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Deep and handcrafted feature supported diabetic retinopathy detection: A study

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Abstract

The eye is the prime sensory organ in physiology, and the abnormality in the eye severely influences the vision system. Therefore, eye irregularity is commonly assessed using imaging schemes, and Fundus Retinal Image (FRI) supported eye screening is one of the ophthalmological practices. This work proposed a Deep-Learning Procedure (DLP) to recognize Diabetic Retinopathy (DR) in FI. The proposed work presents the experimental work with different DLP methods found in the literature. This work is executed with two modes; (i) DR detection using conventional deep-features and (ii) DR discovery using deep ensemble features. To demonstrate this work, 1800 fundus images (900 regular and 900 DR class) are considered for the assessment, and the advantage of proposed plan is confirmed using various performance metrics. The experimental outcome of this study confirms that the AlexNet-based detection provides a better detection (>96%), and the deep ensemble features of AlexNet, VGG16, and ResNet18 provide a detection accuracy of >98% on the chosen FRI database.

Keywords: Eye abnormality; Diabetic retinopathy; Fundus imaging; Deep-Learning; Classification.

1. Main text

The occurrence rates of AAD are gradually rising in the elderly, and the appropriate diagnosis and treatment are essential to cure the disease with suitable medication [1]. The report of the WHO confirms that diabetes is a primary reason for blindness, kidney malfunction, heart attacks, stroke, and lower limb elimination.

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Early detection and treatment will help individuals to have the appropriate medication and guidance to reduce the impact of diabetes [2]. This report also confirms that; nearly 422 million individuals have diabetes globally, and among them, the majority of citizens live in low/middle-income nations Furthermore, this report verifies that around 1.5 million reported deaths are recognized with diabetes annually. Currently, infection and death rates have been progressively rising due to various causes [3]. Therefore, early detection and treatment is the possible option.

The report confirms that diabetes will cause blindness in humans, which is higher in the elderly than in adults. Due to its significance, many diabetes screening procedures are performed with the help of retinal images [4,5]. Therefore, retinal image modalities, such as FRI and OCT, are commonly adopted in ophthalmology to detect retinal abnormalities. Compared to the OCT, the FRI is widely considered due to its simplicity and reputation; further, the FRI is available in RGB scale images and can be quickly recorded using a Fundus camera. In addition, the visibility of the retinal sections, such as the macula, blood vessels, optic-cup, optic-disc, and other infections, are more evident in FRI compared to the OCT.

Due to its significance, researchers proposed many FRI examination methods to detect various retinal diseases [6,7]. DR screening with FRI is a standard clinical procedure, and various methods are discussed in the literature to classify FRI into Healthy/DR classes using conventional and CNN methods [8-10]. This research aims to develop a DLS to sense DR on FRI. The work proposed in this research involves; (i) Preliminary processing, (ii) DF mining, (iii) Binary classification with conventional DF, (iv) Classification with EDF, and (v) Performance evaluation and validation. The proposed scheme implemented 5-fold cross-validation to justify the obtained results.

This research considers the pre-trained DLS, like AlexNet, VGG16, and ResNet18, for the examination. The experimental outcome is separately presented for; (i) Conventional DF and (ii) EDF using classifiers like SM, DR, RF, KNN, and SVM with linear kernel. The experimental investigation is implemented in Python®, and the results are presented and discussed.

The significant contributions of this research include;

(i) Examination of the DR from FRI using pre-trained DLS, like AlexNet, VGG16, and ResNet18
(ii) Accomplishment and justification of the performance of EDF-based DR detection

Other research divisions are prearranged as follows; Section 2 discusses the context, Section 3 demonstrates the methodology, Section 4 presents investigational answer, and the conclusion is discussed in Section 5.

2. Context

The eye is the chief internal organ, and the abnormality in the eye severely affects vision. The retinal abnormality due to diabetes is a severe issue, and early detection and treatment are essential to reduce its impact. In recent years, researchers have discussed many FRI screening procedures, and a summary of a few chosen techniques is discussed in Table 1.

Table 1. Summary of FRI screening methods to detect retinal abnormalities

Reference	Executed scheme
Kadry et al., [11]	Pre-trained DLS based detection of retinal abnormality using FRI is discussed and this work implemented a binary classifier to classify the images into healthy and disease groups
Rajinikanth et al., [12]	This work employs the handcrafted features based assessment of the retinal abnormality in FRI with binary classifiers
Kaushik et al., [13]	Implementation of staked DLS is discussed to detect the DR in FRI of chosen dimension
Alyoubi et al., [14]	DLS based DR detection and diabetic lesion localization is presented using FRI
Zhang et al., [15]	This work proposes a novel predict the happening of tyoe-2 diabetes and kidney infection

	using the clinically collected FRI.
Li et al., [16]	This work implemented a DLS for detection of retinal exudates and drusen in ultra-widefield FRI.
Saravanan et al., [17]	Glaucoma detection in FRI using the DLS based auto encoder is presented in this work.
Zhang et al., [18]	This work presents a detailed procedure to distinguish the harsh DR in FRI using the pre-trained DLS.
Atwany et al., [19]	A detailed survey on DR detection from retinal image and DLS is presented and this confirms the merit of the FRI compared to other image modalities.
Li et al., [20]	A comprehensive review on DR detection is presented using the pre-trained and customary DLS and this work confirms the merit of the FRI compared to other retinal images

Table 1 presents the CNN scheme-based examination of the FRI to detect the retinal abnormalities. In this work, DR screening with FRI is presented using the conventional and EDF, and the obtained results with binary classifier are verified. The experimental result of that study confirms that this framework provided >98% accuracy.

3. Methodology

Automatic disease examination using the clinical images is commonly performed in hospitals, and the outcomes depends on the methodology and the quality of the clinical images. In this work, the DLS-based examination of the FRI is discussed, and the plan of this scheme is presented in Figure 1. Initially, the retinal of the volunteer is recorded using the Fundus camera, and after collecting the necessary image, it is then resized to $227\times227\times3$ (for AlexNet) and $224\times224\times3$ (for VGG16 and ResNet18). The necessary deep features of dimension $1\times1\times1000$ is then extracted from the FRI using the chosen DLS and these features are utilized during classification. The necessary information on the EDF can be found in [21]. The chosen scheme helps to group the test images into healthy/DR class using a binary classifier. The proposed scheme helps to get improved performance measures.

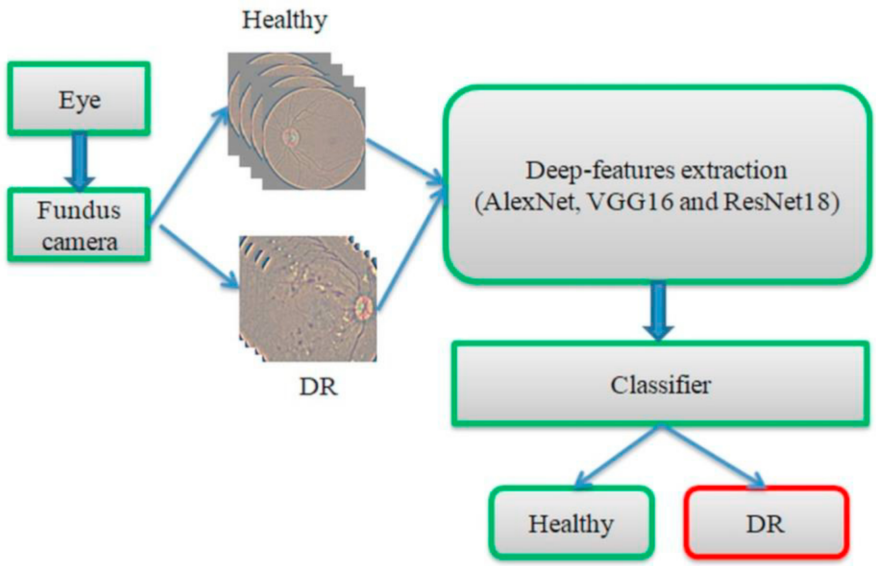


Fig 1. Block diagram of the proposed DR detection method

3.1. Image database

Availability of the clinical-grade medical images is essential to justify the clinical significance of the proposed scheme on authentic hospital images. Therefore, the necessary imagery is collected from [22], and the collected images are grouped into healthy (900 images) and DR (900 images) classes. In this work, 750 images are considered to train and test the DLS, and 150 images in each case validate the DR classification performance using a 5-fold cross-validation, and the results are presented. The considered database is in RGB form (Figure 2), and the collected images are resized and used based on the DLS adopted to extract the DF of images.

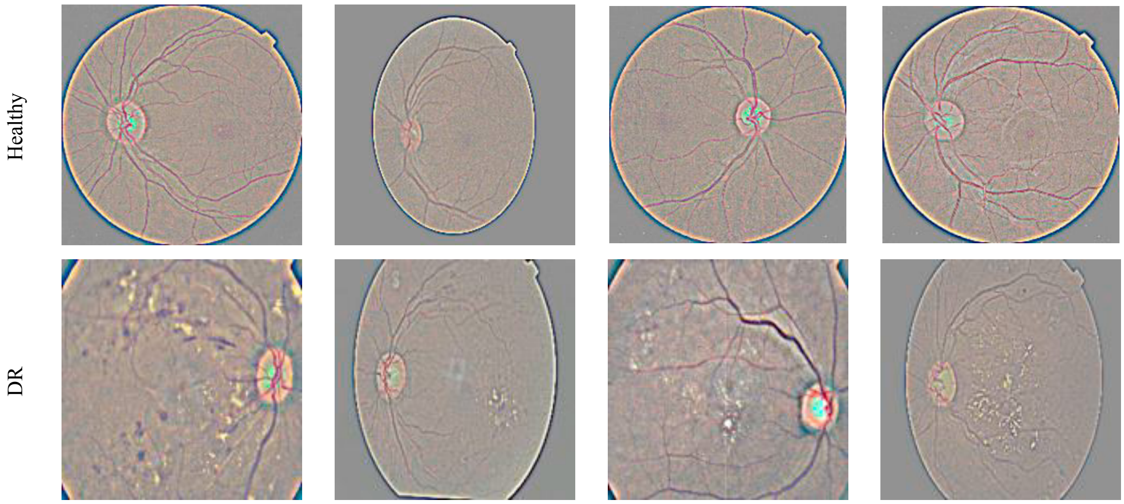


Fig 2. Sample images of the chosen FRI database

3.2. Ensemble of deep-features

The conventional approach supported disease detection with traditional DF is a standard procedure in the literature. The work of Kundu et al. (2021) [21] confirms that the EDF-supported medical image evaluation presents a better result than other methods. Hence, the proposed work considers the EDF scheme to classify the FRI into the Healthy/DR class. The averaging scheme is implemented in this work to get the necessary feature vector to achieve better disease detection. The proposed scheme combines the feature vectors of AlexNet, VGG16, and ResNet18 to get a single attribute vector of aspect $1\times 1\times 1000$; which is then considered to classify the FRI. In every DLS, the initial parameters are assigned as follows; Image augmentation to improve the number of test images of the database, Initial weight= ImageNet, Batch value=8, Epochs=150, Optimizer=Adam, Pooling=average, Monitoring metric= Accuracy and Loss, Classifier=SoftMax.

Let, every DLS (AlexNet, VGG16 and ResNEt18) helps to provide a attribute vector of aspect $1\times 1\times 1000$ and this feature vector is then considered to find the EDF by implementing an averaging technique. Proposed scheme helps to improve the feature vector and provides better classification accuracy.

3.3. Performance metric

The binary classification task is initially executed with the SM, and other methods, like DT, RF, KNN, and SVM, are adopted. In each automatic illness discovery system, the merit of the executed method is verified based on its detection accuracy. Normally, the accuracy can be computed using Eqn. (1) and the other metrics are presented in Eqns. (2) to (4) [23-25].

$$Accuracy = ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = PRE = \frac{TP}{TP + FP} \tag{2}$$

$$Sensitivity = SEN = \frac{TP}{TP + FN} \tag{3}$$

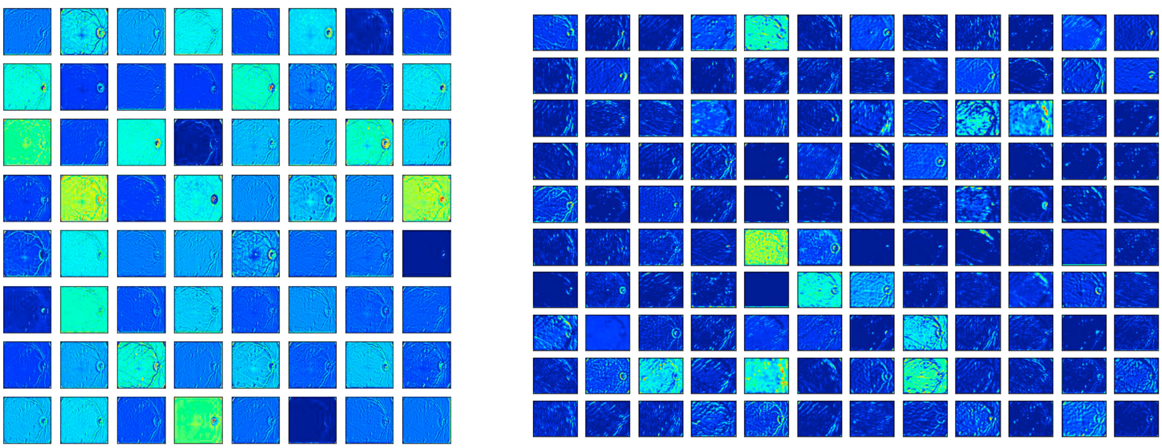
$$Specificity = SPE = \frac{TN}{TN + FP} \tag{4}$$

4. Result and Discussions

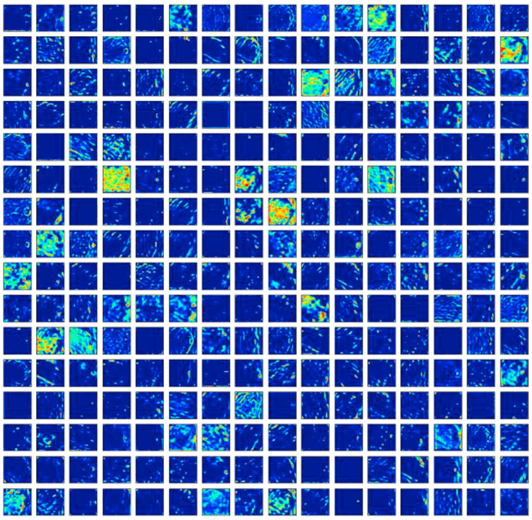
This section presents the experimental results and this task is accomplished using a computer with an Intel i7 processor, 20GB RAM, and 4GB VRAM equipped with Python®. Initially, the AlexNet-supported FRI classification is executed using the SM, and this scheme provides an accuracy of 96.3333%. A similar methodology is then executed using VGG16; which provides an accuracy of 94.3333%. Finally, ResNet18 is considered to classify the FRI into healthy/DR class, and the achieved results are considered for the demonstration.

Figure 3 presents the intermediate layer results of ResNet18 (4 convolution layer results), and this scheme's final section helps achieve a feature vector with an aspect of $1\times1\times1000$. Fig 3(a) to (d) presents the various convolutional layer outcomes achieved, confirming that this method learns well on this database. Finally, the experimental outcomes are presented in Figure 4. Figures 4(a) and (b) depict the convergence of the training and testing functions for a chosen epoch of 150.

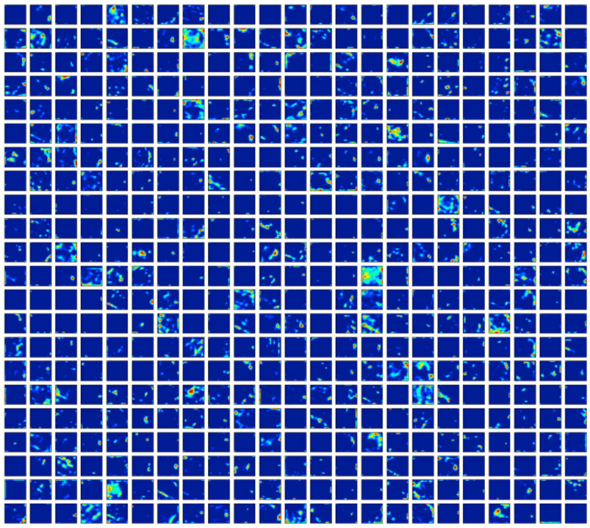
These two images confirm that this method's accuracy and loss value is satisfactory compared to the result of AlexNet and VGG16. Fig 4(c) shows the confusion matrix with TP, TN, FP, and FN values. This confusion matrix provides a classification accuracy of >92%. Fig 4 (d) shows the ROC for the implemented experiment, and this curve confirms that this method helps; no skill ROC with an AUC of 0.50 and logistic: ROC with an AUC of 0.971. The obtained result for this process can be found in Table 2. This table substantiate that the accurateness of AlexNet is greater than other DLS schemes.



(a) Convolution1 (b) Convolution2

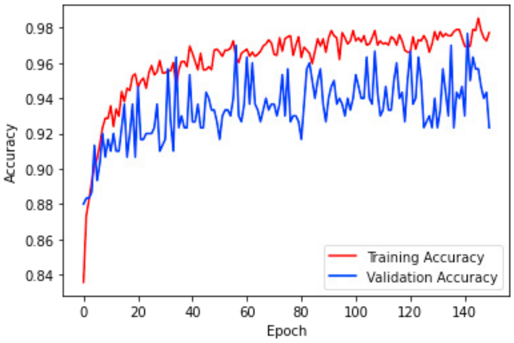


(c) Convolution3

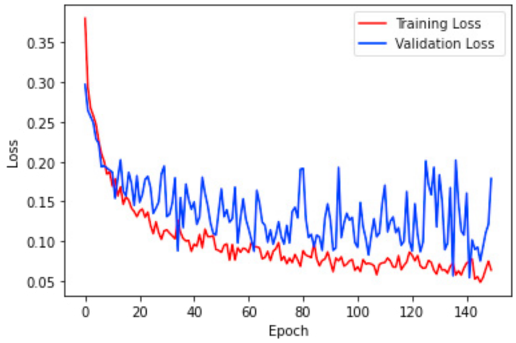


(d) Convolution4

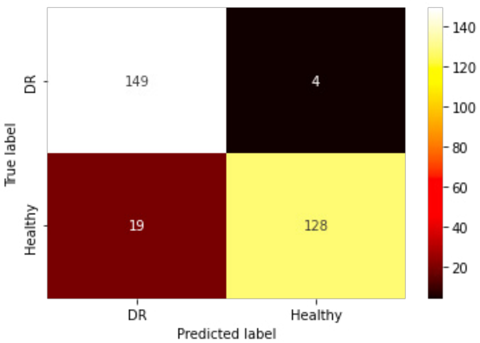
Fig 3. Convolutional layer result achieved using ResNet18



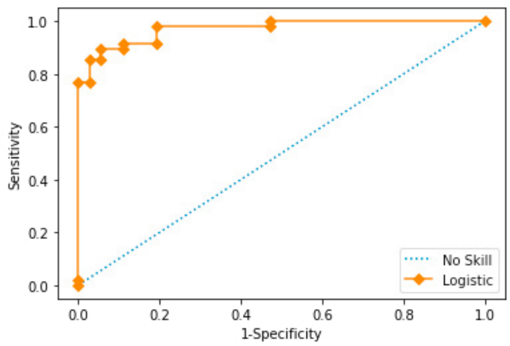
(a) Accuracy Vs Epoch



(b) Loss Vs Epoch



(c) Confusion matrix



(d) ROC

Fig 4. Results achieved with the ResNet18 method

Table 2. Performance metric achieved with individual DLS using SM classifier

Scheme	TP	FN	TN	FP	ACC	PRE	SEN	SPE
AlexNet	142	7	147	4	96.3333	97.2603	95.3020	97.3510

VGG16	143	10	140	7	94.3333	95.3333	93.4641	95.2381
ResNEt18	128	19	149	4	92.3333	96.9697	87.0748	97.3856

After verifying the individual performance of the proposed technique, EDF-based classification is executed, and the obtained outcomes are shown in Table 3. In this table, the achieved results of the binary classifiers are presented, and the achieved result with this scheme confirms that the KNN classifier offered DR detection accuracy of >98%. To verify the result with the graphical technique, a Glyph-plot is constructed as in Figure 5. This figure also confirms that the overall performance (covered area) of the KNN classifier is superior

Table 3. Performance metric achieved with EDF using binary classifiers

Classifier	TP	FN	TN	FP	ACC	PRE	SEN	SPE
SM	146	4	146	4	97.3333	97.3333	97.3333	97.3333
DT	145	3	144	8	96.3333	94.7712	97.9730	94.7368
RF	147	2	146	5	97.6667	96.7105	98.6577	96.6887
KNN	147	2	148	3	98.3333	98.0000	98.6577	98.0132
SVM	146	4	145	5	97.0000	96.6887	97.3333	96.6667

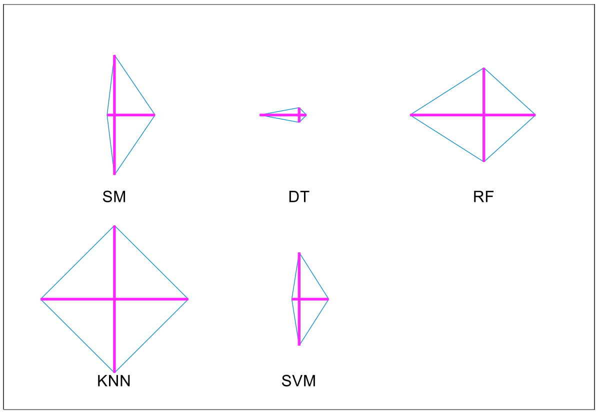


Fig 5. Glyph-Plot to demonstrate the overall performance of Table 3 metrics

The investigational products of this study prove that this scheme provides better result on the chosen FRI database. Therefore, this method can be used to inspect clinical grade FRI. In the future, proposed EDF idea can be implemented to examine clinical grade OCT images.

5. Conclusions

Automatic disease detection methods have been widely employed recently due to humankind's increased disease rates. These schemes aim to detect the abnormality in medical images with better accuracy to plan and execute the treatment. This research implements a DLS-supported DR detection on FRI. This work is implemented as; (i) DR detection with individual DF and (ii) DR detection using the EDF obtained using the average of the individual DF. The experimental investigation was implemented using AlexNet, VGG16, and ResNet18. Initially, the performance of these DLS I verified with the SM classifier and the AlexNet helped achieve a classification accuracy of >96%. On the other hand, the classification task employed with EDF and the binary classifiers helped provide a detection accuracy of >98% with the KNN classifier. Along with the accuracy, the overall merit of the KNN classifier with

EDF is superior compared to SM, DT, RF, and SVM. In the future, the proposed scheme can be considered to examine the retinal OCT and the clinically collected FRI.

Nomenclature

AAD	age associated disease
CNN	convolutional-neural-network
DF	deep features
DLS	deep learning scheme
DR	diabetic retinopathy
DT	decision tree
EDF	ensemble of deep features
FN	false-negative
FP	false-positive
FRI	fundus retinal image
KNN	K-nearest neighbours
OCT	optical coherence tomography
RF	random forest
ROC	receiver-operating-characteristic
SM	Softmax
SVM	support-vector-machine
TN	true-negative
TP	true-positive
WHO	world health organisation

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