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Enhanced Recognition system for Diabetic Retinopathy using Machine Learning with Deep Learning Approach

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ABSTRACT

Diabetic is the primary main reasons for Diabetic Retinopathy (DR). If Diabetic Retinopathy is untreated for long term, then it leads to total eye blindness. Now days, prevention of DR is a major challenging task, and moreover it reduces the overall risk of eye blindness. Machine learning and Deep learning is valuable methods to identifying and aiding DR diagnosis. In this paper, new method is proposed by Machine learning and Deep learning technique. In this proposed system, Kaggle dataset is used for training and testing. Totally 3662 images, in which the 2744 images is used to train and remaining 546 images are used to test the model. This system involves classifying using Convolution Neural Network (CNN), Support Vector Machines (SVM). The simulated results are obtained for the classifiers and its outputs are shown in the paper. From the result, it is found that, the CNN Classifier performs well in term of accuracy to detect diabetic retinopathy, compared with the SVM classifier.

Keywords: *Diabetic Retinopathy, Deep Learning, Machine Learning, Convolutional Neural Network, Support Vector Machine*

INTRODUCTION

Diabetic Retinopathy (DR) is most dangerous diseases in current world. As a result, several Human eyes are affected severely with significant vision impaired. According to the World Diabetes Federation's statistics, over 463 million patients suffered globally in 2019 additionally, it is projected that there will be 7 00 million diabetes patients worldwide by the year 2045. Therefore the diabetic patient is increase rapidly in this connection, the diabetic retinopathy is also increasing continuously and it leads to vision loss.

At present, DR is a more complicated which causes the high blood sugar level and affects the blood vessel in the retina. Appropriate treatment for the DR in the earlier stage could avoid the risk of the blindness. In recent times, the detection and recognition of DR is essential. In worldwide, the challenging and advancement is happening on DR detection to treat DR earlier stage of the disease.

The emerging technologies especially, Machine learning and deep learning is one of the most common techniques used for attains better performance in this area. Many researches are exploring their research investigation for finding the DR at the earlier stage. The literature review on DR motivated to detect and prevent the disease in the earlier stage.

The efficient detection saves the time for the earlier treatment of diabetic retinopathy.

Some of the literature survey is exposed in this paper with respect to the dataset, feature extraction and classifier. In addition, the different datasets and classifiers were mentioned to classify diabetic retinopathy in different classes.

R.S. Rajkumar et al. [1], created a Transfer learning method using CNN architecture based ResNet-50 model to classify normal, abnormal images from Kaggle dataset which contains 35,000 pictures. From the result analysis, it observed that ResNet-50 model gives accuracy of 89.4%. Rocky Yefrenes Dillak et al. [2], develop a VGG model using architecture of a CNN. The Results obtained from two dataset namely Messidor database and Kaggle database to obtain the result of 99.66 % accuracy, 99 % sensitivity, and 98 % specificity for Messidor database. When it tested with the Kaggle database, the obtained results are 98% of sensitivity, 97% of specificity, and 98.43% of accuracy. Deep learning based technique for DR classification was developed and implemented by Alan Lands et al. [3], There are three CNN architectures used namely, ResNet, DenseNet129 and DenseNet169 for DR detection and it achieved the validation loss of 67% for ResNet, 32% for DenseNet129 and 21% for DenseNet169 classifier.

Muhammad Hanif et al. [4], uses the architecture of deep convolutional neural network (DCNN) with (i) EfficientNet-B4 and (ii) EfficientNet-B5 classifier using Kaggle dataset. The accuracy obtained for the two classifier are (i) EfficientNet-B4 is 83.67% and (ii) EfficientNet-B5 is 83.89% respectively. Ahsan Habib Raj et al [5], designed a convolutional neural network to find Blood Vessels and Microaneurysms features. The Kaggle database is utilized and it achieved the accuracy of 95.41%. Vaibhav V. Kamble et al [6], proposed RBF Neural Network classifier for DR Detection. Datasets of DIARETDB0 and DIARETDB1 is utilized and the obtained accuracy of 71.2% for DIARETDB0 and 89.4 % for DIARETDB1 datasets.

Wejdan L. Alyoubi et al. [7], presented a system for classifying the DR images into five stages. The CNN512 and YOLOv3 deep learning-based models are used to differentiate the different DR stages from DDR and APTOS 2019 dataset. It attains an accuracy of 88.6% for CNN512 and 89% for YOLOv3. Mobeen-ur-Rehman et al [8], presented AlexNet, VGG-16, SqueezeNet CNN models. It attains an accuracy of 93.46%, 91.82%, 94.49%. The author proposed a 5-layered CNN model and it produced sensitivity, specificity, accuracy of 98.94%, 97.87%, and 98.15%. Seema Hanchate et al. [9], created a model called DenseNet. In this proposed system, the APTOS dataset is used and extracted the feature from fundus image in the database, in order to detect the DR stages. The obtained an accuracy of 0.9611 is compared with VGG16 and DenseNet121.

Roshini Isaac et al. [10], implemented the deep learning architecture to detect the DR. With Kaggle database, out of 35126 images were taken out which, 90% of images are utilised for training and 10% of images are utilised for validation. Training accuracy obtained is 92%. From the results, it was found that this work can categorise the category of the retinal picture and it is useful for primary screening. Sinthanayothin et al. [11] conducted a study for the classifying the normal and abnormal retinal images. The author used colour features and radial basis function (RBF) kernel to train SVM algorithm. The system shows an accuracy of 82.6%. Mehta et al. [12], presented a proposed system. Texture features are extracted from retinal images and the RBF kernel is used for SVM classifier. The proposed system obtained an accuracy of 95.7% in the classification of normal, non-proliferative DR and proliferative DR.

Gulshan et al. [13] propose an algorithm to detect a DR. The SVM with linear kernel to combine the output of the deep learning algorithm with hand-crafted features. The proposed system achieved a receiver operating characteristic (ROC) curve of 0.99 in detection of referable DR. Haloi et al. [14], used a histogram of oriented gradients (HOG) feature descriptor and RBF kernel for SVM training. The system gives accuracy of 90.2% in detection of DR. Quellec et al. [15], designed a SVM-based DR detection for both fundus pictures, optical coherence tomography (OCT) images. This model achieved receiver operating characteristic curve (AUC) of 0.93 on a kaggle dataset. Zhixiang Qian et al [16], presents a deep learning algorithm for DR detection. These methods use the combination of Kaggle competition datasets. Res2Net and DenseNet-based Convolutional Neural Networks (CNNs) for feature extraction and classifier. it achieved an accuracy of 83.2%. Himshikha Seetah et al [17], uses the convolutional Neural Network, which carries out detection utilizing of fundus image. The

Kaggle dataset is used to training and testing. This system works effectively to improve its specificity of 98.25%, sensitivity of 98 % and accuracy of 84%. Anas Bilal et al. [18], suggested unique hybrid strategy for DR detection using the Kaggle dataset. It employs three classifiers namely, SVM, K-nearest neighbours, binary trees with voting method. It attains maximum accuracy of 98.06%, 83.67% of sensitivity, and 100% of specificity.

Yuchen Wu et al [19], formulated a model for DR recognition based on the transfer learning. This model is trained with VGG19, InceptionV3 and Resnet50. The ImageNet dataset used to train entire network. The Experimental result shows the maximum classification accuracy for InceptionV3 of 60%. Venugopal T et al [20], propose efficient DR Classification using Binary Convolutional Neural Networks (BCNN). The BCNN classifier is able to detect the DR with large scale fundus images. Based on Kaggle dataset, an experiment was conducted to reduce memory consumption by 37% with a runtime accuracy of 49%.

Shahriar Maswood et al. [21], proposed a pre-trained deep learning model of CNN classifier to identify five distinct classes of DR. Kaggle Dataset is utilised to training and testing the images. For training, the accuracy of 0.9402 is obtained and the accuracy of 0.9333 is obtained for the testing. Handayani Tjandrasa et al. [22], proposed DR classification system using SVM and CNN classifier. The proposed system is tested with 77, 70 retinal image from Messidor datasets with base 12 and base 13 respectively. The result shows that, maximum accuracy for base 12 is 95.83% and base 13 is 95.24%. Brahami Menaouer et al [23], proposed a Hybrid DL model using DCNN method with the classifiers namely, VGG16 and VGG19. The APTO-S 2019 dataset is used and it gave a 90.60% of accuracy, 95% of recall, and 94% of F1 score. Shuang Yu et al. [24], developed an automated image processing technique for neovascularisation in the optic disc region for the identification with the help of multilevel Gabor filtering for vessel segmentation and Support Vector Machine for image classification. The chosen features were trained and evaluated on the 424 retinal images from Kaggle Dataset. It obtains 95.23% of accuracy, specificity of 96.30% and 92.90% of sensitivity. Yasashvini R et al [25], created a CNN model using ResNet and DenseNet classifier in order to detect the DR using Kaggle dataset. The Blood vessel exudates and cotton wool spot features are extracted and classified with help of deep learning architectures. It attains an accuracy of 96.22% in ResNet and 93.18% on DenseNet.

Ragendhu S et al. [26], suggested a hybrid classifier, which combines SVM, KNN, random forests, logistic regression and multilayer perceptron networks. Exudates, haemorrhages, and micro aneurysms are used for feature extraction. The hybrid model gives an accuracy of 82%, 0.8119 of a precision score, 0.8116 of a recall score, and 0.8028 of f-measure score. Zhentaogao et al [27], created a method of DCNN network to grade severities of DR fundus images from the Kaggle datasets and it achieves an accuracy of 88.72%. In this proposed method, the classifier had a consistency rate of 91.8% deployed on the cloud computing platform for the DR diagnosis. Zhun Fan et al. [28], designed a CNN algorithm for Optic Disc detection based on structured learning. This method is used to conduct on the three dataset namely, MESSIDOR, DRIONS and ONHSD. 1200 images from the MESSIDOR dataset achieved an accuracy of 0.9770. 110 images from DRIONS dataset achieved an accuracy of 0.9760. 99 images from ONHSD dataset achieved an accuracy of 0.9895.

Carla Agurto et al. [29], proposed a KNN classifier to find exudates in the macula region. In order to detect the exudate areas, the best thresholding of instantaneous amplitude (IA) is employed for the feature extraction. The training and testing the images is done from MESSIDOR dataset and it obtained an receiver operator characteristic curve (AUC) of 0.96, 0.97 of accuracy. Shailesh Kumar et al. [30], uses a SVM classifier to find feature of Microaneurysms. The images are taken from DIARETDB1 dataset for the detection of the DR feature. The principal component analysis and contrast limited adaptive histogram equalization are proposed for feature detection. The proposed system performs a sensitivity of 96% and specificity of 92%.

The above literature motivated to analyse and detect the DR. In this paper, DR detection system is proposed using Machine and deep learning technique. The Kaggle dataset utilizes to detect DR. In that, 2744 images for training, 546 images for testing the method.CNN and SVM classifier is used for classifying the DR images. The classification results are compared and the results obtained shows that CNN classifier performs better, when compared with SVM classifier in terms of accuracy.

The remaining of this paper is structured as; proposed system for detection is represented in section II. Results and discussions are represented in section III, conclusion of proposed work is represented in section IV.

PROPOSED SYSTEM FOR DR DETECTION

In this section, the proposed block diagram is briefly explains for the detection of DR. The general block diagram of detection of DR is shown in the Fig.1. It consists of data acquisition, pre-processing, segmentation, feature extraction and classification. The Schematic diagram of the proposed DR system is mentioned in the Fig.2.

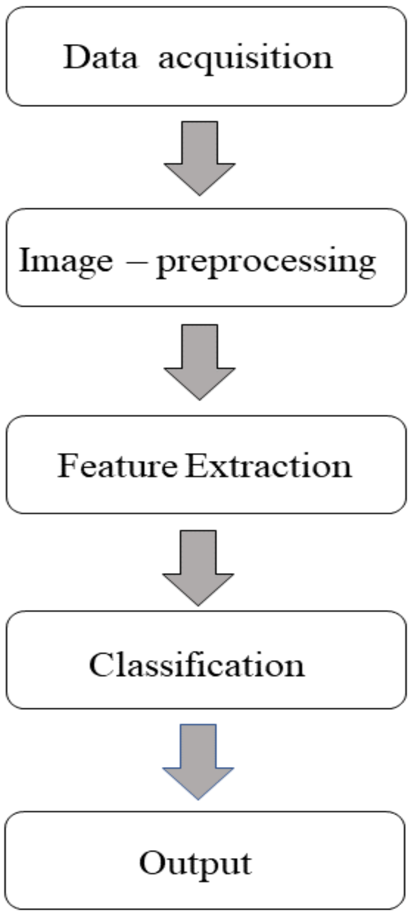


FIG.1: General Block Diagram of DR

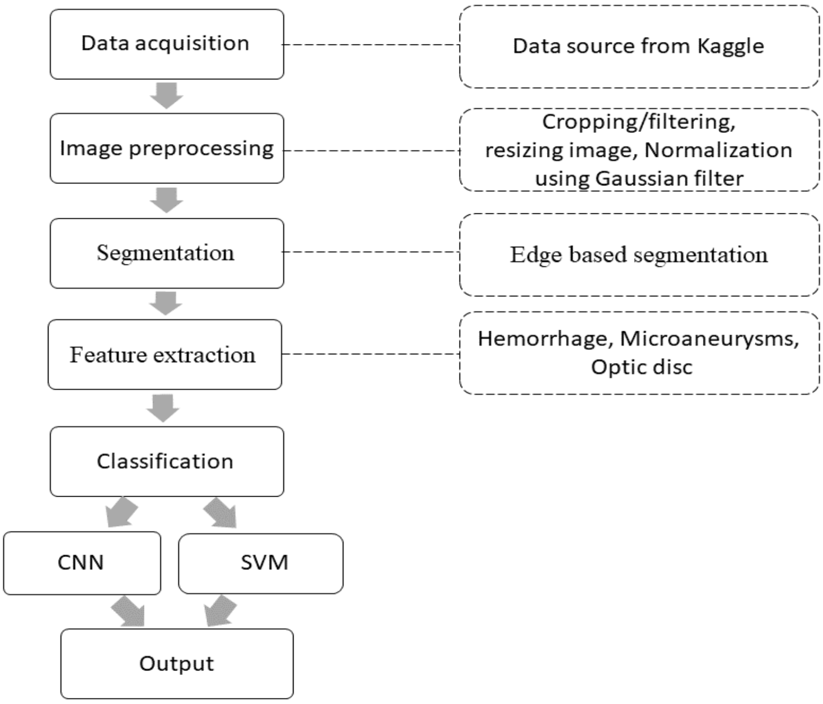
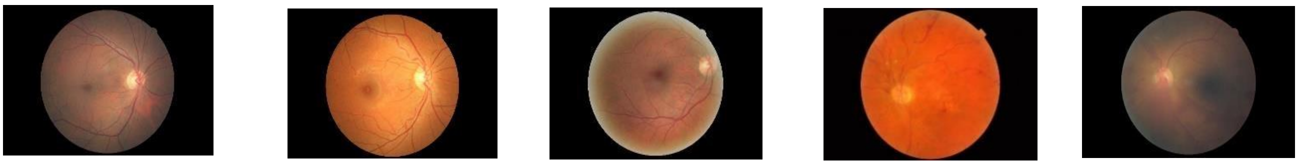


FIG.2: Proposed Block Diagram of the DR Detection

Data Acquisition

Dataset is a collection of data containing retinal images. The input dataset utilized for this paper is sourced from Kaggle provided by EyePACS and it comprises 3662 retinal images of the retina. Further, it splits into 2744 images for training and 546 images for testing. The images in dataset are taken with various noise levels and different quality. The severity rating ranging from 0 to 4 in the dataset and it indicates the level of DR present in image. A grade of 0 signifies a normal image with no signs, grade 1 denotes mild, grade 2 indicates moderate, grade 3 indicates severe, grade 4 indicates non proliferative DR, as shown in Fig.3, [3]. The different stages of retinal images with number of images in each stage in the dataset are mentioned in Table.1.



(a) Grade 0 (b) Grade 1 (c) Grade 2 (d) Grade 3 (e) Grade 4

FIG.3: Samples of different grades of diabetic retinopathy.

TABLE 1: Image Identification in Different Stages

S.NO	Grades	Stage	Identification of images
1	Grade 0	Normal	1805
2	Grade 1	Mild	370
3	Grade 2	Moderate	999
4	Grade 3	Severe	193
5	Grade 4	NPDR	295

Image Pre-Processing

Pre-processing plays a vital role in standardizing the retinal images in the dataset. It contains of significant noise due to various factors such as poor focus, overexposure, underexposure, extra lighting, and dark background. The preprocessing process steps involve cropping, filtering, resizing, and normalization [7]. First of all, to improve the overall clarity of image. The dark background is eliminated and it does not provide any relevant information. Secondly, a filter is used to eliminate the black corners of the image because; the fundus image is in spherical shape. Thirdly, the images are resized to a standard size of 256x256 for consistency. Finally, the images are normalized using Gaussian blur, with the kernel size set to 256/6, to remove Gaussian noise. The pre-processing steps involve in improving the quality and standardization of retinal images. It is essential for accurate diagnosis and analysis of diabetic retinopathy.

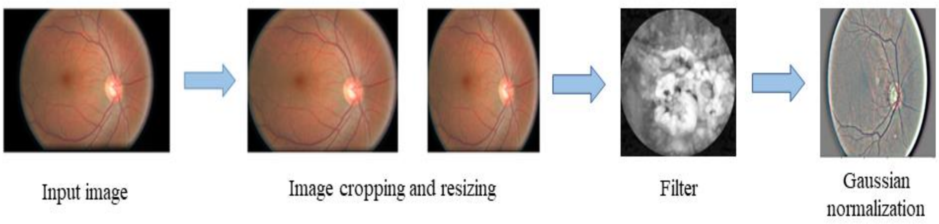


FIG.4: steps involved in pre-processing method

Image Segmentation

It is an essential process in detecting diabetic retinopathy (DR), enabling the localization and identification of regions in eye images. This technique can identify the different structures in eye. Edge-based segmentation is employed in this proposed system. The edge of blood vessels within retinal images is useful in identifying to diagnose diabetic retinopathy. Abnormal blood vessels within the retina are critical diagnostic feature of diabetic retinopathy. The edge-based segmentation can detect and identify their edges with its boundaries in retinal images [28]. Morphological operations are mathematical operations that enhance image contrast and remove unwanted elements. It ultimately helps in identifying relevant feature in the image. The morphological operations utilized can vary depending on the desired outcome and features present in the image. Overall, edge-based segmentation provides an automated method to identify and analyze abnormal blood vessels in the retina. It makes a valuable tool in the management of diabetic retinopathy. Both the Preproessed Image and Edge Based Segmentation Image is mentioned below in Fig.5.

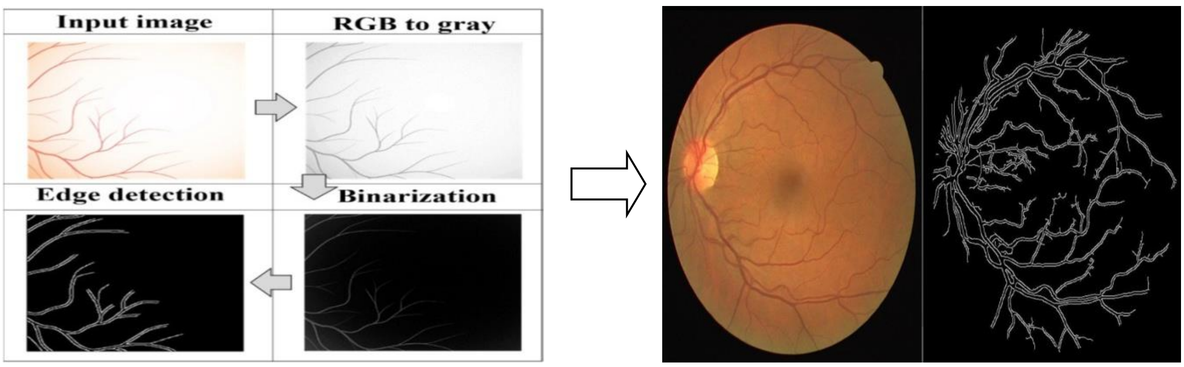


FIG.5 (a) Preproessed Image (b) Edge Based Segmentation Image

Feature Extractions Of Dr

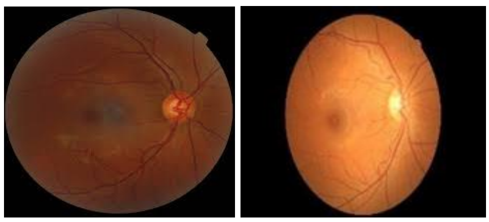
Process of identifying and extracting features from raw data is known as Feature Extractions. It involves analyzing and identifying unique visual characteristics of an image, such as shapes, colors, and textures. It allows more efficient reduction data required for analysis and retain significant information. In this paper, the four features are explained for early detection of DR.

Microaneurysms (MAs) are small outpouchings in walls of blood vessels in retina that occur as a result of diabetic retinopathy, a complication of diabetes [20]. These small aneurysms cause damage to retina and lead to vision loss.

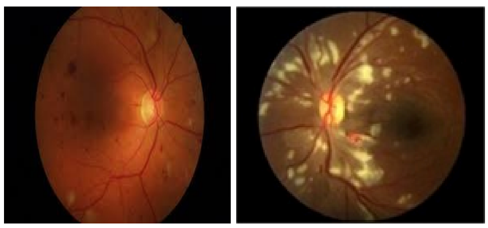
The optic disc (OD) also known as the blind spot, is point where optic nerve enters eye and connects to the retina [28]. It is an important landmark in the retina that can be used to identify various retinal conditions.

Hemorrhages (HEs) are areas of bleeding within the retina, which can be caused by various medical conditions such as DR, hypertension, age-related macular degeneration. Hemorrhages can cause vision loss and are an important finding in the diagnosis of these conditions [26].

The fovea is a small central pit in retina which is responsible in detailed vision. It is important in diagnosis and management of various retinal conditions. Fig.6, shows the sample images of optic disc, fovea, Microaneurysms, haemorrhages. The extracted features are fed into SVM classifier. The classifiers execute the feature extraction process on the identified regions, in order to identify the feature detection stage.



(a) Optic Disc (b) fovea



(c) Microaneurysms (d) haemorrhages

FIG.6: Feature Extractions Method

Classification

The proposed system employs, two classifiers, namely SVM and CNN for investigation. A total of 3662 images is fed into each classifier and it classify the each image into one grade out of the five grades.

Convolutional Neural Network

CNN classifier is designed to learn features from input data with help of sequence of convolutional layers and max pooling layers. In this paper, images are classified into five grade with fully connected layers and softmax layer. Along with max pooling layers incorporation of ReLU activation function is utilised to enables the introduction of non-linearity and reduction of the spatial size of feature maps respectively. Additionally, the softmax function guarantees that the final output is a valid probability distribution across the classes. The proposed CNN method for DR detection is mentioned in Fig.7.

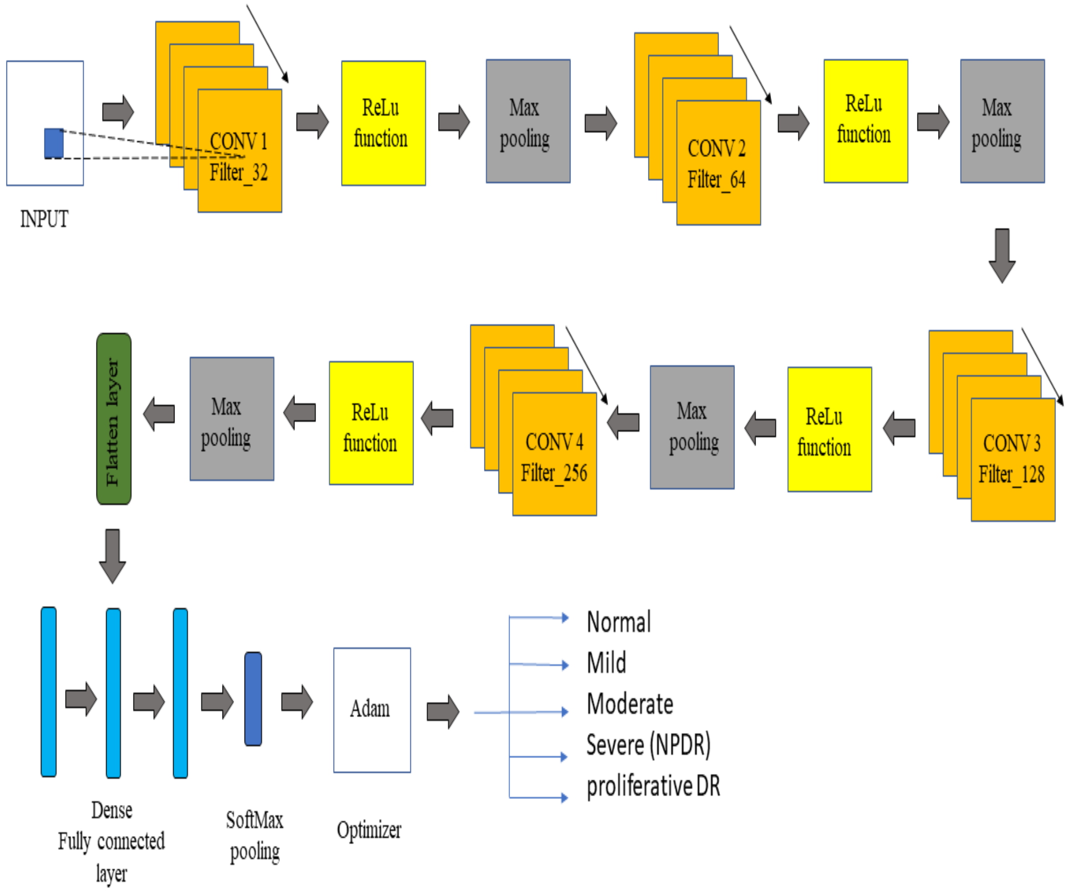


FIG.7: CNN Architecture of the Proposed System

CNN architecture operates sequentially on input images of size (224x224), with multiple layers designed to learn and classify image features. The initial layer of the architecture employs a Convolution2D operation comprising 32 filters with specific dimensions. Subsequently, the next convolutional layer uses the same size of filters but increases the number of filters to 64. The Third layer is convolutional layer with 128 filters, fourth layer is256 filters of the same size. All these layers utilize ReLU activation function and max pooling layer with pool size of 2 x 2. The input shape parameter specifies that the input data should be a 3-channel image (RGB).

The fifth layer is a Flatten layer that converts the 3D tensor output of previous layer into a 1D tensor. The sixth layer is fully connected dense layer with 4048 units, ReLU activation function. Seventh and eighth layers are also fully connected dense layers with 4048, 2024 units, respectively, and both utilize ReLU activation functions. The ninth and final layer is a fully connected dense layer with 5 classes with softmax function.

The compile method is used to specify loss function. The Adam optimizer is used and it is the extended version of stochastic gradient descentto evaluation metrics in this system. The proposed deep CNN architecture utilizes four convolutional layers with max pooling, four fully connected layers to classify images into one of five categories. The Proposed CNN feature extractor is shown Fig.7.

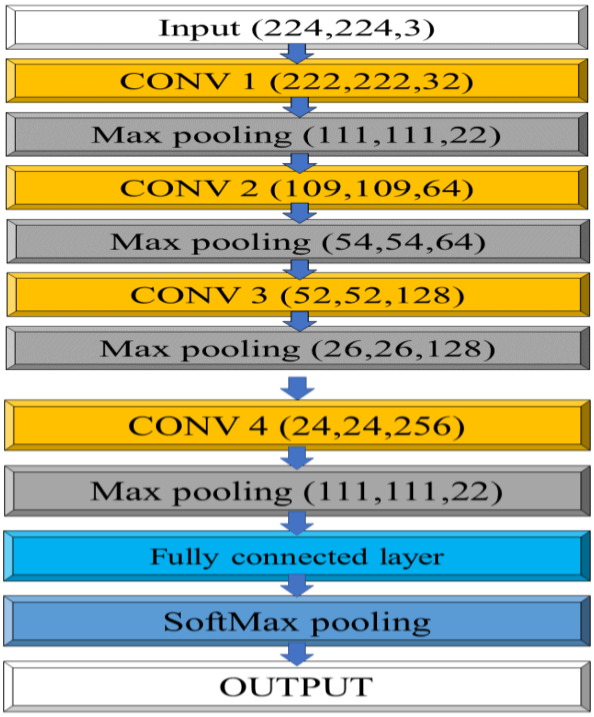


FIG.8: The Proposed CNN Feature Extractor Model.

This paper proposes a DL method for image classification consist of several convolutional and dense layers. This system can achieve high accuracy with dataset of five classes and it provides a detailed analysis of the CNN architecture which includes the output shape and number of parameters for each layer. Table.2 shows Total no of Parameters used in each and every layers of the CNN architecture.

TABLE 2: List of Total No of Parameters in the Each Layers

S.No	Layer (Type)	Output Shape	Parameter
1	Convolutional Layer 1	(None, 222, 222, 32)	896
2	max_pooling Layer	(None, 111, 111, 32)	0
3	Convolutional Layer 2	(None, 109, 109, 64)	18496
4	max_pooling Layer	(None, 54, 54, 64)	0
5	Convolutional Layer 3	(None, 52, 52, 128)	73856
6	max_pooling Layer	(None, 26, 26, 128)	0
7	Convolutional Layer 4	(None, 24, 24, 256)	295168
8	max_pooling Layer	(None, 12, 12, 256)	0
9	Flatten Layer	(None, 36864)	0
10	Dense Layer	(None, 4048)	149229520
11	Activation Layer	(None, 4048)	0
12	Dense Layer 1	(None, 4048)	16390352
13	Activation Layer 1	(None, 4048)	0
14	Dense Layer 2	(None, 2024)	8195176
15	Activation Layer 2	(None, 2024)	0
16	Dense Layer 3	(None, 5)	10125
17	Activation Layer 3	(None, 5)	0

In the proposed system, an analysis was conducted to determine the maximum accuracy with respect to maximum number of epochs, as measured by validation loss, validation accuracy. The results of analysis are summarized in Table 3. It was found that maximum accuracy of 95% was achieved at the 90th epoch. This leads to a conclusion that the network is trained for maximum of 90 epochs. The values of every 10 epochs with their loss, validation loss, validation accuracy and accuracy is shown in the Table.3. Simulation parameters is used for the proposed convolutional Neural Network is present in Table.4.

TABLE 3: Training and Validation Accuracy for Different Epochs

Sl.No	Epochs	Loss	Validation Loss	Validation Accuracy	Accuracy
1	10	0.7568	0.7739	0.7132	0.7246
2	20	0.6306	0.7894	0.7371	0.7659
3	30	0.5034	0.7745	0.7463	0.8219
4	40	0.3519	0.8701	0.7390	0.8695
5	50	0.3011	1.0124	0.7518	0.8890
6	60	0.2241	1.2569	0.7206	0.9174
7	70	0.1696	1.2406	0.7408	0.9351
8	80	0.1316	1.8642	0.7353	0.9506
9	90	0.0691	1.7691	0.7114	0.9775

TABLE 4: Simulation Parameters for the Convolutional Neural Network:

S. NO	Parameter Name	Parameter Value
1	LR	0.01
2	Optimizer	ADAM
3	Number of Epochs	90
4	Steps Per Epochs	85
5	Number of Layers	4
6	Batch Size	3

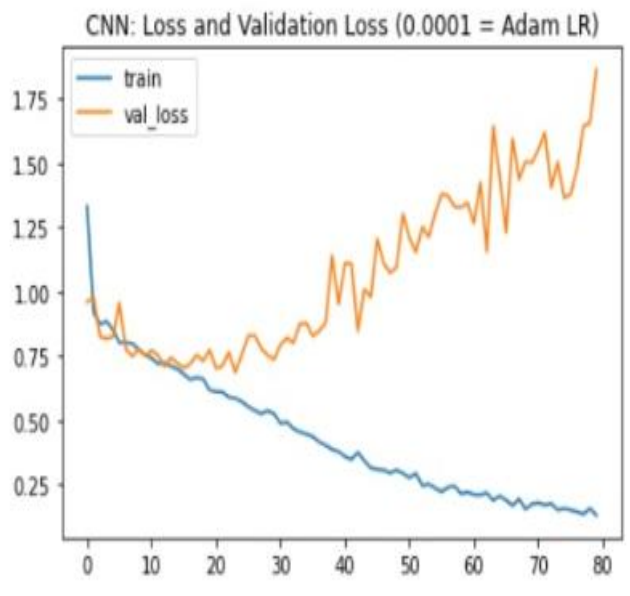


FIG 9: Training Loss and Validation Loss of Kaggle Dataset with 90 Epochs

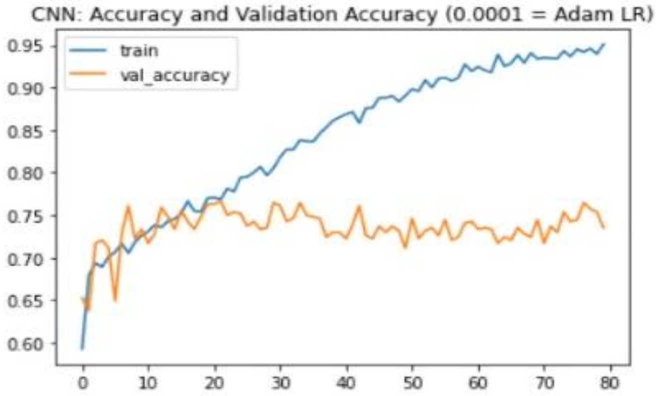


FIG 10: Training Accuracy and Validation Accuracy of Kaggle Dataset with 90 Epochs

From the CNN architecture, graphical representation has been obtained for both training and validation data with respect to their loss and accuracy. All this data were obtained from the input dataset, the training loss, the validation loss are shown in Fig.9 and training accuracy, the validation accuracy is mentioned in the Fig.10.

Performance matrices

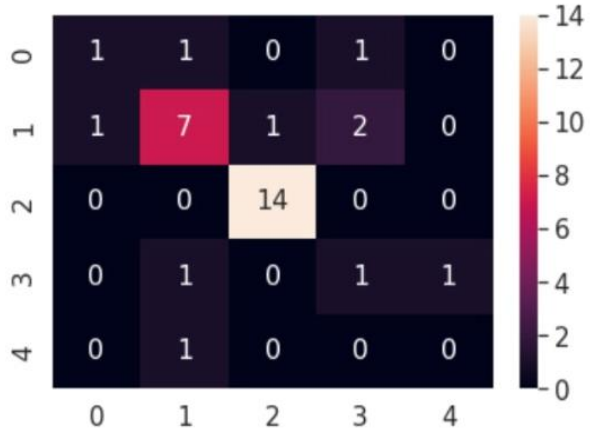


FIG 11: Performance Matrices

The Performance matrices are more useful to evaluate performance of the classification. It is useful in the evaluating performance of a CNN for diabetic retinopathy detection. A 5x5 matrixes with five categories corresponding to the different levels of severity explicitly, no diabetic retinopathy, mild, moderate, severe, proliferative. Severity levels that the retinal images actually label as true are the predicted severity levels by CNN, whereas the true labels correspond to the severity levels that the retinal pictures actually label as true.

By analyzing the Performance matrix, it is found that the performance metrics (i) Accuracy, (ii) Precision, (iii) recall, and (iv) F1 score. It provides insights into the strengths and weaknesses of the CNN model. These metrics can be used to fine-tune the model, improve its performance for diabetic retinopathy detection. The obtained values are listed in Table. 5.

TABLE 5: show the precision, recall, f1-score, and support value obtained from the confusion matrix.

Grade	Precision	Recall	F1-score	Support
0	0.50	0.33	0.40	3
1	0.70	0.64	0.67	11
2	0.93	1.00	0.97	14
3	0.25	0.33	0.293	3
4	0.00	0.00	0.00	1
Accuracy	-	-	0.72	32
Macro Avg	0.48	0.46	0.46	32
Weighted Avg	0.72	0.72	0.72	32

Support Vector Machine

SVM is a supervised Machine Learning algorithm used for classification and outlier detection. The fundamental concept behind SVM is to identify optimal boundary that it separates different classes in the feature space. It achieves maximizing the margin between the classes and selecting the decision boundary with the least classification error.

To implement the SVM classifier, the dataset is first split into x features and y as target. Next, dataset is further divided into training, testing sets using split function from scikit-learn. Training set is used to train SVM classifier with linear kernel function. Following the training phase, classifier is employed to predict the classes of the test set using the predict function. Finally, the accuracy of the classifier is computed using the accuracy score function and displayed. In the proposed system, the optic disc, fovea, Microaneurysms, haemorrhagesare extracted features are fed into SVM classifier and result obtained is tabulated in the Table.6.

RESULT AND DISCUSSION

In the paper, Google Collaboratory environment is used for the investigation. It allows writing and executing Python code in the browser, the resource allocated for this work is 80 GB of disk storage memory data. Finally, it is divided into two sets, 80% is utilized to training, and 20% is utilized to testing. The dataset composed of totally 3662 images, in that 2744 images is utilized for training and 546 images is used to testing. The obtained results using two classifiers CNN and SVM are shown in Table.6.

TABLE 6: Obtained Accuracy Model with Two Classifiers

Classifiers	Training Loss	Validation Loss	Training Accuracy	Testing Accuracy
SVM	-	-	78.1%	48%
CNN	45.2%	75.67%	71.12%	97.7%

Table 6 shows the accuracies obtained from the proposed model with two classifiers namely, CNN and SVM. The classifier of CNN performs higher accuracy when compared with SVM.

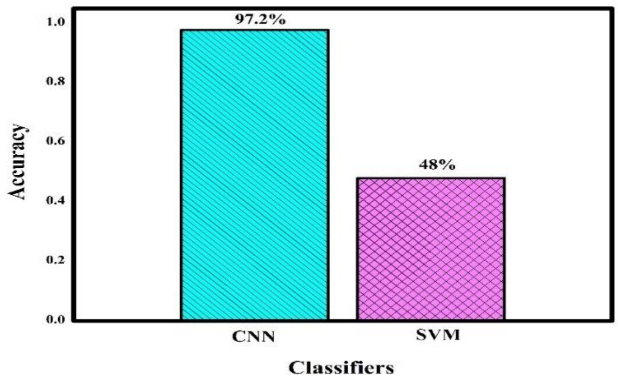


FIG. 11 Comparison Graph Between the Two Classifiers of CNN and SVM

From the above literature a comparison of various studies with different datasets and classifiers are used for diabetic retinopathy (DR) detection. In the below comparison table.7, the proposed work is compared by using the classifier, dataset and feature extraction with the previous models.

TABLE 7: Comparison of Proposed Work with Previous Model

S.No	Authors	Dataset	Classifier	Feature Extraction	Experimental Results
1	Ahsan Habib Raj et al [5]	Kaggle Dataset	CNN	Microaneurysms, Blood Vessels	Accuracy = 95.41%
2	Vaibhav V. Kamble et al [6]	DIARETDB1 Dataset	RBF Neural Network	Microaneurysms, Exudates, blood vessels	Sensitivity = 94% Accuracy = 89.4%
3	Wejdan L. Alyoubi et al [7]	Aptos 2019 Dataset	CNN	DR Lesions Found	Accuracy= 89%
4	Enrique V. Carrera et al [20]	Messidor Dataset	SVM	blood vessels, microaneurysms and hard exudates	Sensitivity = 95% Accuracy = 94%
5	Shuang Yu et al. [24]	NVD Image Dataset	SVM	Optic Disc Blood Vessels	Accuracy = 95.23% Sensitivity = 92.90%
6	Yasashvini R et al [25],	Kaggle Dataset	DenseNet	DR lesions found	Accuracy = 95.22%
7	Ragendhu et al [26]	Kaggle Dataset	Hybrid Classifier (SVM, KNN)	Microaneurysms, Exudates, Hemorrhages	Accuracy= 82%
8	Zhun Fan et al. [28],	Messidor Dataset	CNN	Optic Disc	Accuracy = 0.997
9	Carla Agurto et al. [29],	Messidor Dataset	KNN	Exudates	Accuracy = 97%
10	Muhammad Zubair et al [31]	STARE Dataset	DCNN	Microaneurysms, Hemorrhages, Exudates	Accuracy = 95.33%
11	Proposed Model	Kaggle Dataset	CNN	Optic Disc, Fovea, Hemorrhages, Microaneurysms	Accuracy = 97.7%

CONCLUSION

The proposed work is to detect DR using machine learning and deep learning techniques. In this proposed system, Kaggle dataset is used for training and testing the images with two classifiers namely, CNN and SVM. After conducting a comparison of CNN and SVM in detection of diabetic retinopathy, it is found that CNN methods exhibit the high accuracy rate of 97.7% of accuracy. However, the CNN outperforms well, when compared to SVM in terms of accuracy, sensitivity, specificity, and overall performance. Therefore, it can be concluded that CNN is a more suitable and effective method for predicting the diabetic retinopathy from retinal fundus images.

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