and includes activities such as image acquisition, storage, transmission, and display [6]. Furthermore, digital pictures may be utilized for a variety of purposes, including low-cost processing, rapid, instantaneous quality evaluation, low-cost replication, and adaptive modification. The medical field states that the retinopathy Disease (CVD) was difficult to identify the stages. While using retinal image, the noise factors were released and it doesn't give the clarity output. The image processing made easier to diagnose the medical images [7]. The images were generally visual to view and also give the detailed clarification for each body parts. The retina is an extraordinary sort of photograph sensitive tissue-lined to the inside layer of the eye [8], which is the most evolved tangible organ of the human body [2]. The incident light sign is changed over to a neural sign and is then changed by the mind with the assistance of visual focuses and helps in vision [9]. Retinal veins are a piece of the focal retinal conduit [10], vein, and their branches. Any progressions in these retinal vessels as far as their geography are utilized to recognize a few irregularities,

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for example, expanded glucose levels [11], diabetic retinopathy [12], and surprisingly expanded circulatory strain [13].

Diabetic Retinopathy (DR) is an extreme instance of delayed uncontrolled glucose content [14] bringing about retinal vessel enlarging and may prompt visual impairment [15]. The steps involved in diabetic retinopathy classification is described in fig. 1. Usually, the estimation of disorders has higher priority than treatment in the medical field [16]. Consequently, it is critical to have a superior expedient and profoundly exact analysis framework [17]. The progression in advancing innovation clears the way for better arrangements as far as exactness and quick determination [18]. Ordinarily, X-beams are broadly utilized for bone visualization purpose [19] and to isolate the different kinds of tissues such as delicate and hard tissues from the bone image. Typically, the fundus cameras are deployed to capture retinal images [20]. These captured images by the fundus camera are termed as fundus pictures. This contains retinal images and numerical information regarding the retina [21]. Furthermore, this fundus picture is deployed to examine the retina level as sound or harmed [22]. These pictures have a colossal commitment to the distinguishing proof of various infections like vascular and non-vascular pathogenic criteria's [23].

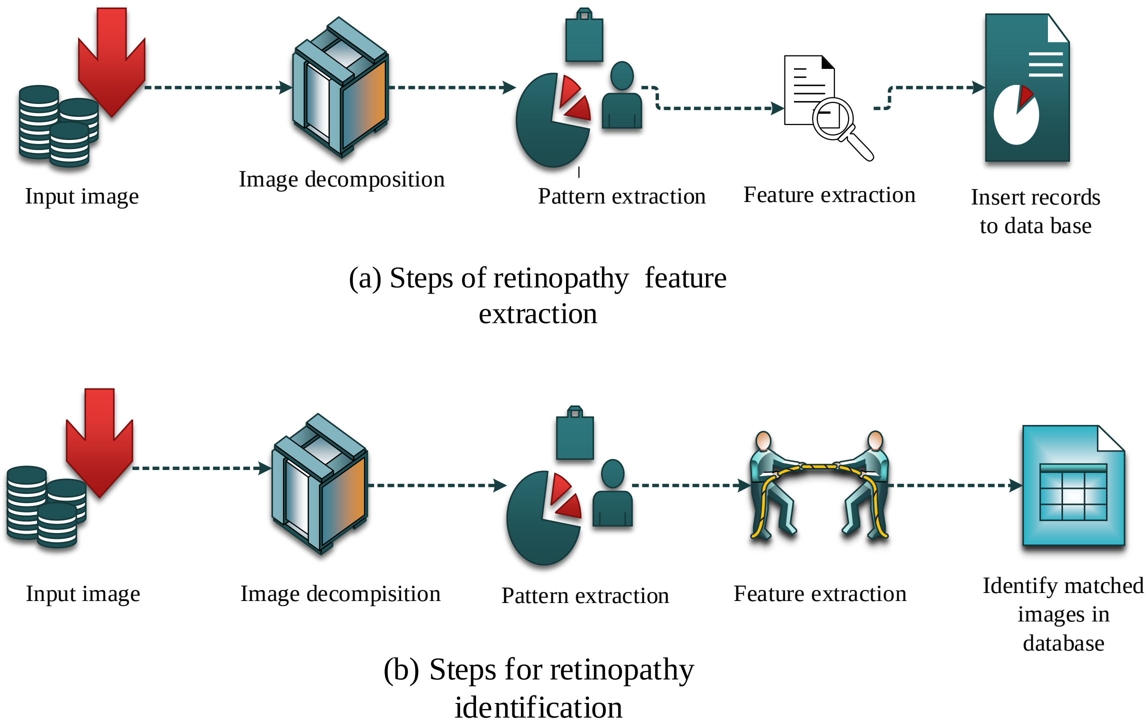


Fig. 1 Retinopathy feature extraction and identification

Finally, the structure of this paper is demonstrated at end of the introduction section. Section II demonstrates recently proposed techniques and their concepts. Consequently, section III explains the detailed structure of the system model and existing problems. Then, the designed classification methodology along with its detailed explanations is described in section IV. Section V illustrates the case study concept and the results are enclosed. Finally, the research article ends with the conclusion section VI.

2. Related Works

Recent literatures are summarized below,

Diabetic retinopathy detection and classification is the most significant analytical strategy for many of the retinal based disease. So, Mulagalasandhya *et al.*[24] has proposed a diabetic retinopathy model for ensample classifiers to detect the severity level. Here, large amount of data is taken as training purpose. Moreover, to enhance the image quality pre-processing and data augmentation models were used. In addition, synthetic images are taken for entire process. However, the existing problems cannot overcome this method.

Jude Hemanth *et al.* [25] has proposed a hybrid model named as deep convolution neural framework for examining the diabetic retinopathy from the collected retinal dataset. Moreover, this recommended hybrid model is efficiently utilizes both image processing and DL for enhanced outcomes. The main of this examination is to perform the detection process from the retinal vessels. Additionally, the convolution framework is used to perform the retinopathy classification.

Kanimozhi et al. [26] has developed the fundus image lesion detection strategy to analyse the diabetic retinopathy in an earlier stage. Here, diabetic retinopathy is detected based on the three different early stage symptoms such as exudates, hemorrhages and microaneurysms. Moreover, the newly developed framework contains four stages such as contrast improvement, removal, lesion detection and finally classification. In the extraction process principle component analysis is utilized. For the implementation net based datasets are used and performance metrics are evaluated.

Often, the retinal images-based vessel classification and detection is more challenging because due to the presence of pathologies. To reduce these issues, Qureshiet al. [27] introduced the Convolution based Adaptive DL (CADL) framework for preforming the mage segmentation. It is one of the supervised learning framework efficiently improve the image quality and execution speed. However, from the comparison false detection rate (FDR) is higher than other models.

Yuhan Zhang et al. [28] has developed the supervised twin self-learning approach for perform both labeled and unlabeled images. Here, the retinal vessels are categorized based on the pixel representations. The objective of this framework is to divide the blood vessels from the trained fundus database. Furthermore, supervised twin model is has attained better results. While utilizing large dataset then the accuracy is less.

3. System Model An Problem Statement

In the retinal imaging, the pixel worth of pictures is changed for the more straightforward investigation of the portioned retina. Most of the methodology of sectioning, the shaded pictures are changed over to monochrome and further changed over to bi-level pictures for simplicity of segmentation. Moreover, the segmentation technique applies the idea for retinal vessel segmentation [29]. It arranges the fragmentation cycle into the handling stage and order stage. By carrying out this methodology of segmentation, the commotion can be better decreased and the examples are fragmented plainly. The basic structure of retinal image fragmentation is illustrated in fig. 2.

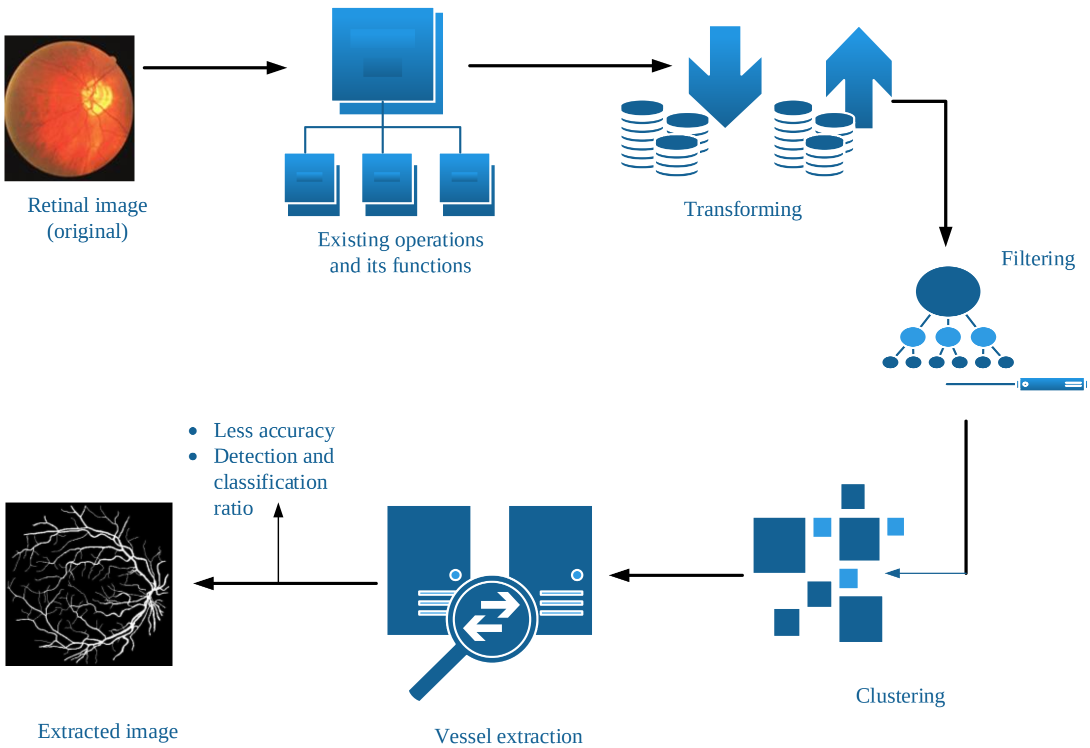


Fig. 2 Basic system model

Retinal Segmentation is the main indicative strategy for some sicknesses. Henceforth different strategies to improve the location exactness are utilized. This article shows an assessment of numerous techniques utilized for retinal vein fragmentation step. Additionally, the performances of these algorithms are examined with publically available databases namely: DRIVE, STARE, and CHASE_DB1 [30]. Also, this cycle is grouped into different categories in view of the principles utilized for the separation of veins further orders are made relying upon the procedures utilized for the segmentation.

4. Proposed Methodology

Retinopathy is the classification of malignant disease, which is easily, affects the both men and women. Based on these problems the affected people can loss the vision capability an small age. To identify and classify the retinopathy disease in an earlier stage is the most essential section since lacking of affected part tracking is incredible. Therefore, Novel Strawberry based convolution Neural Framework (SbCNF) is proposed.

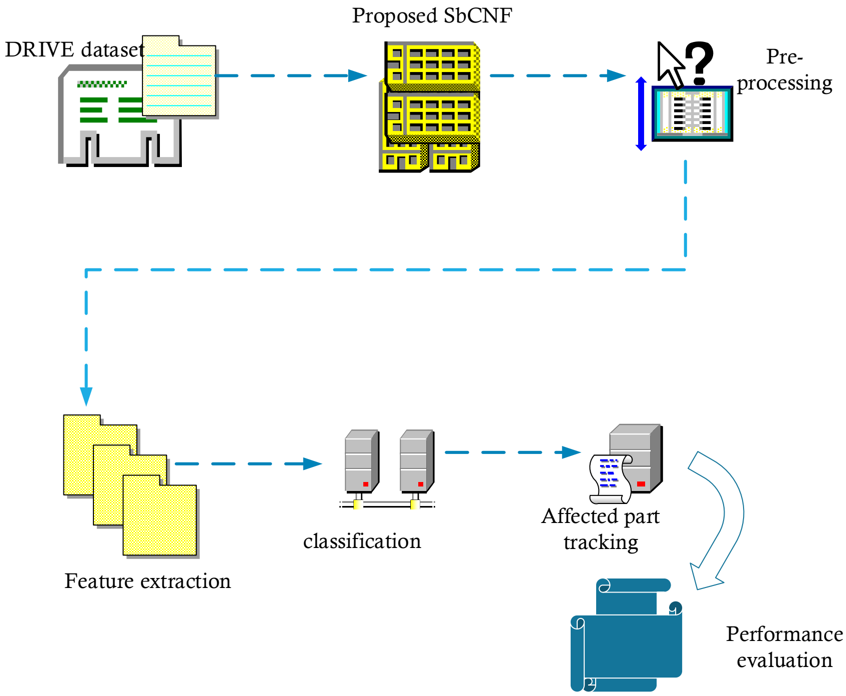


Fig.3 Proposed architecture

Firstly, the retinal images were taken DRIVEdataset, which identify the disease better. Due to the patient's blood circulation, eye blink were induced in DRIVE dataset. So that noisy retinal images are obtained. The outputs were classified as the high prediction error, low image quality and lower disease accuracy classification.

4.1 process of proposed SbCNF technique

- ***Pre-processing***

Initially, the collected SRIVE datasets are set up for pre-processing and standardization. This involves, removing data from the larger database and splitting it into various subsets for various purpose, and combining the classified subsets to apply the pre-processing algorithm. Moreover, Pre-processing strategy that changes large amount of dataset into a reasonable arrangement for the purpose unwanted case removal. Here, real-world dataset is dependably fragmented and that information can't be sent through a model because it affects the entire model. Here, convolution kernel function is used for pre-processing stage. Convolution kernel function is expressed in following eqn.(1),

$$g(t) = p(t).q(t) \quad (1)$$

Where, $p(t)$ is represented as input dataset and $q(t)$ indicates the kernel operation and t is the total of datasets are taken to the entire process. Then, the eqn.(1) can re-written as following eqn.(2),

$$g(t) = \sum_{t=-\infty}^{t=\infty} p(t)\,q(t-\tau) \quad (2)$$

For this reason, pre-processing is very important prior to sending it through a proposed model. Moreover, dataset cleaning and changing is the common steps, that are used to eliminate exceptions and normalize the datasets so they take a structure that can be effortlessly used to make a model.

- ***Max-pooling***

Typically, in image processing application, feature engineering has named the course of dimensionality decrease in view of the dataset attributes. Here, the pre-processed dataset is isolated and diminished to more reasonable information that is significant for recognition and grouping. Furthermore, the course of feature extraction further develops the precision while removing the features from the info dataset. Moreover, max-pooling operation is combined with runner fitness function of the strawberry algorithm. Here, the feature extraction process that is mentioned in eqn. (3),

$$F'(e') = \frac{g'(d'_n)}{P\,(d'_n)} \qquad (3)$$

Here, $g'(d'_n)$ represents the grey scale value of each retinal image and $P\,(d'_n)$ defines the pixel range of each pre-processed data. Feature engineering aims to minimize the number of attributes available in the dataset by extracting the optimal or more relevant attributes. This involves the process of creation of the new features and disposal of the current attributes. These new diminished arrangement of features should then have the option to sum up the majority of the data contained in the first arrangement of features.

- ***Softmax for classification***

Softmax operation mainly is considered for the classification process, which is classified using the following eqn. (4),

$$f'(m') = Arg\_s\_\max_i z'(h' =| m') = Arg\_s\_\max_i \frac{e'^{\bar{m}y_k}}{\sum_{u=1}^{N'} e'^{\bar{m}y_v}}$$

(4)

Where N' is the class numbers, the weight vector is represented as y', z' is the label variable, the features of sample is denotes as m' and the label of class is represented as *i*, respectively. Consequently, after completing the feed-forward separation the error rate can occur with the function of loss. Thus, the trained network is used to classify the activities.

- ***Detection (affected part tracking)***

From the beginning, retinopathy disease has regularly ended the eye and their association in the pieces of retinal images. Besides, the retinal is the most impacted locale of the retinopathy sickness. Impacted part following contains three stages like feature extraction, division and grouping. Area following advances is finished with the assistance of enhancement wellness work and neural structure. Moreover, internal operation of CNF is demonstrated in fig.4

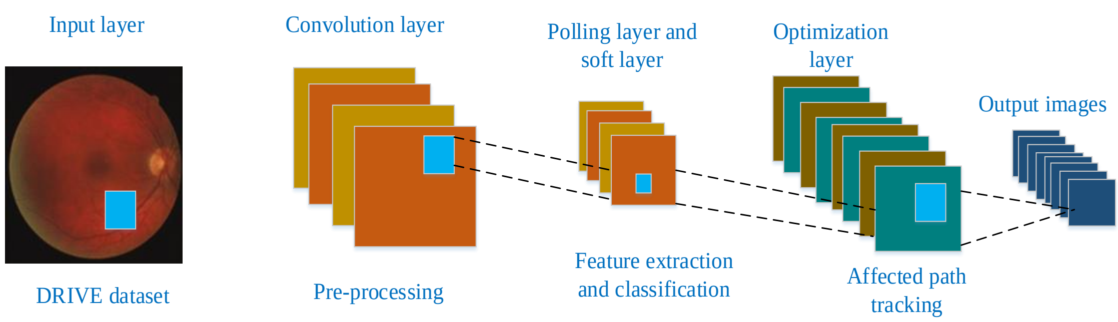


Fig.4 Internal operation of CNF

Here, the runner fitness of the max-pooling operation is expressed following eq.(5),

$$Y'(n) = \{Y'_{runner} * Y'_{runner}\} + \{D'_{runner}.(Y') * D'_{runner}.(Y')\}$$

(5)

Where, Y' is the feed forward function, Y'_{runner} is the runner fitness of the strawberry function and D'_{runner} is runner fitness s mapped to the max-pooling function to extract the images.Internal structure of proposed neural framework is illustrated in fig. 2.

Algorithm.1: Process of SMCM
Input: *DEIVE dataset*
Start
{
// initialize the dataset
$\text{int}(D)$ ***// initialize the dataset***
// dataset training performance

for $(i = 1,2,3.......n)$ ***// number of datasets***

end for

// pre-processing at convolution layer

testing DEIVE dataset for $(i = 1,2,3.......n)$ ***//input layer***

Dataset cleaning and unwanted information removed ***//convolution layer***

// Feature extraction at polling layer

Extract the retinal images // ***pooling layer***

Classification at softmax function ***//dense layer***

$f'(m')$ ***= arg function*** ***// classification and segmentation***

end

Affected part tracking *//* ***output layer***

Output best solution

}

Stop

5. Results and Discussion

In this article, an efficient SbCNF technique is developed to detect and classify the retinopathy disease from the retinal images. In addition, the performance of the designed classification model was evaluated using the DRIVE database. Here, this database was trained based on the original retinal images. Moreover, the efficient and successful detection and classification is done on the classification layer of the neural networks. Hereafter, the retinal blood images are extracted and continuously improve the output pixel resolution.

5.1 Case study

Retinal image investigation is acquiring unmistakable quality in current ophthalmology process because of its non-intrusive analysing technique. From retinal picture examination and morphological optical circle investigation and blood vessels, different irregularities like diabetic retinopathy, glaucoma, and hypertension can be analysed. Early indications of diabetic retinopathy can be determined to have the identification of the injury in the retina. The visualization of normal and diabetic retinopathy is shown in fig.5. Generally, the early identification of disorder is more significant than treatment process. Therefore, developing an accurate and early disease identification framework is important for proper treatment process.

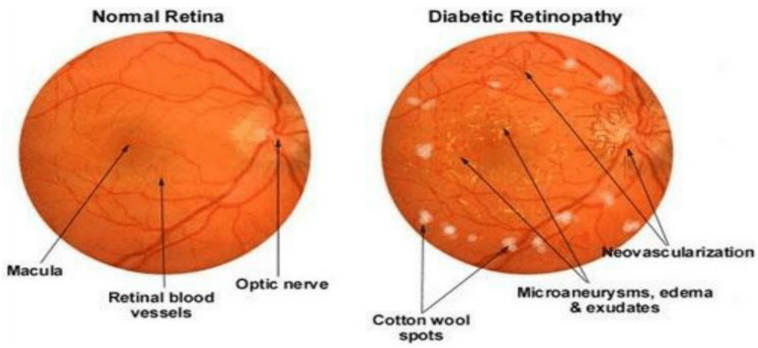


Fig.5 Normal and diabetic retinopathy

The DRIVE database is the most commonly utilized dataset for retinopathy detection and classification. It contains an assortment of 40 shaded fundus pictures, in which 33 images are without diabetic retinopathy and the remaining images are with mild diabetic retinopathy. Here, the ordinary CR53-CCD camera was deployed to trap the fundus images present in the dataset.

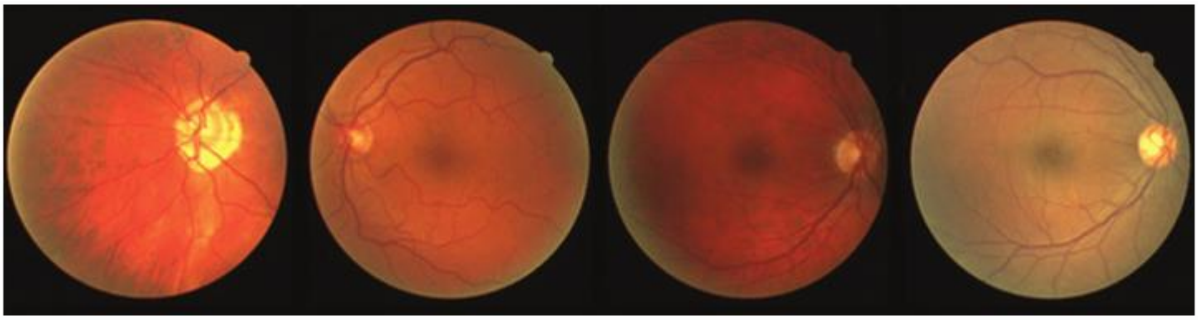


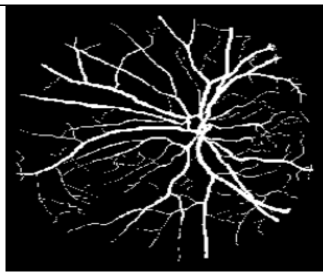
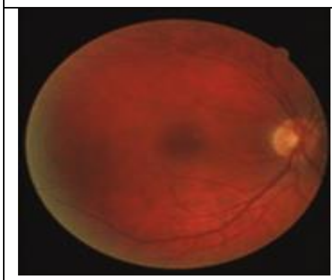
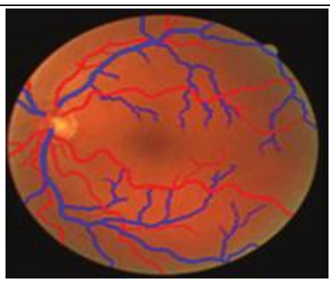
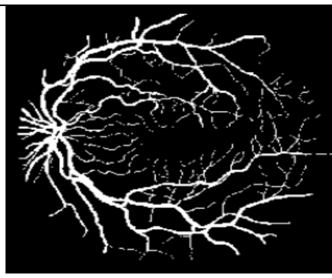
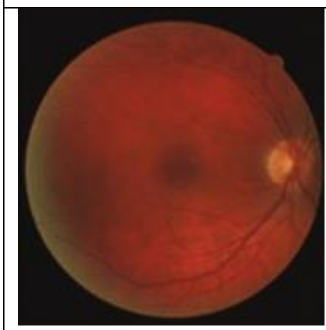
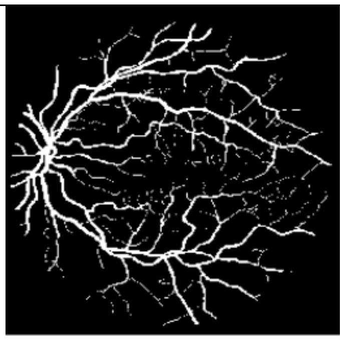
Fig.6 drive dataset

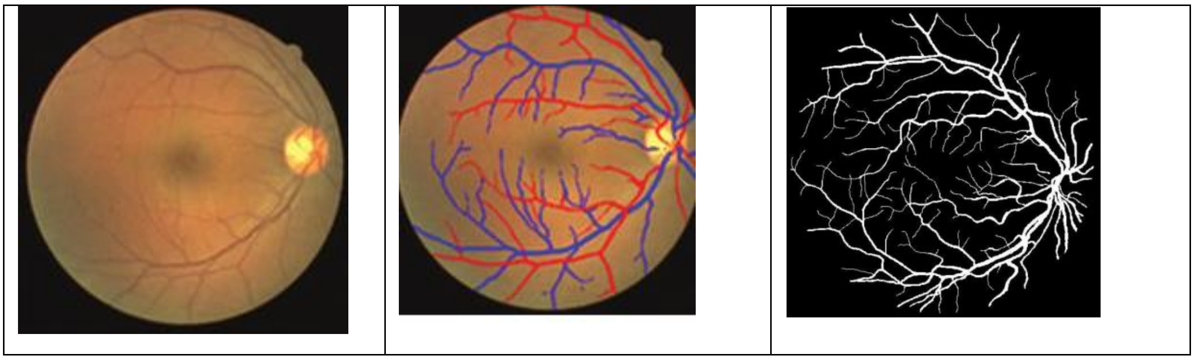
The camera utilized to collect the retinal images is of 8-bits and the pixel proportion is 768*584. The DRIVE dataset is characterized into two major groups: one as testing set and the other as preparing set to enlighten. There are about 20 images available in both preparation and test sets.

Table.1 Dataset description

Database	**Number of available images**	**Normal image**	**Image with abnormality**	**Type of Camera used**	**Pixel resolution**
Drive	100	75	25	Topcon-50	700*605

Table.2 segmented retina images

Original images	Affected part tracked	Ground truth image
		
		
		



The classification of normal and abnormal retinal images is assessed by contrasting the image pixel-by-pixel with the ground truth image. Further, to denote that the pixels are grouped accurately the variables (true positive [TP] and true negative [TN]) are used or to denote the error grouping the parameters (false positive [FP] and false negative [FN]) are utilized. TP pixels are the pixels, which has features like retinal vessels, optic circle, macula, fovea, or exudates. TNs are the pixels, which has normal eye image features. FPs is pixels misclassified as normal eye features. FN pixels are those, which are inaccurately identified as abnormal attribute. The retinal image [24] is displayed in table.2.

5.2 Performance evaluation

The proposed technique implementation is done using python software tool and attaining all the results from that software. ML based capsule network (ML-CN) [31] strategy, adaptive ML classification (AML) [32], multipath CNN (MCNN) model [33], DL-SVM [34].

5.2.1 Accuracy

Accuracy of the proposed SbCNF methodology is estimatedbased on the efficiency of the entire system performance such as detection and classification. In other hand, accuracy is called as ratio between correctly predicted and classified non-vessel pixel values to the whole pixel values. Moreover, accuracy calculation is using following eqn.(6),

$$A'_{cc} = \frac{T_p^* + T_n^*}{T_p^* + F_n^* + T_n^* + F_p^*} \qquad (6)$$

Where, T_p^* states the true positive range of the identification and classification of the non-vessel pixel values, T_n^* defines the true negative range of the identification of the non-vessel pixel values. Consequently, false positive range of the inaccurate detection and accurate classification of the non-vessel pixel values are represented as F_p^*, F_n^* refers to the false negative range of the misclassification of the non-vessel pixel values. Furthermore, comparative assessment of the model accuracy is demonstrated in fig.7.

Table.3 Accuracy comparison

Sl.no	Approaches	Accuracy (%)
1	ML-CN	98.64
2	AML	82.7
3	MCNN	90.56
4	DL-SVM	80
5	Proposed SbCNF	99

To evaluate the classification efficiency of the designed framework, it is compared with conventional segmentation methods like ML-CN, AML, MCNN and DL-SVM. Moreover, the ML-CN earned accuracy of 98.64% and the AML model gained 82.7%. Furthermore, the existing MCNN approach achieved 80% of accurate classifications. Moreover, the conventional DL-SVM earned 77% accuracy. However, the designed classification framework achieved greater accuracy of 99%, which is greater when compared to the accuracy of the traditional models and the comparative accuracy performance is tabulated in table.3.

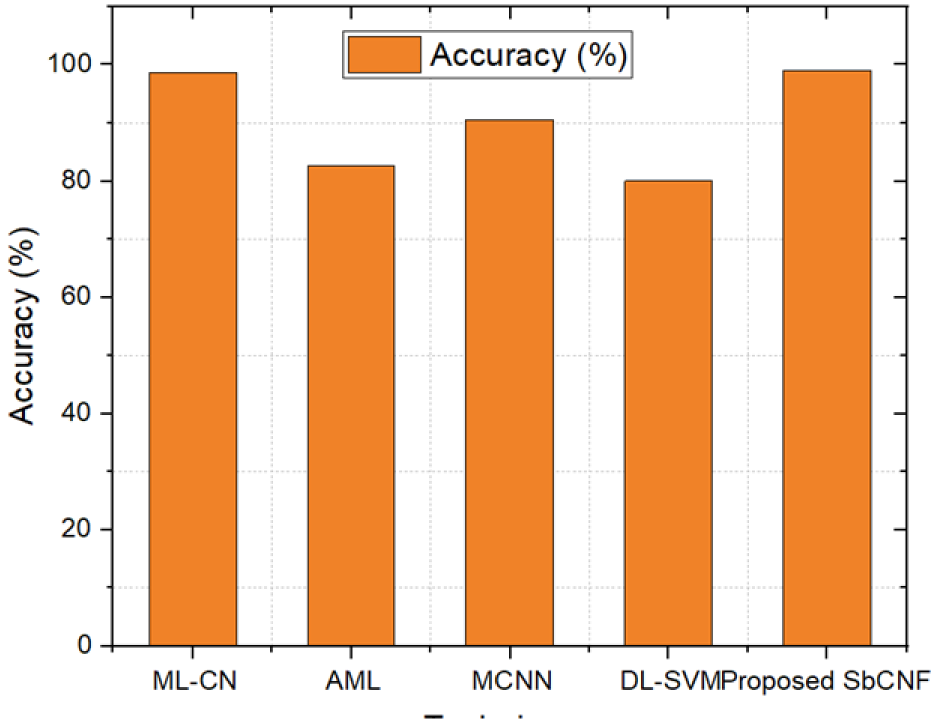


Fig.7 Graphical representation of accuracy

5.2.2 Precision

Precision measure is the process for detecting the number of accurate positive pixel values are classified and detected by the whole positive pixels values. Otherwise precision is the ratio of precise retinal affected part, and it is formulated in eqn.(7)

$$P_r' = \frac{T_p^*}{T_P^* + F_p^*} \tag{7}$$

Here, the precision percentage was quantified based on the predicted and retinopathy disease available in the input retinal images. In addition the developed SbCNF is attained the precision rate as for,

Table.4 Performance comparison of Precision

Sl.no	Approaches	Precision (%)
1	ML-CN	92.98
2	AML	93
3	MCNN	89.8
4	DL-SVM	78.67
5	Proposed SbCNF	98.2

The gained performance of developed SbCNF framework is validated with conventional classification methods like ML-CN, AML, MCNN and DL-SVM. Moreover, ML-CN technique attained precision is 92.98% and AML technique gained 93% in precision. Furthermore, MCNN method attains 89.8% in precision and DL-SVM technique gained 78.67% in precision but the developed SbCNF technique attains high performance in precision as 98.2% is demonstrated in fig.8 ad table.4.

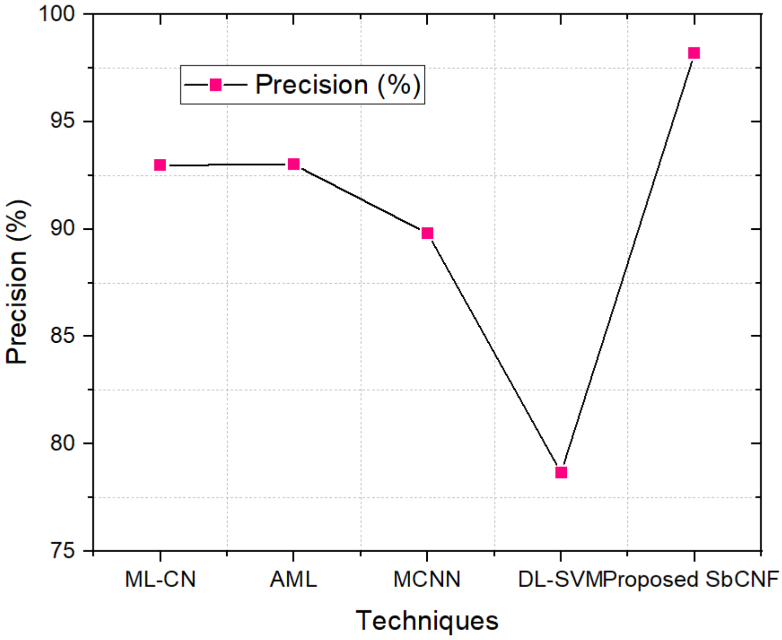


Fig.8 Graphical representation of precision

5.2.3 Sensitivity

Sensitivity alludes to an analysing capacity to assign a person with the retinopathy disease as positive is mentioned in eqn. (8). An exceptionally sensitivity test truly intends that there are not many bogus adverse outcomes, and along these lines less instances of the disease are neglected. Generally, high sensitivityexamination having low specificity. Moreover, they are really great for contracting real instances of the retinopathy disease; however they likewise accompany a genuinely high pace of bogus up-sides. A test with a responsiveness and particularity of around 90% would be considered to have great demonstrative execution retinopathy disease tests can perform at this level.

$$S'_n = \frac{t_p^*}{t_p^* + t_n^*} \tag{8}$$

Table.5 Sensitivity validation

Sl.no	Methodologies	Sensitivity (%)
1	ML-CN	94.18
2	AML	96.37
3	MCNN	93.11
4	DL-SVM	94.39
5	Proposed SbCNF	98.87

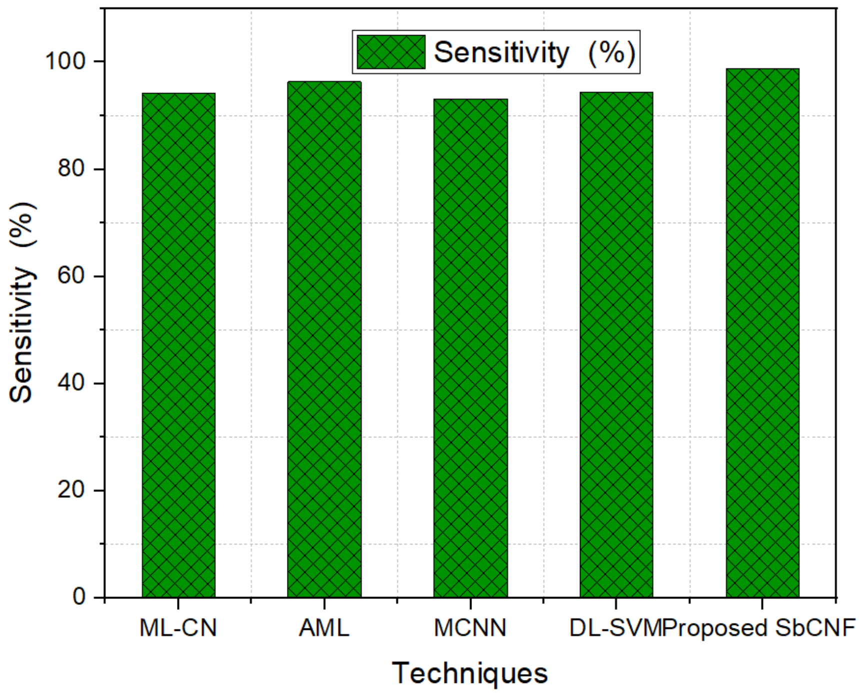


Fig.9 Graphical representation of sensitivity

The designed classification approach achieved greater sensitivity percentage of 98.87%, which is shown in fig.9 and table.5. Concurrently, the existing approach ML-CN attained a sensitive rate of 94.18% AML pertained sensitivity rate as 96.37% and MCNN gained 93.11% of sensitivity measure. Moreover, DL-SVM has attained sensitivity rate as 94.39%.

5.2.4 Specificity

Specificity is referred as the capacity of an assessment to accurately detect the patients without the retinopathy disease. Here, if the person has retinopathy disease it is recognized as true positive and the person does not having retinopathy disease, it is examined as true negative.

$$S'_p = \frac{t_n^*}{t_n^* + f_p^*} \tag{9}$$

The explicitness is determined as the quantity of non-infected accurately arranged partitioned by all non-diseased people. The specificity rate is also defined as True Negative Rate (TNR) of the extent of individuals without the illness who will have an adverse outcome. Moreover, it represents how exactly the designed model identifies the normal image.

Table.6 Performance comparison of Specificity

Sl.no	Techniques	Specificity (%)
1	ML-CN	92
2	AML	96.37
3	MCNN	95.34
4	DL SVM	78.59
5	Proposed SbCNF	98

Moreover, the specificity of ML-CN attained 92%, and AML achieved 96.37% in specificity rate. Moreover, the MCNN technique has gained 95.34% in specificity rate, and DL-SVM replica has achieved 78.59%. Also, the proposed SbCNF replica has achieved 98% in specificity rate. The developed replica gains a high rate in specificity compared to the existing method, and the validation of specificity percentage is demonstrated in fig.10 and table.6

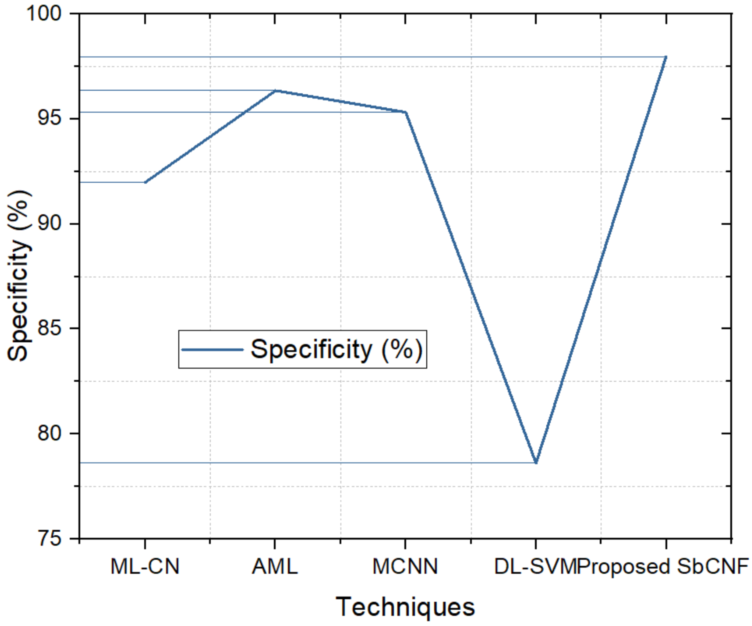


Fig. 10 Graphical representation of specificity

5.2.5 F-1 measure

F-1 measure is the most significant metric, which is efficiently detected and classifies the retinopathy disease from the retina images. In addition, F-1 measure is otherwise called as f-1 score. It is the tradeoff between a precision and recall rates of the retinopathy detection and classified rages. Here, recall is maintained based on the specificity and sensitivity of the each retinal pixel.

$$F_1'(s) = \frac{2*[t_p^*]}{2*[t_p^* + f_p^* + f_n^*]} \tag{10}$$

Table.7 F-1 measure evaluation

Sl.no	Methods	F-1 measure (%)
1	ML-CN	96.35
2	AML	90.23
3	MCNN	89.44
4	DL SVM	82.37
5	Proposed SbCNF	99.5

To verify that the designed SbCNF achieved greater efficiency, it is evaluated with some traditional classification approaches like ML-CN, AML, MCNN and DL-SVM. ML-CN is achieved 96.35% of F-1 measure, MCNN attained 89.44% as the F-1 measure, DL-SVM has attained F-1 measure rate as 82.37% and the AML technique attained 90.23% F-1 measure. But the designed classification model earned the F-1 measure rate of 99.88%, for particular datasets and the values are enclosed in Table.7 and fig.11.

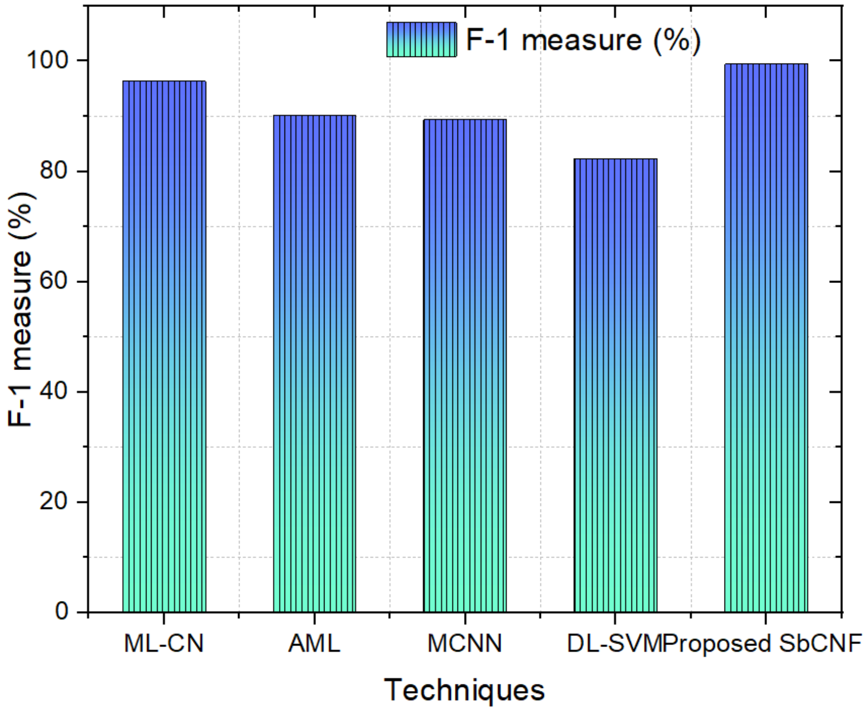


Fig.11 Graphical representation of F-1 measure

6. Conclusion

Retinopathy detection and classification is a significant role in identifying the abnormalities in eye, which helps the healthcare units for better treatment process. The retinal vessel segmentation enables to predict the level of pathogenic infection in the eye. In the present study, the DRIVE datasets are used to classify retinal blood vessels. Previously, many datasets are also applicable but the publically available datasets like DRIVE, STARE, and CHASE_DB1 proved to be more efficient and provided better outcomes. Moreover, the importance of retinopathy detection and classification diagnosis is discussedbased on the SbCNF technique. Various methods available for retinal segmentation but the accurate solution is not found. The outcomes of the developed classification approach were examined regarding sensitivity, specificity, and accuracy. From the intensive result analysis, it is proven that the retinal vessel segmentation algorithm with the neural network based methods proved to have a good performance. So, in the future, a neural network based method implemented with a machine learning technique incorporated with the anotherdataset will provide a better disease diagnosis at an earlier stage resulting in better pathogenic treatment.

Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interest.

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

Informed consent does not apply as this was a retrospective review with no identifying patient information.

Funding: Not applicable

Conflicts of interest Statement: Not applicable

Consent to participate: Not applicable

Consent for publication: Not applicable

Availability of data and material:

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Code availability: Not applicable

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