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Performance Analysis of Machine Learning Techniques for Diabetic Retinopathy Detection

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Area Under Curve, Classification Accuracy, Diabetic Retinopathy.

ABSTRACT:

Diabetic retinopathy is an eye disease that affects the light sensitive area of retina. It does not give any sign at initially but later it become very difficult to cure it. So it is very essential to detect it at initial stage for this various computer aided software is designed using machine learning techniques. This paper analyzed the most widely used machine learning techniques used for this disease detection i.e. SVM, KNN, decision tree, random forest, logistic regression neural network, naive bayes and deep learning architecture i.e. CNN, VGG16, ResNet50, EfficientNetB0, InceptionV3, CNN and SVM . Performance of these techniques is analyzed using five different datasets. AUC, CA, F1 score, precision, and recall are used for evaluation purpose.

Introduction

Diabetes is a long life disease that occurs due to high ratio of glucose in blood. If a person have this disease than he/she will be at high risk of many other disease e.g. kidney damage, neuropathy retinopathy, hearing impairment etc. diabetic retinopathy is one of these disease that occur due the diabetes. Diabetic retinopathy does not give any sign or symptom initially but after some time it become very dangerous and can lead to partial or even complete vision loss. And according to a survey upto 25000 thousand Indian loss their eye sight due to these diseases [1]. DR affects the light sensitive area of retina. Fig 1. Shows the five stages of DR. For identifying DR affects at different levels this disease is categorize in four stages mild, moderate, severe and proliferate stage.

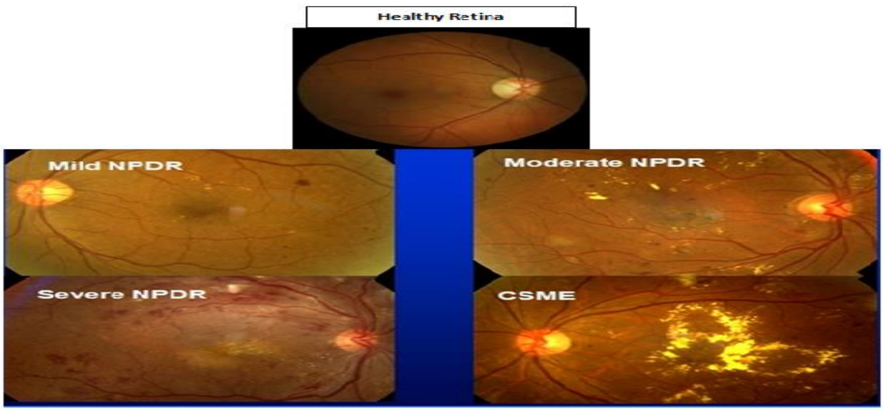

Fig. 1 Stages of Diabetic retinopathy

Each stage has different signs and symptoms with the help of which experts identify the stage of disease so that proper treatment can be given to patient at appropriate time. Table no. 1 shows the identification signs of all stages of DR.

Table 1: DR pathologies and their indication

Stage of Diabetic Retinopathy	**Pathologies**	**Identification**
No_DR	Normal retinal image	
Mild	Microneurisms	Bulges Red spots on Border of Retina
Moderate	Haemorrhages, hard and soft exudates	White/ Yellowish Patches on Retina
Severe	Haemorrhages, hard and soft exudates and MA in all quadrants	Red patches Deposits on Retina
Proliferate	Haemorrhages, hard and soft exudates, Vitreous haemorrhages, New blood vessel formation	Dark Yellowish patches on retina

With the help of these signs and symptoms various machine learning techniques are used to classify this disease so that proper treatment can be given to patient at proper time. This paper provides a comparative analysis of various machine learning techniques that are widely used for detecting this disease. Main contribution of this paper is :

- This paper helps in analyzing existing DR detection techniques in a more appropriate way.
- It provides an overview of the classification techniques that are used in this field.
- This paper helps researches in choosing appropriate technique for building new model.

This paper is divided into following subsections. First section is an introductory part of diabetic retinopathy and its stages. Second section provides to an overview of work that was done in this field. Third section describes material and methods used. Fourth section discuss about result observed. And in last section conclusion and future scope is described. After this references are given

Related Work

S. Kaur and D. Singh [2] developed a curvelet transforms and SVM based model for DR detection. In this model first Canny edge detection was applied on retinal fundus image for eyeball extraction. Then morphological operations were employed to remove impurities from the dataset. After that SVM was used for classification of images into normal, proliferate or non-proliferate images. C. Bhardwaj *et. al.* [3] presented a model for DR identification making the fusion of CNN and SVM techniques. In this model first deep neural network were used for extracting features than these features were ensembled with support vector machine for DR grading. This model provides 0.295 cross-entropy loss thus, maintains a trade-off. S. Das and S.K. Shah [4] purposed a DR classification based on genetic algorithms. In this model genetic algorithm was used for determining the hyper-parameters used in this model like number of convolutional and maxpooling layer, kernel function, number of dense layer. The developed model was tested on Messidor dataset. G. Saman *et.al.* [5] introduced a method for the automatic detection DR detection using microneurysm identification. This model has two phases in first features were extracted from retinal images i.e. optic disc, microaneurysms, blood vessels, and hard and soft exudates. In second phase, images were classified as either mild, moderate, proliferate or severe using SVM. S. Ambaji *et.al.* [6] developed a framework for DR detection by evaluating blood vessels, optic disc, and retinal abnormalities. First pre-processing was performed using green channel extraction and CLAHE histogram equalization. Further, optic disc segmentation was done using open-close watershed transformation algorithm and blood vessel segmentation was performed using grey level thresholding and abnormalities like hard

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exudates, haemorrhages, Microaneurysm and soft exudates were identified using was top hat transform and filter employed in this process are Gabor. From these segmented images features i.e. texture energy measurement, local binary pattern, Shanon's and Kapur's entropy were extracted, which were than provided to DNN for classifying images. Di Nui *et. al.* [7] proposed a deep learning based cascading localization method which improve the OD localization accuracy. This model employed the saliency-based visual attention to detect the most ROI and utilize deep CNN to find optic disc or not OD images. If a region on the image is detected as a non-OD region, then model found the next salient region and provide it as input to the classifier. This process ends when OD region was found. This model was evaluated on the ORIGA and MESSIDOR datasets. V. Agarwal *et. al.*[8] developed a CNN based robust method for glaucoma detection from retinal fundus images. In this work authors first segmented the optic disk and optic cup, then extract a patch which is centered around the optic disk and input these to CNN for classifying the image as DR or healthy. During segmentation spatial co-ordinate (X & Y) space was used for performing learning better. In classification network DenseNet201 and a ResNet18 was used for training purpose. This model has AUC value 0.85 and validation of model was performed on REFUSE dataset. S. Chatterjee [9] developed a hybrid deep learning model DRISTI (Diabetic Retinopathy classification by analyzing retinal images) Model was built using VGG16 and capsule network. This model provided five-class training and validation accuracy for the expanded dataset is 99.21% and 75.50%.

Material and methods:

Main goal of this paper is to evaluate the performance of different machine learning classifiers. Research methodology we have followed to achieve this goal is shown in fig. 2.

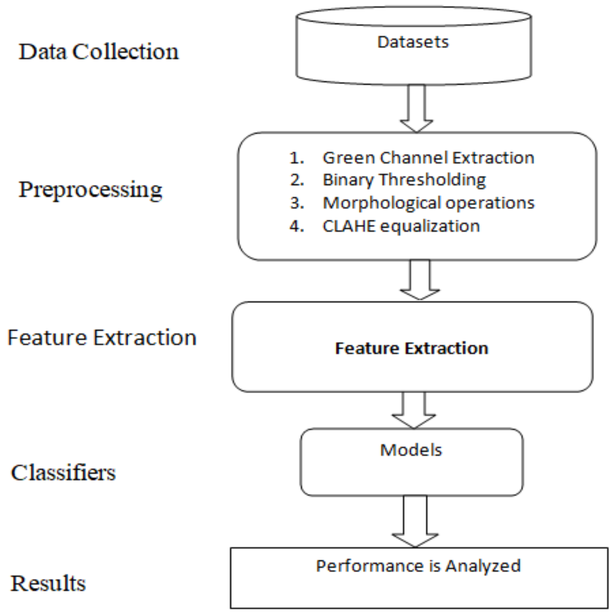

Fig: 2 Research Methodology used in this work

Data Collection

For analyzing the performance of different classifiers. We use five datasets of different sizes. Each has different images. The datasets are publically available and taken from Kagggle database. Each datasets have five subfolders each having images of different stages of Diabetic Retinopathy i.e. No_DR, Mild, Moderate, Severe, Proliferate stages. Datasets are divided into 7:3 for training and testing purposes. Web links from where these can be downloaded and size of dataset are given in Table2:

Dataset Information

Table 2

Dataset	No. of Images	Link
Dataset1	1800	https://www.kaggle.com/datasets/mohammadasimbluemoon/diabeticretinopathy-messidor-eyepac-preprocessed
Dataset2	3662	https://www.kaggle.com/datasets/sovitrath/diabetic-retinopathy-224x224-gaussian-filtered
Dataset3	9675	https://www.kaggle.com/datasets/sovitrath/diabetic-retinopathy-2015-data-colored-resized
Dataset4	10838	https://www.kaggle.com/datasets/mohammadasimbluemoon/aptos2019-diabetic-retinopathy-oversampled-256x256 APTOS2019
Dataset5	15496	https://www.kaggle.com/datasets/sohaibanwaar1203/diabetic-rateinopathy-full?select=224+diminsion

Preprocessing

The pre-processing is an essential step for preparation of retinal images for classification due to the continuous variation in image quality. Some images are non-uniformly illuminated, some are noisy or poor contrast. These kinds of sorts generally affect the effectiveness of models. Hence, the captured RGB image should pass through several preprocessing methods. This step enhances the datasets so that these can be easily processed by models and helps in feature extraction. Fig. 3 shows the retinal image after applying each step.

Green channel extraction

The original retinal images are RGB, and have low contrast and noisy. So for obtaining best vessel-background contrast we extract the green channel from RGB images. Each pixel of image is taken as intensity feature [10].

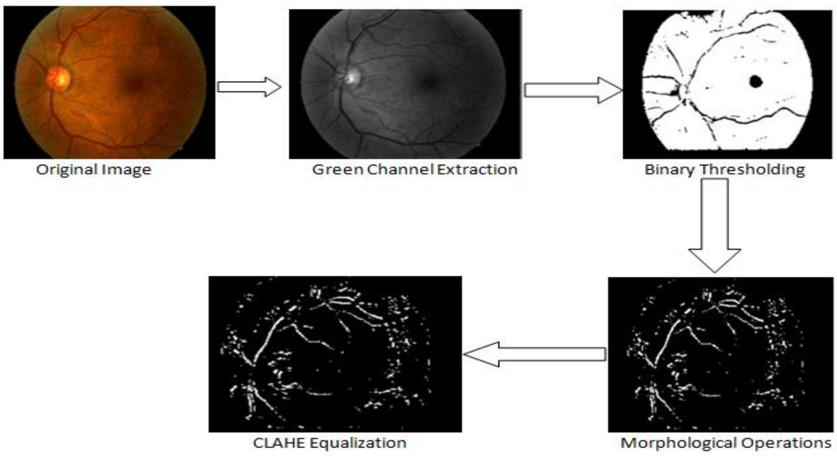

Fig3. Preprocessing Steps

Binary Thresholding: Thresholding creates a bitonal image by setting a threshold value on the pixel intensity of the green channel images. Thresholding makes the image suitable for feature extraction in this pixels below the threshold value are converted to black and pixels above the threshold value are converted to white. This process contributes in separating forground material like blood vessel, hard/soft exudates and microneurisms from background.

Morphological operations: further Morph operations are used to remove imperfections from images. In this step four operation are performed:

Erosion: The erosion of an image i is done by structuring an element e (denoted by $i \ominus e$). It produces a new erosion image $n = i \ominus e$ in which one at all the locations (x,y) of a structuring element where element (e) fits the input image i,

i.e. n(x,y) = 1 if e fits i

otherwise 0

this step removes the small unnecessary details from a binary image and thus reduces the size of RoI. Boundaries (b) of each region can be found:

$$b = i - (i \ominus e).$$

Dilation does the opposite to erosion -- it highlights the the inner and outer boundaries of regions by adding a layer of pixels. The dilation of an input image i done by a structuring element e (denoted $i \oplus e$) it outputs a new binary image(b)

$$b = i \oplus e$$

in which one at all the locations (x,y) of a structuring element's where element e fits the input image i, i.e. n(x,y) = 1 if e hits i

and 0 otherwise.

Opening and closing: Opening is generally used to smooth the contour objects whereas closing is a kind of dilation operation which removes background pixels, which fit the structuring element. It tends to close the gaps in the image.

CLAHE Equalization: CLAHE is generally used to increase the contrast of images using adaptive histogram equalization. It takes care of over amplification of contrast. It operates on the small region of image called tiles and neighboring tiles are combined using bilinear interpolation to remove the artificial boundaries.

Feature Extraction

After preprocessing images obtained are high contrast images from which features can be extracted and applied to different classifier. Feature extraction is a process of transforming raw data or information into numerical, useful features that can be processed while preserves the information of original data set. In this work we used SqueezeNet for feature extraction. SqueezNet is Network which uses convolutional filters to extract features from images. It uses fewer floating point operation to extract features. It uses 16 convolutional filters. Besides SqueezNet we can also use principle component analyses, peoples for features extraction.

Models

for our research work we have used following machine learning models

SVM

Support vector machine is a supervised machine learning models which is widely used in analyzing image/text data for classification, regression and outliers detection. For this SVM make hyperplanes in a high- dimensional space [11]. Intuitively, larger the distance from nearest training-data point of any class in hyperplane better the classification done means larger the margin, lower the generalization error. For our research work we have used cost function 1.0 and regression loss epsilon (€) value 0.10, to create a margin of tolerance when errors have no penalty. And sigmoid tanh(gx.y+c) as kernel function for multiclass classification with numerical tolerance of 0.0010 as optimization parameters and 10 fold cross validation to generalize the classifier.

KNN

k-nearest neighbor is a non parametric supervised machine learning model, generally used for classification and regression purpose as SVM. This algorithm uses distance parameters for classification, and feature similarity for new data prediction [12]. For our research work we have taken K=5 as number of neighbors and this parameter also reduces the effect of noise during classification. For distance metrics we have used euclidian distance as it is widely used for continuous and variable data.

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Random Forest

RF is a supervised machine learning model which builds decision trees on different samples of data and takes their majority vote for classification purpose. In RF as all trees don't use all the features so features are reduced [13]. This model achieved the stability because decisions are based on the majority of votes. In our research work we have takes 10 trees and split level of 5 for dividing nodes into multiple sub-nodes to achieve relatively pure nodes.

Neural Network

Artificial neural networks simply called neural networks works are inspired by the biological neural networks of human brain. Neural networks architecture is madeup of connected nodes simply called neurons. Each connection can send a signal or value that trigger another neurons. A neuron receives a signal (real number) then processes it and can trigger the neurons connected to it or provides output. Output of each neuron is computed by some non-linear function. The connections between the nodes are called edges. Neurons and edges have weight associated with it which adjusts automatically as learning proceeds. Typically neurons are aggregated or organized in form of layers. Different layers perform different transformations functions on their inputs For our research work we have taken 100 neuron and ReLu as activation function which introduces linearity in data. And ADAM as optimizer to minimize the error function and regularizer (α) having value 0.0004 and total 50 iteration are applied for classification.

Naïve Bayes:

Naive Bayes classifiers are probabilistic based classifier which employs the strong naive independent assumptions among the features or Bayes' theorem for classification. With kernel density estimation, this classifier can achieve high accuracy levels. In our research work we have used Gaussian normal distribution function for handling features of data.

Logistic regression

Logistic regression is a supervised machine Learning algorithm widely employed for predicting or computing the categorical dependent variable from a given set of independent variables. This model can easily determine the most effective or valuable variables for the classification by using different types of data observations. Logistic regression uses the logistic equation for determining dependant and independent variables below shows the logistic equation:

$$log\left[\frac{y}{1-y}\right] = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \cdots + b_nx_n$$

For our research work we have used Ridge L2 regularizer and C=2 as strength parameter.

Decision Tree: Decision Tree is a supervised machine learning model that is widely used for classification and Regression problems. This model uses tree like structure in which features are represented by internal nodes and branches denote the decision rules and outcomes are described through each leaf node. In our research work we have used induced binary tree with the split level of 5 and minimum level of instances in leaves are set to 2. And maximum depth limit of tree is set to 100 so that it can deal with overflow situation.

Besides these machine learning models we also applied some DNN architecture for analyses and comparison purpose on these datasets.

EfficientNetB0

EfficientNetB0 is a most commonly used DNN model for image processing that is trained on more than a million images from the ImageNet database and this model provides better result in some real application area. Architecture of Efficient NetB0 are shown in Fig 4.

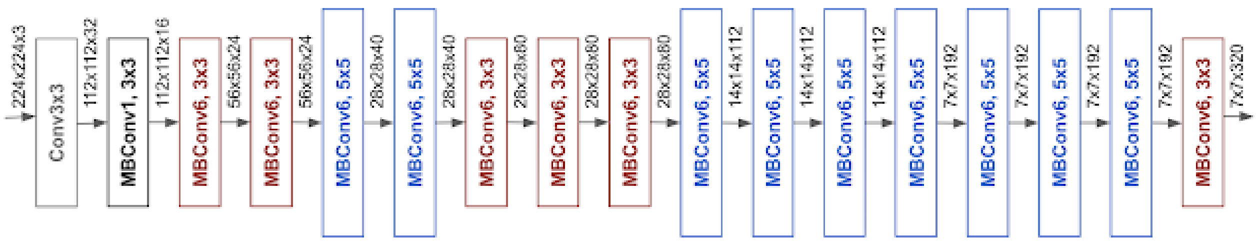

Fig. 4 EfficientNet Architecture

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in this model we have categorical_crossentropy as loss function and ADAM as optimizer for improving learning rate of the model. In this work we have taken output after 35 epochs or earlier if it does not change for 3 or more epochs.

CNN + SVM

In this model we have combined convolutional neural network technique with SVM classifier. Whole model was divided into two part feature extraction and classification as shown in Fig 5.

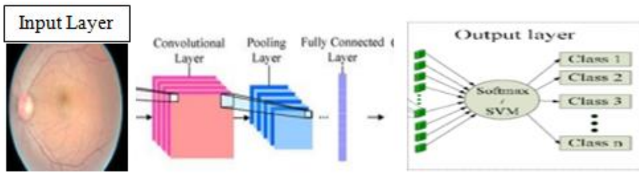

Fig. 5 CNN + SVM architecture

In feature extraction process, a model which consist of 2 convolutional layer with kernel (3,3), filter size 32, stride value 2 each followed by maxpool layer of pool size is 2 is build. In this model one flatten layer and 1dense layer of unit size 128 is connected to extract features from the images. In second phase SVM classifier with softmax activation function is employed to classify the images into five stages of DR. in this work we have taken Hinge function in loss parameter.

VGG16

VGG 16 is considered as one of excellent computer vision model for image processing. This is a large network in which approximate 138 million parameters to analyse the data[14]. VGG 16 architecture constitutes of convolution layer each having 3x3 filter and max pool layers of 2x2 filters. In the end it has 2 fully connected layers followed by one softmax layer for output. VGG16 architecture is shown in Fig 6.

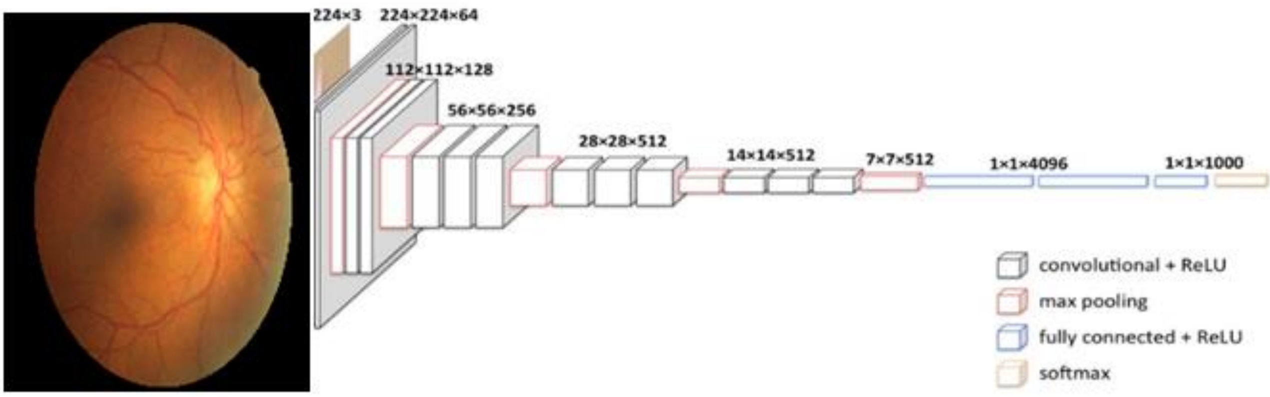

Fig. 6 VGG 16Architecture

ResNet50: As VGG, ResNet50 is also one of the most popularly used model for vision applications this model has 48 convolution layers with 1 max pooling and 1 average pooling layer. It has approximate 3.8 x 10^9 Floating points operations which make it better than VGG. When implementing ResNet50 we have used SGD (Stochastic gradient descent) as learning parameter as it have smoothening properties and loss function we used is binary crossentrophy.

InceptionV3

Inception Networks are more computationally efficient than VGG network , both in terms of the number of hyper-parameters generated by the architecture and the economical cost incurred. In this model we have employed RMSProp(Root Mean Squared Propagation) with learning rate 0.0001 because it uses decaying average of partial gradients for updation of weights for next iteration.

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CNN

In this, we have build a model which uses 4 convolutional layer having kernel(3×3), filters from 32, 64, 128, 128 respectively each followed by one maxpool layer of size 2. At the end of the model one flatten layer followed by two dense layer of unit size 512 and 1, having activation function ReLu and sigmoid is attached. In this model we have used RMSProp (le-4) as optimizer binary crossentrophy as loss function for computing loss between input and output value.

Result and Discussion

This works presents the performance of different machine classifier on diabetic retinopathy datasets. Performance is evaluated on the basis of Area Under Cover (AUC), Classifying Accuracy(CA), F1 score, precision and Recall. Performance of each dataset is shown in Table 3.

Table 3

DATASET 1					
Model	**AUC**	**CA**	**F1**	**Precision**	**Recall**
KNN	0.776	0.457	0.457	0.467	0.457
Tree	0.701	0.504	0.501	0.503	0.504
SVM	0.821	0.439	0.417	0.428	0.439
Random Forest	0.833	0.550	0.548	0.548	0.550
Neural Network	0.850	0.568	0.567	0.568	0.568
Naive Bayes	0.820	0.505	0.495	0.498	0.505
Logistic Regression	0.836	0.516	0.515	0.514	0.516
DATASET 2					
Model	**AUC**	**CA**	**F1**	**Precision**	**Recall**
KNN	0.843	0.703	0.677	0.672	0.703
Tree	0.679	0.643	0.641	0640	0.643
SVM	0.680	0.493	0.476	0.465	0.493
Random Forest	0.863	0.711	0.684	0.676	0.711
Neural Network	0.886	0.706	0.698	0.691	0.706
Naive Bayes	0.825	0.595	0606	0.644	0.595
Logistic Regression	0.890	0.711	0.687	0.682	0.711
DATASET 3					
Model	**AUC**	**CA**	**F1**	**Precision**	**Recall**

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KNN	0.516	0.662	0.601	0.562	0.662
Tree	0.502	0.542	0.547	0.552	0.542
SVM	0.518	0.335	0.396	0.561	0.335
Random Forest	0.520	0.693	0.602	0.549	0.693
Neural Network	0.525	0.639	0.592	0.557	0.639
Naive Bayes	0.528	0.291	0.077	0.537	0.291
Logistic Regression	0.556	0.720	0.604	0.573	0.720
DATASET 4					
Model	**AUC**	**CA**	**F1**	**Precision**	**Recall**
KNN	0.790	0.492	0.484	0.481	0.492
Tree	0.744	0.584	0.569	0.560	0.584
SVM	0.666	0.300	0.299	0.327	0.300
Random Forest	0.859	0.624	0.610	0.602	0.624
Neural Network	0.885	0.670	0.660	0.654	0.670
Naive Bayes	0.686	0.375	0.348	0.373	0.375
Logistic Regression	0.814	0.512	0.508	0.560	0.512
DATASET 5					
Model	**AUC**	**CA**	**F1**	**Precision**	**Recall**
KNN	0.587	0.630	0.586	0.566	0.630
Tree	0.533	0.537	0.540	0.544	0.537
SVM	0.588	0.318	0.248	0.558	0.218
Random Forest	0.595	0.668	0.589	0.561	0.668
Neural Network	0.653	0.639	0.608	0.587	0.639
Naive Bayes	0.583	0.221	0.258	0.579	0.221
Logistic Regression	0.676	0.693	0.598	0.572	0.693
Deep Learning Architecture Accuracy					

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Model	Dataset1	Dataset2	Dataset3	Dataset4	Dataset5
Efficient Net	0.48	0.71	0.63	0.50	0.53
CNN + SVM	0.47	0.71	0.72	0.52	0.53
VGG16	0.52	0.74	0.72	0.48	0.55
ResNet50	0.75	0.79	0.80		0.76
Inception	0.80	0.80	0.80	0.80	0.80
CNN	0.80	0.80	0.80	0.80	0.80

After evaluating the results it is observed that navy bayes and support vector machine are less efficient than KNN, decision tree, RF, NN and logistic regression and others deep learning architecture in all matrix evaluation on these types of datasets. KNN classifier have good results as it have AUC 77%, 84%, ,51%, 79% and 58% respectively as shown as in tables and f1 score are also far better than SVM and navy bayes classifier. Next decision tree performance is evaluated, model provide not such good result as it have precision 50%, 64%, 55%, 56% and 54% respectively in all five datasets. In case of Random forest it provides better precision results on dataset1, 2, and 4; than KNN but less on two other datasets so performance of this model is approximately same as KNN. Next ANN in which we have used 100 hidden layers have this classifier far better results than SVM, Navy bayse, KNN and tree. This model have CA of on five datasets which are good than other four models. After that performance of Logistic Regression is evaluated and after analysis we can say that this model performed excellent when compared with previously discussed models as AUC is 83%, 89%, 55%, 81 and 67% respectively and precision and F1 results of this model are highly better than other six classifiers.

After analyzing seven machine learning techniques KNN, Decision Tree, SVM Random Forest, Artificial Neural Network and Logistic regression we have concluded that logistic Regression provides better results than these six techniques

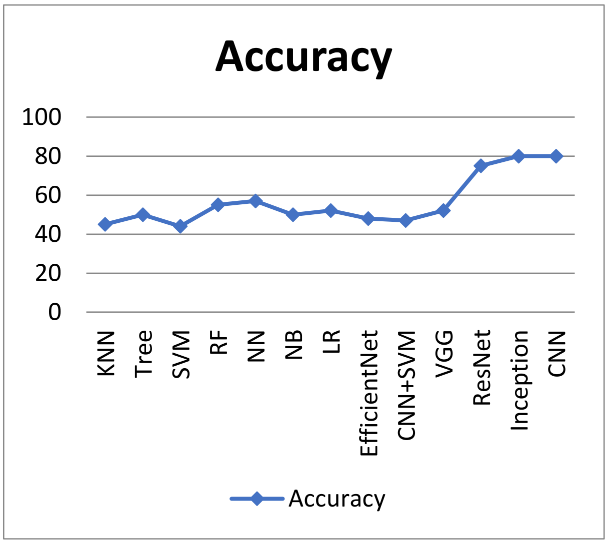

Fig. 7(a) Dataset1

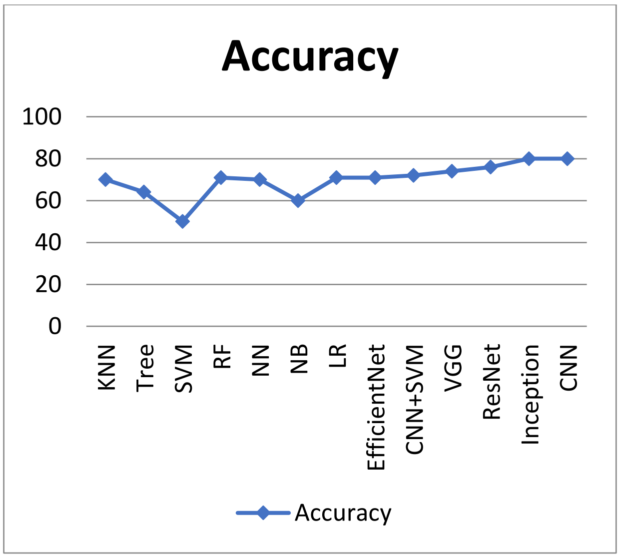

Fig. 7(b) Dataset2

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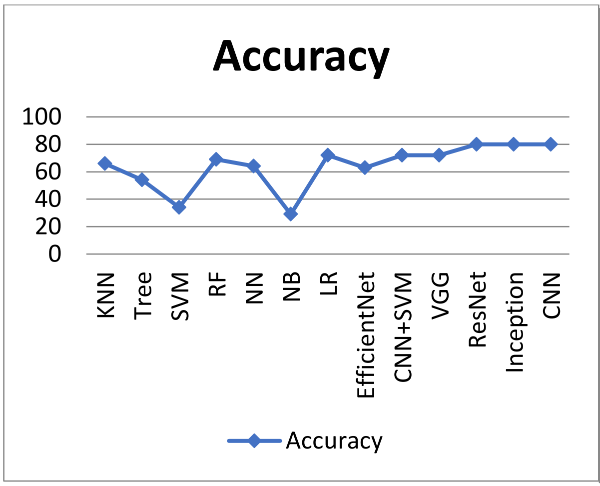

Fig. 7(c) Dataset 3

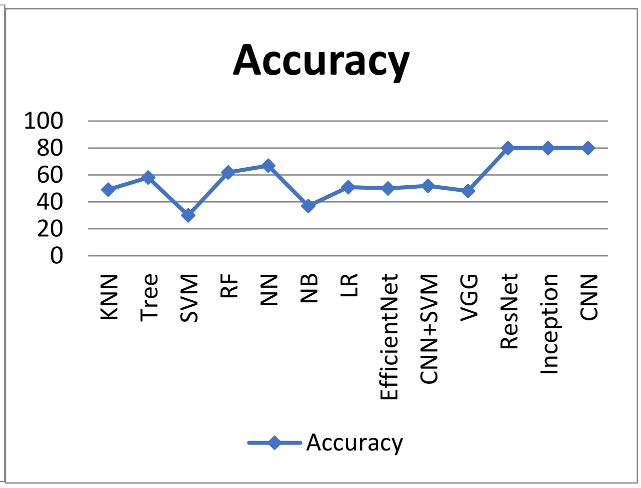

Fig .7(d) Dataset4

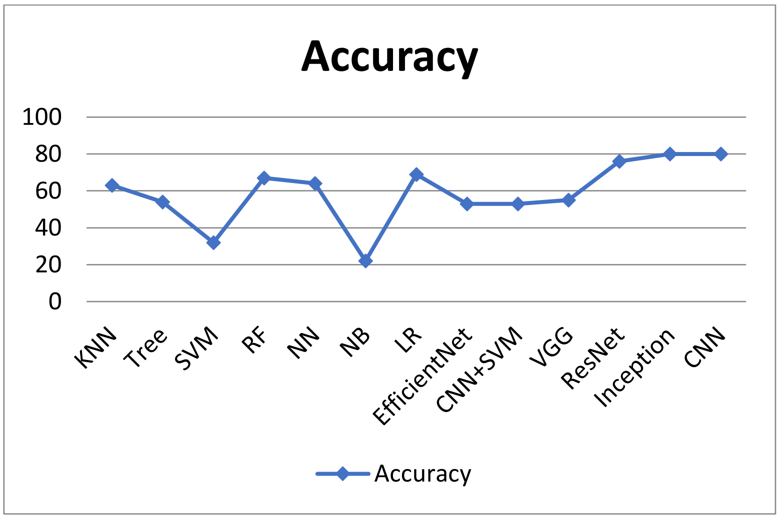

Fig. 7(e) Dataset 5

Fig. 7 Comparative analysis of different machine learning models based on Accuracy

Next we have analyzed six different DNN architectures on these datasets based on accuracy. In table validation accuracy of these architecture are shown. First EfficientNet model have accuracy of 71,48, 63 on these datasets and VGG16 have accuracy of 74,52,72,55,48. which is better than EfficientNet on all the datasets. Further CNN+SVM in which CNN architecture is used for feature extraction and SVM is used as classifier have 71,47,72,53 accuracy which is good than EfficientNet but comparable with VGG16 model. Next ResNet, InceptionV3 and CNN models are employed these models provide accuracy of 80% in all cases which is far better than all evaluated machine learning in this paper. A comparative analysis of these techniques is shown in graphs in Fig . In which we have taken accuracy as evaluation parameter. Accuracy of all these techniques are compared separately in different datasets and from analysis we have concluded that Deep CNN and Logistic regression are better classifier than other machine learning models.

Conclusion: This paper analyzed the performance of machine learning techniques on Diabetic Retinopathy datasets. Evaluation parameters AUC, Classification accuracy, F1 score, Precision and Recall are used to analyze the performance of these techniques. After the research work we can conclude that CNN model offers highest accuracy 80% over all other classifiers. In future we will make a deep learning based model which will be more robust and achieve higher accuracy by making fusion of the two networks using their fully connected layers and improve the network architecture and develop cost functions that fits on large heterogeneous data set.

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