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Improved CNN Model for Diabetic Retinopathy Analysis and Classification

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Abstract: Diabetes causes an increase in the amount of glucose in the blood due to a lack of insulin. Diabetes affects the retina, heart, nerves, and kidneys. Diabetic retinopathy is a significant complication. Mechanized methods for detecting diabetic retinopathy are more cost-effective and time-efficient than manual analysis. Deep Learning is an approach for computer-aided medical diagnosis. This research is an attempt to establish an automatic treatment for diabetic retinopathy in its early stages. Using Artificial Intelligence and Deep Learning, doctors can detect blindness before it occurs.In this study, we are utilizing a supervised learning strategy to classify fundus photos. For this task, we are using several image processing procedures and filters to improve many significant features such as microaneurysms, hemorrhages, exudates, and swollen blood vessels, all of which are features of fundus images that indicate that a person has Diabetic Retinopathy, and then using neural networks for classification.

Keywords*: Deep learning,Diabetic Retinopathy,SVM,KNN,fundus images, CNNs, activation functions*

Introduction

Abnormal blood sugar levels develop in blood vessels as glucose is turned into energy. Diabetic retinopathy (DR) develops after a patient has had diabetes for at least ten years. High blood pressure induces DR, which destroys the retina and retinal vascularization, potentially resulting in blindness or death. Ophthalmologists can only examine retinal vascular enlargement with fundoscopy studies, which are time-consuming and costly. By 2030, there are expected to be 552 million people with diabetes globally, with DR being the major cause of blindness.

Preventing vision loss requires early detection and treatment. In severe situations, the vessels bulge, leak fluid, or get blocked, causing aberrant blood vessel growth and blindness. The most common signs of DR on the retina are microaneurysms, hemorrhages, and exudates. The severity of a lesion is determined by its shape, size, and appearance. Fundus photography is an ophthalmologic screening technique for DR. Using an automated assessment technique, diabetes-related blindness can be prevented in a clinically and economically efficient manner.

Ophthalmologists evaluate the presence and severity of DR using a visual assessment that includes a direct examination and evaluation of the eyes. This method is costly and time-consuming for many diabetic people around the world. DR severity and early detection of the condition remain difficult, with numbers among trained ophthalmologists ranging significantly . Furthermore, 75% of DR patients live in poor areas where adequate ophthalmologists and detection facilities are inadequate. Global screening initiatives have been established to combat the spread of preventable eye illnesses, although DR exists on a too big scale to be detected and treated efficiently on an individual basis.

High blood pressure induces DR, which damages the retina. It affects retinal vascularization, which can lead to blindness and possibly death. Ophthalmologists can

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only examine retinal vascular enlargement with fundoscopy studies, which are time-consuming and costly. There is a need to automatically identify DR using retinal fundus images. Deep learning models have been shown to be a more effective method for detecting DR than ophthalmologists [9].

The convolutional neural network (CNN) is one of the most used deep learning models used to detect, predict, and classify medical pictures. The goal of this study is to identify DR automatically by using the CNN model's updated activation function. The suggested new activation function is compared to various activation functions using the publicly available datasets DIARETDB0, DRIVE, CHASE, and Kaggle. The current CNN version has been improved by incorporating a novel activation mechanism that produces great results.

Our contribution is to identify DR by the efficient and precise examination of retinal fundus pictures. In addition, the upgraded CNN model will be examined and demonstrated for performance. The proposed methodology for grading fundus photos does not require any specialized, inaccessible, or expensive equipment; it may be run on a PC or laptop with average processors. In addition to detection and classification, the proposed model accurately depicts aberrant regions in fundus pictures, allowing for clinical examination and verification of the automated diagnosis. Ophthalmologists find it challenging to detect microaneurysms due to their small appearance.

Table 1: Different activation functions and definitions.

Function	Definition	Equation	Limitations
Linear type	The final activation function of the last layer is just a linear function of the first layer of the input, and it can be used in the output layer.	$Y = x$; $-\infty$ to $+\infty$	Nonlinearity is difficult to achieve.
Binary type	The binary classification is used mainly when inputs exceed thresholds, otherwise, outputs are zero.	0; if input < threshold, otherwise 1; if input > threshold; Range: {0, 1}	Cannot classify the multiclass problems
Nonlinear			
Sigmoid	A small change in input will result in a large change in output. To convert the output into a predictable score, this layer is placed at the end of the model.	$1/(1+e^{x})$; Range:0 to1 or -1 to 1	During training, a model other than the output layer is invalid due to the vanishing gradients
Tanh	It is used as an alternative to the Sigmoid function if the output is other than zero and one.	$Tanh(x = (e^{x} - e^{-x})/(e^{x} + e^{-x})$; Range: -1 to $+1$	If the weighted sum of the input is very large, then the function gradient becomes very small and close to zero. It has the vanishing gradient problem.
ReLu	It is implemented in the hidden layers of the model. It is computationally less expensive and much faster than the tanh and Sigmoid and solves the vanishing gradient problem	max (0, x); if x is positive, output x, otherwise 0; Range: 0 to $+\infty$	It does not compute the exponentials and the divisions. It overfits more than the Sigmoid function. It does not avoid the exploding gradient problem.
Swish	It deals with the vanishing gradient problem. It helps in normalizing the output. The output does not saturate to a maximum value, i.e., the gradient does not become zero.	$x.\sigma(x)$; Range: $-\infty$ to $+\infty$	It is computationally more expensive than the Sigmoid.
Mish	It is continuously differentiable and nonmonotonic. It is used in the hidden layer.	$x.tanh(ln(1+e^{x}))$; Range: $-\infty$ to $+\infty$	It is computationally more expensive than the ReLu.

The neural network's activation functions activate the neurons, and the mathematical functions associated with the neurons determine whether or not to fire the present neuron. The activation function generates nonlinearity in the output neurons. A model without the activation function works similarly to a linear regression. The activation function changes the nonlinear input, allowing it to learn and execute complex datasets with great precision. Many activation functions already exist in neural networks, which are further explained in following table

Based on the various activation functions shown in the table above, we intend to build a novel activation function for CNN. The proposed novel activation function's performance was compared to the other activation functions in the publicly accessible dataset using DIARETDB0. The goal is to provide a highly effective, low-cost DR detection technology that eliminates the need for doctors to manually evaluate and grade photos.

A fully automated CNN model could accurately interpret thousands of diverse fundus images for disease identification. In other words, it eliminates the need for resource-intensive manual fundus picture processing in clinical settings while directing high-risk patients to appropriate therapy.

We describe an enhanced activation function-based CNN model that was applied to the DIARETDB1 diabetic retinopathy datasets, all of which are publically available.

Related Work

H. Jiang employed three deep learning models: Inception V3, ResNet151, and Inception-ResNet-V2. They each performed with an accuracy of 87.91%, 87.20%, and 86.18%. When all of these models were combined using the AdaBoost algorithm, the accuracy improved to 88.21%. A. Roy and D. Dutta introduced a filter-based retinal vascular extraction approach called "fuzzy C means" for exudate identification and "Convex Hull" for detection and removal of the optical disk.The model had an accuracy of 83.2%. The research described the E-DenseNet model, a hybrid deep learning technique used to diagnose various phases of DR. The E-DenseNet model combines EyeNet and DenseNet and takes advantage of transfer learning. The researchers benefited greatly from integrating the two models and tailoring the embedded dense blocks of the EyeNet architecture. The model's key advantage was its ability to reliably categorize images while requiring less time (training) and memory. This model had an accuracy of 91.6% and a Kappa of 0.883. The "SOFT-MAX BoVW" method was used in the methodology proposed in, and the area under the curve was 93.4%. S. Dua concentrated on quadtrees, a blood vessel detecting approach, and edge post-filtration.Anomalies were identified by comparing information on retinal blood vessel morphology to the diameters of blood vessels in a normal eye. discusses various fusion strategies for integrating different classifiers to accurately classify diabetic retinopathy photos. This strategy proved useful.

Bourouis and Sami created an SVM-based kernel with a finite mixture of SDD (Scaled Dirichlet Distributions).The model allowed for greater classification flexibility. Support Vector Machine (SVM) and KNN classifiers were employed to classify pictures into two classes: NPDR and PDR based on the presence of micro-aneurysms and lesions. It was found that the SVM algorithm outperformed the KNN algorithm. A. P. Bhatkar and G. U. Kharat designed a Multi-Layer Perceptron Neural Network to identify diabetic retinopathy in retinal pictures. The classifier divided retinal pictures into two groups (DR and No DR) using a feature vector created with the Discrete Cosine Transform (DCT), however it was unable to predict the severity of diabetic retinopathy.A comparison of two CNN architectures, DenseNet and VGG16, was conducted in. The DenseNet model achieved an accuracy of 90.11%. Lesions were discovered using background subtraction methodology, and incorrectly diagnosed lesions were removed using a decorrelation stretch-based method. When evaluated on the DiaretDB database, the method demonstrated a sensitivity of 0.87 and an F-Score of 0.78. Exudates and microaneurysms must be identified to determine the stage of diabetic retinopathy.

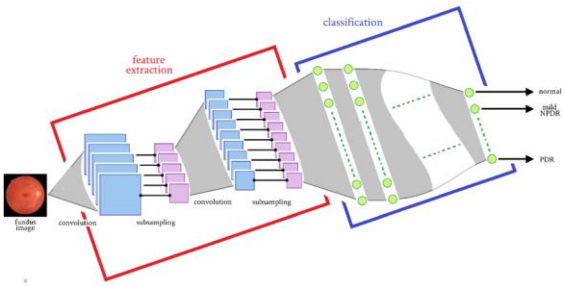
Prasad et al. used multiple morphological and segmentation techniques to identify blood vessels, exudates, and microaneurysms. The image was broken into four subimages. Haar wavelet treatments are applied to the retrieved features. Principal component analysis and linear discriminant analysis were used to pick key features. A back propagation neural network was utilized to categorize the photos as diabetes or non-diabetic. Deep learning techniques such as Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) were utilized in. CNN detected lesions, and the LSTM generated descriptive words based on those lesions. The CNN output was provided as an input to the LSTM.This algorithm achieved an accuracy of 90%. A. T. Nagi proposed a novel technique, the two stage classifier. It is an ensemble technique that combines various machine learning algorithms for classification. It was observed that it performed better in terms of parallelism and accuracy.

Jayant Yadav employed computer vision and neural networks to diagnose diabetic retinopathy, and the results were satisfactory.a principal component analysis-based deep neural network model with the Grey Wolf Optimization (GWO) method was used to categorize the collected features from the diabetic retinopathy dataset. D. Jude Hemanth created a Modified Hopfield Neural Network (MHNN) model for identifying anomalies in retinal pictures. Unlike the standard method, the weights in the suggested system are constantly changing. A Multipath Convolutional Neural Network (M-CNN) was utilized to extract features from photos.The above algorithm (M-CNN) performed better with the J48 classifier. A comparative analysis of multiple algorithms such as SVM, AlexNet, VGG16, and LSTM was conducted and LSTM found to be considerably more accurate.

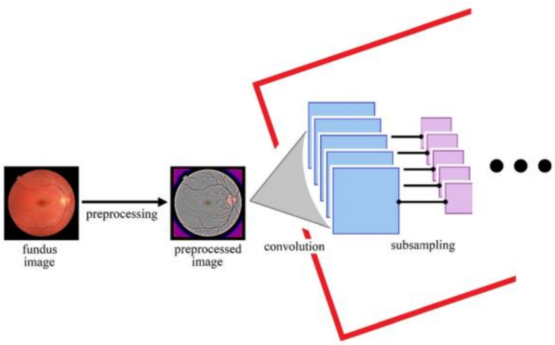
Our Algorithm

Convolutional neural networks use the feed forward method and are commonly used to analyze images. It is particularly effective for item recognition and classification. CNN represents each image as a pixel array. The primary operation is convolution, which serves as the foundation for the convolutional neural network. A deep CNN network consists of two layers: the convolutional layer ,the pooling layer, fully connected layer,dropout layer and finally activation function Transfer learning is an advanced idea in the field of machine learning methods. In this strategy, a previously trained model for a certain job is used as the starting point for the second model. It is widely used in conjunction with deep learning architectures, with the weights from pre-trained models serving as the starting point. This notion is mostly applied in computer vision and image processing applications.

Image Pre-processing



For the images before passing to CNN are preprocessed . The preprocessing includes apply filters, and other image processing operations to generate desired input for the CNN model as shown in following figure



The inputs were 512x512 pictures, which were enhanced in real time by

1. Cropping with a specific probability
2. Color balance correction.
3. Brightness adjustment
4. Contrast adjustment
5. Flipping photos with a 50% chance.
6. Rotating photos by x degrees in [0, 360] and zooming (equal cropping on x and y dimensions).

Along with their original image proportions. Because of the significant class imbalance, some classes were oversampled to ensure a more uniform distribution of classes in batches. Oversampling halted somewhere in the midst of training, and photos were sampled from the true distribution of the training set.Try to avoid overfitting, which is especially difficult when the network encounters some photos nearly ten times more frequently than others. Allow the network to fine-tune its predictions on the true class distribution

CNN Model

The model used is a convolutional network with the following relatively basic architecture (listing the output size of each layer) as shown in following figures

Where a/b in the last column denotes pool or filter size a x a with stride b x b. where the reshape was done to combine the representations of the two eyes belonging to the same patient. All layers were initialized with the SVD variant of the orthogonal initialisation and the non-linear layers used leaky rectify units max(alpha*x, x) with *alpha=0.5*.

Training was done using Stochastic Gradient Descent (SGD) and Nesterov momentum for over 100k iterations on a loss that was a combination of a continuous kappa loss and the cross-entropy (or log) loss:

kappalogclipped = cont_kappa + 0.5 * T.clip(log_loss, log_cutoff, 103)**

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten (Flatten)           (None, 25088)             0

 dense (Dense)               (None, 100)               2508900

 dropout (Dropout)           (None, 100)               0

 dense_1 (Dense)             (None, 50)                5050

 dropout_1 (Dropout)         (None, 50)                0

 dense_2 (Dense)             (None, 4)                 204

=================================================================
Total params: 2514154 (9.59 MB)
Trainable params: 2514154 (9.59 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

A crucial step was to transform the softmax probability for each label to discrete predictions. Using the label with the highest probability (i.e., argmax) performed well but is unstable; a significant improvement comes from converting these probabilities to a single continuous value (by weighted sum), ranking these values, and then assigning labels using some boundaries (e.g., first 10% is label 0, next 20% is label 1, etc.).All of this adds up to roughly +0.835 for a single model.

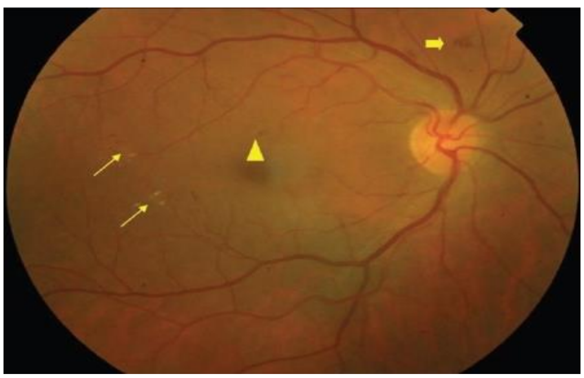
A final significant improvement came from assembling a few models using the mean of their log probabilities for each class, transforming them to normal probabilities in [0, 1], and applying

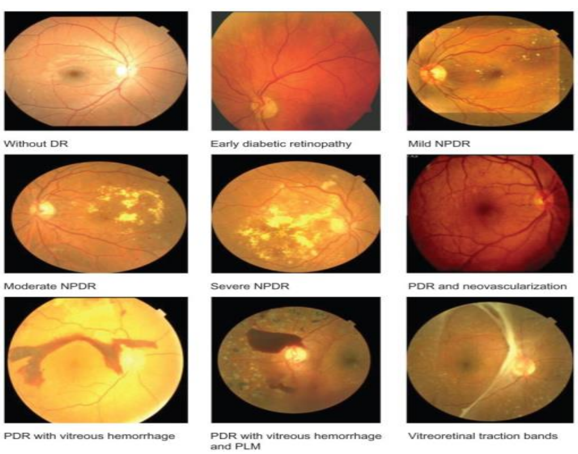
weighted_probs = probs[:, 1] + probs[:, 2] * 2 + probs[:, 3] * 3 + probs[:, 4] * 4

To obtain one vector of predictions, we can use the ranking technique from the previous paragraph to assign labels. A few possible boundaries were found using scipy's minimize function on several ensembles' kappa scores.

Dataset

In this investigation, we employed the datasets DIARETDB1. The DIARETDB1 dataset contains 4126 images, of which 2063 are utilized for training and 2063 for testing..





Evaluation

The efficiency of any deep learning model is determined by measurements such as True Positive Rate, False Positive Rate, True Negative Rate, and False Negative Rate. The accuracy, precision, and recall measurements are often employed for evaluation purpose

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} 100\%$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

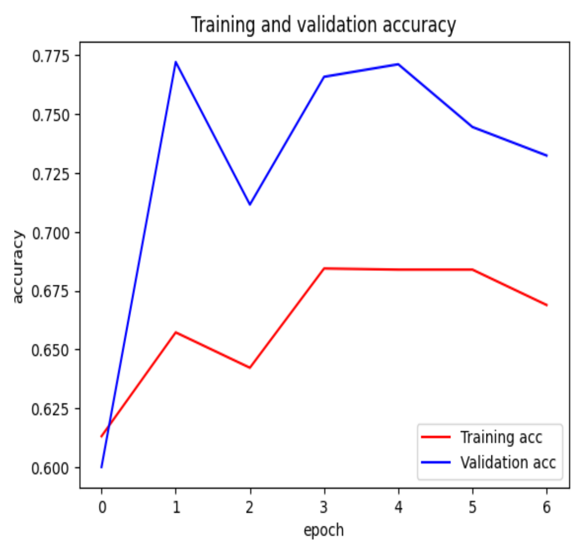
$$\text{Recall} = \frac{TP}{TP + FN}$$

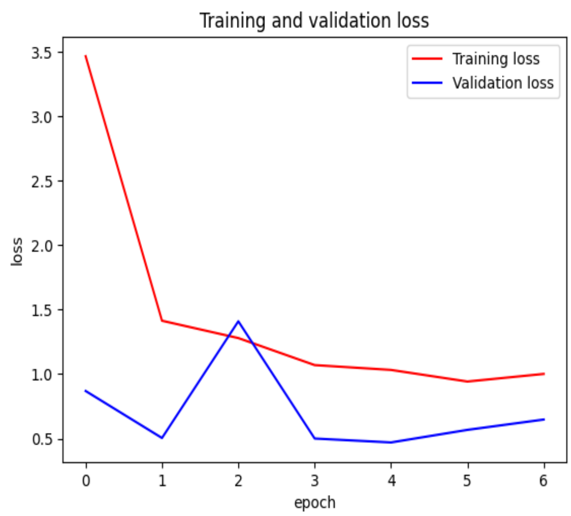
$$\text{F-measure} = \frac{2 * precision * recall}{precision + recall}$$

Results

	KNN	SVM	CNN
Accuracy	66.93%	67.71%	73.24%
Precision	83.88%	82.97%	78.66%
F1-Score	72.51%	72.59%	25.40%

Train and Testing Graphs of CNN Model is as shown below





Conclusion

Work's goal is to evaluate machine learning algorithms and deep learning methods for diagnosing diabetic retinopathy and its stage. Extensive image processing has helped to emphasize the exudates, blood arteries, and cotton wool patches. Based on study and analysis of numerous approaches, it is feasible to conclude that deep learning algorithms have a wide variety of applications in predicting diabetic retinopathy. Traditional machine learning classifiers, such as Support Vector Machine (SVM) and K-Nearest Neighbour (KNN), have failed to accurately categorize photographs. Although CNN outperformed classical algorithms, only transfer learning techniques like ResNet and DenseNet achieved the required accuracy without overfitting.As a result, this model, which was built using bespoke CNN and pre-trained models, as well as appropriate image processing, was effective in predicting the presence of diabetic retinopathy. This improved CNN with DenseNet outperformed the others, with an accuracy of 96.22%. Doctors can utilize the established model to recommend preventive measures at a far earlier stage, preventing people from losing sight.

People are currently unable to receive medicine and treatment at an early stage. When diseases are predicted automatically, time is saved, allowing people to take preventive steps in advance. In the future, the algorithm parameters can be fine-tuned to produce better results, and the model's accuracy can be enhanced using more effective optimization techniques.

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