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Multiclass Adaptive Boosting Approach for Diabetic Retinopathy Prediction Using Diabetic Retinal Images

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ABSTRACT

Scaling up diabetic retinopathy (DR) screening is crucial for preventing blindness caused by this prevalent eye condition, which affects an increasing number of individuals with diabetes worldwide. Early detection of DR and related complications through fundus imaging can effectively halt the progression of the disease to more severe stages. Although recent advancements in convolutional neural network (CNN) techniques have addressed some key challenges in DR screening, the issue of overfitting during the classification process remains due to the limited performance of CNNs in this context. In this study, we propose a novel multiclass adaptive boosting approach to overcome overfitting and enhance classification accuracy. We employ the VGG16 pretrained model for feature learning and the factor analysis method for preprocessing DR images. By integrating the adaptive boosting technique with CNN-based classification, our approach achieves significantly improved accuracy and area under the curve (AUC) scores. This research contributes to the development of more effective and efficient DR screening methods, with the potential to substantially impact diabetes management and patient outcomes.

1. INTRODUCTION

The term "diabetes" is now widely used and is a significant problem in both advanced and developing economies [1]. The health industry with the fastest issue in the 21st century is diabetes. By 2030, the world will have 578 million adults who have diabetes, according to the World Chronic Disease Atlas [2]. An eye disease known as "Diabetic Retinopathy" seems to be more common among people who have diabetes. It's considered that diabetic retinopathy is a catastrophic eye condition as it can result in blindness and vision loss in people with diabetes. The blood vessels in the retina suffer substantial damage from very high glucose levels. Sometimes, abnormally growing new blood vessels can be seen. The conditions listed above can all result in permanent eyesight loss.

Diabetic retinopathy comes in two forms proliferative diabetic retinopathy (DPDR) and no proliferative diabetic retinopathy (NPDR).

The NPDR is then categorized as "mild," "moderate," or "severe" depending on how the symptoms are progressing [3].

- Mild NPDR with a few little aneurysms.
- Moderate NPDR-Hematomas and spots on cotton wool are present.
- Severe NPDR- There is intraretinal bleeding in four of the eye's quadrants, two of which have venous beading or one of which has an intraretinal microvascular abnormality.

Diabetic retinopathy that has been proliferative is a more chronic stage of diabetic retinopathy that occurs when untreated (PDR). For this kind, the retina's growing new blood vessels begin to form at an accelerated rate. When the newly formed blood vessels disrupt the fluid flow, pressure builds inside the eyeball and the retina separates from the backside of the eye. Additionally, blood penetrates into the intraocular, a raspberry jam substance found in the middle of the eye. The abovementioned occurrences result in damage to the optic nerve, which transmits confused images from the eye to the brain and is responsible for vision loss. The optic nerve is the nerve that travels through the blind spot. The goal of the CNN method is to speed up the process and make accurate predictions. CNN has already been used to make precise predictions in some industries, including healthcare [4, 5] and intelligent automation [6].

Table 1. Cases of diabetic retinopathy in the US between 2000 and 2010 [7]

Year's	Number of DR Cases	Small Range
2000	4,063,247	4,063
2010	7,685,237	7,685

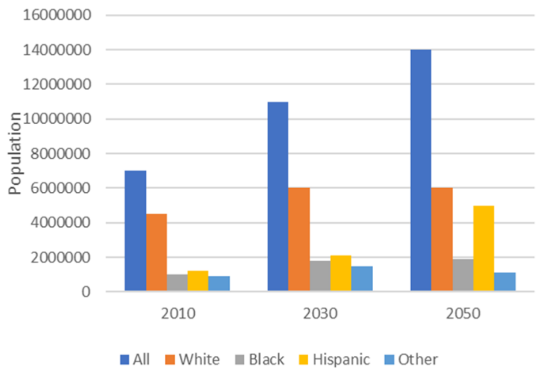
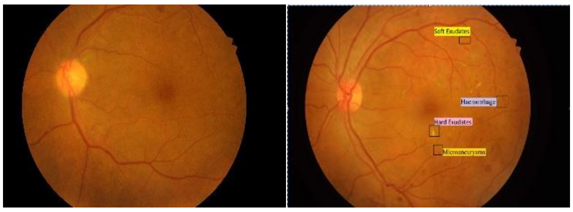


Figure 1. Diabetic retinopathy in 2030 and 2050(in millions) in the US [7]

According to Figure 1 & Table 1, between 2010 and 2050, it is projected that the number of Americans with diabetes mellitus will rise from 7.7 million to 14.6 million and Cases of DR.

Figure 2 shows some samples of fundus images with severe diseases.



Normal Diabetic retinopathy

Figure 2. Example DR fundus image with different kinds of lesions (right) and a normal fundus image (left)

The Diabetic Retinopathy Detection Dataset comes from the Kaggle repository and is made up of five classes that represent the appearance of Diabetic Retinopathy: No DR, mild, moderate, severe, or proliferative DR.

Researchers and Ophthalmologists can use the DR dataset to create automated algorithms for Diabetic Retinopathy Detection (DR).

Images of the retina or fundus are extremely useful in identifying a wide range of eye-related conditions. Structures like blood vessels, the optic disc, the macula, and the fovea can all be seen in retinal pictures. These retinal image structures provide data that is used to diagnose and manage a wide range of eye disorders.

Latest developments in the fields of machine learning (ML) and artificial intelligence (AI) could contribute health care professionals along with doctor useful strategies for a range of diseases, clinical prediction, such as cholesterol [8], continual glucose monitor [9], short-term glucose prediction [10], CKD [11], ALF and cancer [12].

2. RELATED WORK

It has been encouraging to see automated DR pathological screening improve in recent years. In the literature, a lot of deep learning and machine learning-based techniques have been presented.

Ji et al. [13] presented work in which a multi-feature combination classification strategy uses the four-module stacking DWKNN algorithm. The observed optimal accuracy was 99.01%. The majority of the above-mentioned stacking model fusion techniques define the fusion of classifiers, whereas a few of them also investigate a confluence of classifiers. However, the selection of classifier combinations in the stacking approach is a major issue worth examining which will take more time for further computation time for large datasets.

Lin et al. [14] DR can be grouped into 5 classes as per the kind and amount of lesions visible in fundus images: 0 (normal), 1 (mild DR), 2 (moderate DR), 3 (severe DR), and 4 (proliferative DR), Microaneurysms in the form of red dots are the earliest detectable indication of a low grade of DR. Hard and soft exudates are examples of yellow-white lesions, and red lesions, such as intracranial hemorrhage, have a variety of morphologies that might be tiny spots or large expanses. More of these lesions would indicate a higher DR grade. A crucial indication of proliferative DR is neovascularization, or the development of new retinal vessels in the optic disc or its periphery.

Hashir et al. [15] compared a couple of multi-view techniques for fusing lateral and posteroanterior views of X-ray scans in order to predict radiological outcomes. These techniques concentrate on learning feature-level multi-view correlations.

Dai et al. [16] use the DeepDR to trained for real-time image quality.

Majumder and Kehtarnavaz [17] used modified Squeeze Excitation Densely Connected deep neural network to measure the highest performance to the largest datasets.

de La Torre et al. [18] presented work for DR categorization. By giving every input and hiding point area a value, its classifier can utilize those values to explain the classification results. Their classifier obtains 91% accuracy in binary classification using the Messidor-2 data set.

Qummar et al. [19] The recommended strategy beat the earlier techniques on the publicly available Kaggle dataset, obtaining an accuracy of 80%.

Zhang et al. [20] used a 13,767 image private dataset broken into four sections to suggest a method for identifying the DR. To meet the specifications of every network, the photos were resized and cropped. Identify the DR and the improved pre-trained CNN architectures used ResNet-50, Inception-V2, Inception-V3, Xception, and DenseNet. AbdelMaksoud et al. [21] proposed the E-DenseNet model, a hybrid deep learning approach for identifying various DR phases. Transfer learning is used in the E-DenseNet model, which combines EyeNet with DenseNet. The researchers have gained a lot of advantages by integrating the two prototypes and tailoring the integrated dense blocks of the Eye Net's building blocks. The model's key benefit was that it required less training time and memory to properly categorize photos. With a Kappa score of 0.883, this model has an accuracy rate of 91.6%.

Prasad et al. [22] utilised a range of segmentation and morphological methods for identify blood vessels, exudates, and microaneurysms. There have been four smaller versions of the main picture. On the extracted features, Haar wavelet treatments are used. We choose the majority of the parameters using discriminant function analysis and principal component analysis. A back propagation neural network was used to classify the images as diabetes or non-diabetic.

Gadekallu et al. [23] Using principal component analysis and the Grey Wolf Optimization (GWO) technique, the dataset for diabetic retinopathy's extracted features was classified using a deep neural network model.

Jiang et al. [24] categorized their dataset using the Inception-V3, Inception-ResNetV2, and ResNet-152 pre-trained CNN architectures.

Zhang et al. [25] utilised a private database of 13,767 photos broken into four categories to suggest a method for identifying the DR. To meet the specifications of every network, the photos were resized and cropped. For the purpose of identifying the DR, Pre-trained CNN architectures were improved using ResNet-50, Inception-V2, Inception-V3, Xception, and DenseNet.

Rajpoot et al. [26] technique was then used to match the damaged leaf test images to the illnesses being trained. The use of CNN and BBHE for pattern recognition.

Rajpoot et al. [27] proposed work in real time health care application uses the GMM and grabCut method.

3. METHODOLOGY

This paper presented is a multi-class adaptive boosting ensemble Learning strategy for diabetic retinopathy detection based on eye image categorization, which will be more significant for the early detection of diabetes. The suggested model is employed to identify diabetic retinopathy based on problems in fundus images in the initial phase and significantly intercept its progress to the last stage. The model framework covered all required steps like image preprocessing and image feature retrieval using a pretrained VGG16 CNN feature extractor to feed low-level features to an adaptive boosting model for classification, which will avoid overfitting by improving the progressive performance of weak classifiers enclosed in it.

The proposed system as shown in Figure 3 which uses ensemble methods and deep learning to enhance image classification. The proposed task has these three aspects:

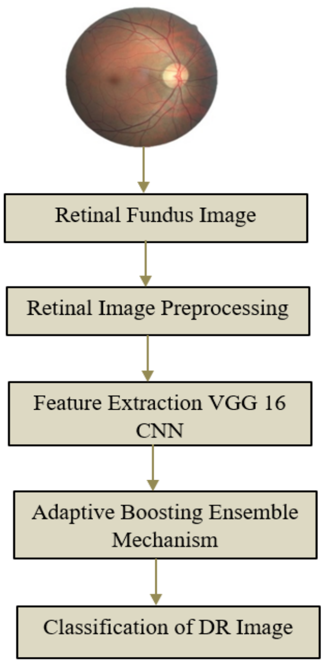


Figure 3. Proposed work

Steps:

3.1 Image Preprocessing- Resize, Noise removal, Data augmentation.

3.2 Feature Extraction using VGG16 pretrained model.

3.3 Classification using adaptive boosting by employing multiple VGG-16-CNN estimators.

3.1 Image preprocessing

The first step is carried out by resizing the target image dataset and increasing the dataset volume with an image data generator data augmentation model. For reducing noise and fluctuation, preprocessing improves the quality and contrast of the retinal fundus image. Image preprocessing is important to eliminate image noise, enhance image properties, and ensure image consistency. Image normalisation, non-uniform intensity correction, contrast enhancement, and noise reduction can be at the preprocessing stage to get remove the artefacts, enhance the accuracy of the subsequent processing steps. Several methods of reducing noise include the use of a median filter, a Gaussian filter, and nonlocal means denoising techniques [28]. Translating, rotating, shearing, inverting, contrast scaling, and resizing are methods for improving data. A morphological strategy was utilised to enhance the contrast, as can be seen in the study of Chudzik et al. [29].

3.2 Feature extraction using VGG16 pretrained model

A cutting-edge image classification algorithm called VGG-16 can handle up to 16 layers. VGG, which was designed as a deep CNN, performs better than baselines on many tasks and datasets outside of ImageNet. One of the most popular illustration recognition systems right now is VGG-16. The second step is to use the VGG16 CNN model to capture low-level features as shown in fundus images in Figure 4. The VGG16 model from TensorFlow Kera's is imported first in this case as well. The image element is loaded to preprocess the image element, and the input module for preprocessing and pixel values are adjusted appropriately for the VGG16 model. In order to create a new model that is a subset of the layers in the complete VGG16 model, the Model module must also be loaded. The output of a certain convolutional layer, which we know would be the activation of the layer or the feature map, would be different from the model's input layer, which would remain the same as it was in the original model.

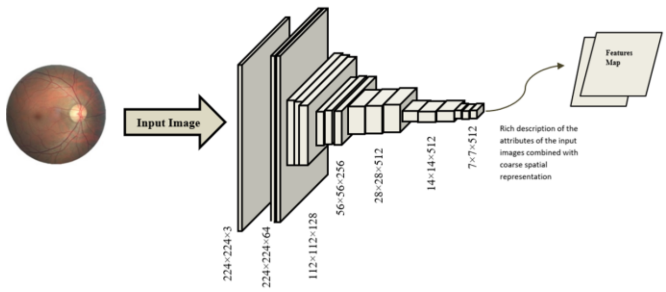


Figure 4. Features extraction using convolutional neural network (VGG-16)

The VGG16 model is then given the pre-trained values from the ImageNet dataset. A feature extractor model that generates a feature map from the pooling layer for input image instances can be defined after the VGG model has been loaded. The input image was scaled to 224*224 to match the VGG 16 input image size in the input layer. Then, for the VGG model to get the low levels of features, the pixel values must be scaled in the right way.

Feature Extraction using VGG16

1. Load the dataset.
2. Extract people and fish data from the dataset.
3. Reshape and preprocess the images.
4. Load the VGG16 model from Keras using imagenet weights.
5. Extract features using pretrained VGG16 model.

The convolutional neural network VGG16 was trained using data from a subset of the ImageNet dataset, which comprises data from around 14 million images organized into 22,000 categories. The VGG16 model comprises three dense layers for the fully connected layer in addition to 16 convolutional and max-pooling layers. There are 1,000 nodes in the output layer as well. The VGG16 model extracted features using the method given below:

1. Get the pre-trained model downloaded.
2. Make sure that the Fully Connected layer, which makes up the "top" of the model, is not used.
3. Pre-trained layers should be applied to the image data to obtain convolved visual features.
4. The obtained feature stack, which significantly used input for classification with the proposed model.

The diabetic retinopathy image features are extracted using VGG-16 CNN model and the extracted micro level features of input image in Figure 5. are visualized for all filers used to acquire image features in Figure 6.

3.3 Adaptive boosting classifier

The preferred approach for imbalanced datasets is adaptive boosting ensemble, this approach significantly boost the proposed algorithm adaptively which adjusts future weak learners to take advantage of instances that were incorrectly classified by earlier classifiers. As there five classes of DR images for classification, the multiclass adaptive boosting is used significantly in proposed work. The multiclass classification [30] is significantly classified using adaptive boosting which adopts the Bayes rule by training a forward phase wise additive model for multi-class problems.

In comparison to using a single estimator, ensemble models can boost the dependability of machine learning by integrating a number of base estimators to reach high accuracy. In this study, a convolutional neural network (CNN) and the ability of adaptive boosting are combined to create adaptive boosting-CNN, a cutting-edge machine learning method that can successfully handle severely unbalanced datasets. Adaptive Boosting is an ensemble technique that trains a series of classifiers. single adaptive-boosting factor assigned weight to the training sample, while non-adaptive-boosting training samples are assigned a higher weight.

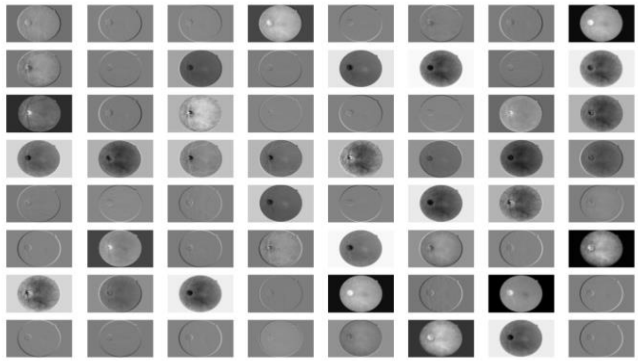


Figure 5. Input image

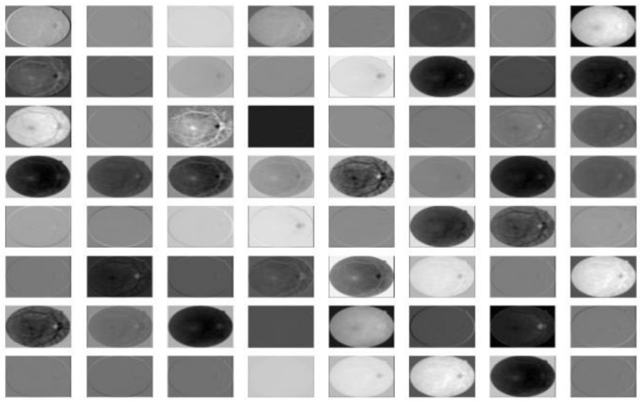


Figure 6. Visualize all filter

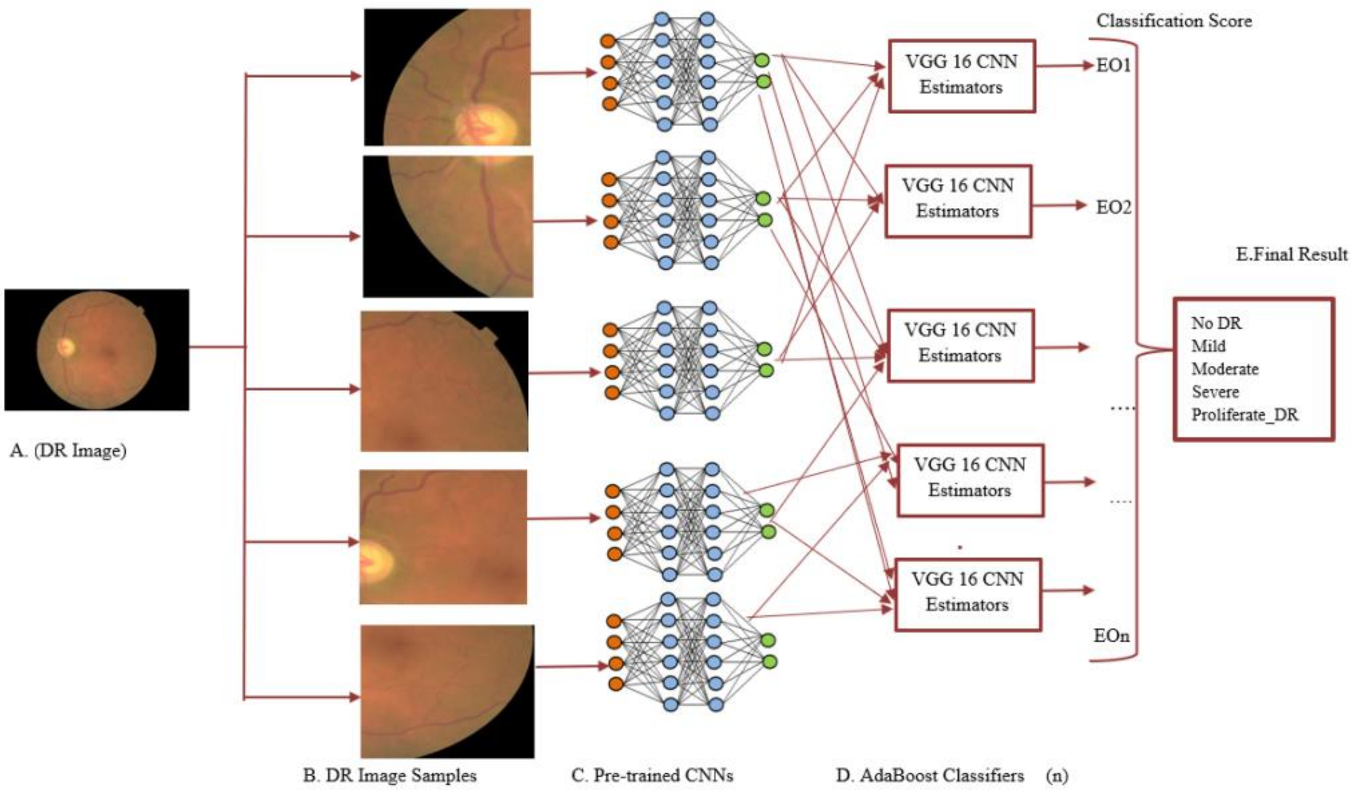


Figure 7. Proposed architecture

The adaptive boosting technique is used to increase accuracy and decrease training time. Using transfer learning, CNN adjusts the sample weights in the training set. The trained data of one CNN estimator is successively transformed to the subsequent CNN estimator using this method. This research provides a method that extends adaptive boosting abilities to categorize big data using CNN features. Adaptive boosting is an algorithmic technique that has been used to overcome the problems that traditional machine learning approaches have with identifying imbalanced data. This review proposes a new method based on adaptive boosting CNN that integrates enhanced abilities of CNN in examining and identifying patterns in large -scale data with adaptive boosting capabilities of handling massive amounts of inconsistent data to embed CNN's competence for the task of dealing with imbalanced data in adaptive boosting. This proposed work offers a technique that expands adaptive boosting ability to classify large amounts of data using the CNN estimators.

The adaptive boosting is an algorithmic technique that has been used to get around the problems that traditional machine learning methods have with identifying imbalanced data. A multi-class adaptive boosting for CNN, is suggested in this study in which a there are several CNNs used cheap estimators in the proposed technique as shown in Figure 7. Sequential training is done on CNN. The sample value for its subsequent CNN is updated using the errors of the previous CNN. The learned CNN learning parameters are then applied to the subsequent CNN after the sample weights have been updated. Accuracy is increased via transfer learning in the suggested adaptive boosting approach. During training, the updated sample value is utilised.

Pseudocode of adaptive boosting Classifier

The training dataset samples are input to algorithm presented as, Steps a to h

pi (1,2,3,4……. n) labels qi ∈ Q,

a. Set sample instances (pi, qi) ……. (pn , qn); pi ϵ P, qi ∈{-1, +1}
b. Define weights of DIt (i)=1/ M, i =1…..., M
c. For loop It=1……, T
d. Train the samples that is weak using distribution DIt
e. Get hypothesis of week hIt: P→{-1, +1} along with its error = εIt = $\sum_{hIt}^{n} \quad (p) \neq qi$ DIt (i)
f. Modify allocation DIt: DIt +1 (i) = DIt (i) exp (−αIt qIt TIt (pIt))/ Cit
g. Next It that, It+1
h. Final hypothesis Outputs: H(x) =sign [$\sum_{It=1}^{T} \quad (\alpha It)\ hIt \neq qi$ DIt (i)]

4. EXPERIMENTAL RESULT AND ANALYSIS

This analysis examines AdaBoost-performance CNN's using the DR dataset. The impact of various imbalance levels is then examined.

4.1 Performance evaluation metric

Accuracy may not be using metric in unbalanced datasets. Accuracy defines as the number of examples that were properly classified, divide by the overall count of data instances.

The accuracy is calculated using:

$$Accuracy = \frac{TPs + TNs}{TPs + TNs + FPs + FNs} \tag{1}$$

4.2 Results of a classical AdaBoost with a decision tree

A classical AdaBoost approach that perhaps utilized to tackle asymmetrical input is AdaBoost with a decision tree. In this traditional AdaBoost, 400 poor classifiers using decision trees were employed. Each decision tree's maximum depth is set at 2. The standard AdaBoost strategy has a training dataset accuracy of 87.45% and a testing dataset accuracy of 77.08%.

4.3 Observed outcomes after applying the single CNN baseline estimator

Sample weights are employed in the proposed methodology to regulate the learning process on various training samples.

VGG 16 CNN baseline estimators were used in the DR dataset adaptive boosting model. Following a one-dimensional (1D) Max-Pooling level with a pooling size of 2×1, it contains a one-dimensional (2D) convolutional with an activated ReLU function. The convolution filtration system has a 3×1 dimension. 32 extracted features encompass the layer. The remaining 25% of neurons are then randomly excluded using a dropout layer. The next step involves using two thoroughly linked hidden layers with 256 and 72 neurons. In hidden layers, the ReLU activation function is utilised. Then, a SoftMax function and a three-neuron output layer were used. Additionally, the Keras "Adam" optimizer with the default parameters was applied. Based on whether a parameter is modified, this optimizer changes the parameter values. The loss function is categorical cross-entropy.

The basic networks with 6 to 12 layers are built. Then, in order to determine the ideal number of layers, the values of the various networks' testing accuracy are given. The results in Table 2 show that there are greater testing accuracy values for networks with ninth layers.

The optimal base network has 9 layers; therefore, the testing accuracy for it is 91.05%, which is less accurate than the suggested AdaBoost-accuracy CNNs of 96.08%.

Table 2. Performance accuracy of the single CNN system with many layers counts

Layers	6	7	8	9	10	11	12
Training Accuracy	89.01	89.99	90.31	94.03	95.34	95.34	96.45
Testing Accuracy	78.45	79.45	84.09	91.05	89.91	87.56	88.10

Table 2 shows, it is observed that as the number of layers is increased, the accuracy increases, but the computation time required increases due to the increased number of parameters. The deeper the model, the more layers and parameters it has. The number of layers you select will depend on your data, how big it is, and what degree of precision is present in your data. More complex models work better when a larger training set is available. Figure 8 shows, as per the volume of the dataset, the optimal number of layers is 12.

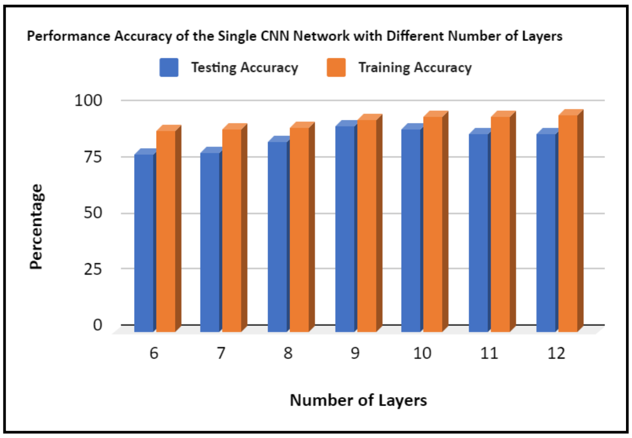


Figure 8. Performance accuracy of the single CNN system with many layers counts

4.4 Observations after applying the suggested Adaptive Boosting CNN classifier

Table 3 displays the AdaBoost-training CNN's and testing prediction performance using the DR dataset. The base estimator in Adaptive Boosting-CNN is the 9-layer single VGG 16 CNN that had been exploited in the earlier experiment.

In the Adaptive Boosting-CNN, performance is examined for various estimators. The estimators employed in adaptive boosting classifiers are pretrained VGG16 CNN. For one learning epoch, each estimator utilises the sample weights it acquired during training. The accuracy rate improves from 91.76% to 95.56% as the test sample increases by 10,000. There are between 6 and 20 estimators. The accuracy drops to 95.56% as the number of estimators increases.

Table 3. Observations after applying the Adaptive Boosting CNN classifier

Estimators VGG-16 CNN	Training Accuracy Performance (%)	Testing Accuracy Performance (%)
6	92.05	91.76
12	94.00	93.01
16	97.67	95.56
20	95.45	92.78

As the number of estimators increases, there are fewer samples for the new estimators without training, and they are trained using a limited number of training instances with heavily weights (Because they have already been trained using the prior estimators, the weights for the other training samples are small enough to be ignored) As a result, the method's overall performance cannot be enhanced when there are more than 16 estimators, since the entire dataset was not trained because the additional estimators were not trained.

Figure 9 shows 16 CNN estimators are utilized, AdaBoost-CNN reaches its peak evaluating accuracy of 97.67%, which is greater than better accuracy attained by a single CNN of 91.05%. More than the unique CNN, the recommended AdaBoost-CNN properly identified 203 testing samples.

Table 4 compares the proposed accuracy levels for Adaptive Boosting VGG-16 CNN, the single CNN estimator and the traditional decision tree-based AdaBoost. The highest level of accuracy for each technique is shown in Table 4. Sixteen estimators make up Adaptive Boosting VGG-16 CNN, and for each learning epoch, one is trained. using its sample weights. For both the Adaptive Boosting VGG-16 CNN and the single CNN, there are a total of 50 learning epochs. At 50 learning epochs, CNN had the best accuracy.

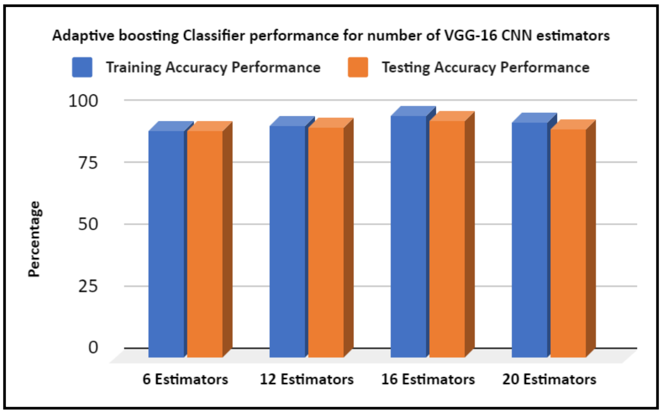


Figure 9. Adaptive boosting Classifier performance for number of VGG-16 CNN estimators

Adaptive Boosting-CNN has the highest accuracy of the three approaches, according to the data.

The experimental findings also demonstrate that Adaptive Boosting accuracy VGG-16 CNN's is substantially greater than that of classical Adaptive Boosting, which employs a decision tree as an estimator. Comparing Adaptive Boosting-CNN to the standard Adaptive Boosting with decision tree, the former has testing accuracy that is 20% higher. The outcome demonstrates that the standard adaptive boost with a decision tree is significantly less accurate and cannot meet the accuracy level of a single CNN estimator. Therefore, in the subsequent studies, the traditional Adaptive Boosting with decision tree was not taken into account.

Examining the significance of transfer learning:

In proposed work AdaBoost-VGG 16-CNN exhibits transfer learning as a key feature. AdaBoost VGG-16 CNN is equal to an AdaBoost method utilizing CNN estimators, in which the CNN estimator is generated from the start for numerous training epochs to assess the impacts of transfer learning on computing cost and correctness.

The first estimator is trained using the adaptive boosting technique for 30 epochs, and using the sample weights produced from the initial CNN estimator, a secondary estimator is trained over 20 epochs from the beginning using the evaluated sample weights, and so on for the successive CNNs.

This AdaBoost with CNN estimator total testing accuracy is lower than that of the planned AdaBoost VGG-16 CNN, which attained a measuring accuracy of 95.56% for approximately 10 epochs.

Additionally, the suggested approach lowers computing costs by reducing training epochs are used in subsequent CNN estimators. The proposed Adaptive Boosting VGG-16 CNN uses each pre-trained and transfer learning VGG-16 CNN estimate is trained for a limited number of training epochs in order to prepare the given estimator, as opposed to training each successive estimator from the start for many learning epochs. The comparison of Adaptive boosting CNN model without transfer learning and Adaptive boosting with VGG 16 as shown in Table 5. Also, the computation time required less as compared to time for classification without transfer learning model as shown in Figure 10.

Table 4. Comparison of performance of proposed model with classifier with single CNN estimator and Adaptive Boosting using decision tree

Model	Number of Estimators	Training Accuracy Performance	Testing Accuracy Performance	Epochs
Adaptive Boosting using Decision Tree	400	87.45	77.08	-
VGG-16 CNN Classifier	1	94.03	91.05	30
Adaptive Boosting VGG-16 CNN Classifier	6	92.05	91.76	10
	12	94	93.01	10
	16	97.67	95.56	10
	20	95.45	92.78	10

Table 5. Examining the significance of transfer learning in Adaptive classifier

Model	Epochs	Training Accuracy Performance	Testing Accuracy Performance	Computation
Adaptive Boosting CNN Classifier (Without pretrained model)	6	90.66	82.76	214.45
	12	92.01	90.11	287.55
	16	95.66	93.16	389.45
	20	95.45	92.78	401.66
Adaptive Boosting VGG-16 CNN Classifier (With pretrained model)	6	92.05	91.76	68.45
	12	94	93.01	76.34
	16	97.67	95.56	81.55
	20	95.45	92.78	91.09

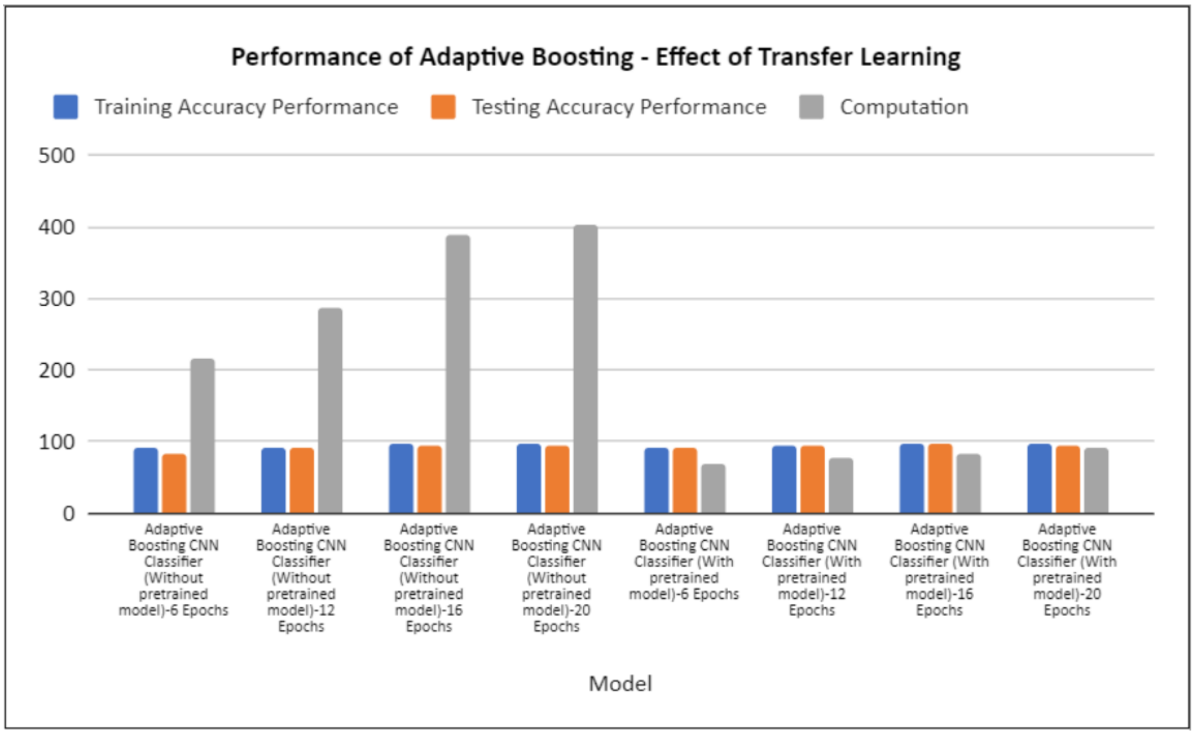


Figure 10. Examining the significance of transfer learning in adaptive classifier

5. CONCLUSIONS

Ensemble learning is estimated to be a fruitful technique for offering technical solutions in prediction and classification tasks. In the proposed method, multiclass adaptive boosting is utilized for boosting the performance of weak estimators and is significantly implemented on the DR dataset to classify the DR images into respective classes. This proposed work employs a multiclass adaptive ensemble learning approach using VGG16 CNN classifiers.

The proposed system performance is verified using a number of VGG16 CNN classifiers, and it is observed that as the number of estimators increases, the accuracy will decrease due to an increase in model complexity. As the VGG 16 CNN is incorporated with multiclass adaptive boosting, which notably extracts the features for further classification, the performance of the proposed algorithm is better than traditional CNN model and adaptive boosting using a decision tree.

In this proposed work, the computation time increased as the number of VGG 16 CNN estimators increased, and the complexity increased as the number of estimators increased, which affected the accuracy of the model. So certain recommendation for future scope in research is to propagate the dataset to an ensemble learning framework using cross validation method that would enable diabetic retinopathy detection at an early stage.

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