A Diagnostic Information System Utilizing Convolutional Neural Networks for Automated Detection of Diabetic Indicators from Fundus Images

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Abstract:

Diabetes can cause serious problems around the world. Early detection can help patients receive better treatment and live better lives. The IDRID dataset is used to propose a Convolutional Neural Network (CNN) model for automatic diabetes detection. This is done by using retinal fundus images. The suggested model has an input layer, three convolutional layers, three pooling layers, two fully connected layers, and an output layer of two neurons for classification. Cross-validation was done to evaluate the model performance using 512 fundus images followed by comparison with classical machine learning classifiers like RF, Extra Trees, Support Vector Machine, and AdaBoost. The proposed CNN model was able to get by 91.8% accuracy, which was found to be better than the other compared models. This shows that DL techniques could help in reliable and efficient detection of diabetes.

Keywords: Convolutional neural network, diabetes screening, machine learning, Deep learning.

نظام معلومات تشخيصي يستخدم الشبكات العصبية التلافيفية للكشف الآلي عن مؤشرات مرض السكري من صور قاع العين

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ملخص:

يُمكن أن يُسبب داء السكري مشاكل خطيرة حول العالم. يُمكن للكشف المُبكر أن يُساعد المرضى على الحصول على علاج أفضل وعيش حياة أفضل. تُستخدم مجموعة بيانات IDRID لاقتراح نموذج شبكة عصبية تلافيفية (CNN) للكشف التلقائي عن داء السكري. يتم ذلك باستخدام صور قاع الشبكية. يتكون النموذج المُقترح من طبقة إدخال، وثلاث طبقات تلافيفيه، وثلاث طبقات تجميع، وطبقتين مُتصلتين بالكامل، وطبقة إخراج مُكونة من خليتين عصبيتين للتصنيف. أُجري التحقق المُتبادل لتقييم أداء النموذج باستخدام 512 صورة لقاع العين، تلتها مُقارنة مع مُصنفات التعلم الآلي الكلاسيكية مثلRF ، و Extra Trees، وSupport Vector Machine، و AdaBoost.حقق نموذج CNN المُقترح دقة بلغت 91.8%، وهي نسبة أفضل من النماذج المُقارنة الأخرى. يُظهر هذا أن تقنيات التعلم الآلي يُمكن أن تُساعد في الكشف المُوثوق والفعال عن داء السكري.

1-Introduction

Diabetic retinopathy (DR) is one of the most severe complications of diabetes mellitus which is also leading blindness and impaired vision in the working-age population worldwide. The advancement of diabetic retinopathy (DR) occurs slowly and frequently without symptoms at first, so detecting it early is critical to circumvent irreversible visual loss. In 2017, the International Diabetes Federation (IDF) reported that around 451 million people worldwide had diabetes, with over a third showing DR signs [3]. It is projected that by 2045, the number of people suffering from diabetes-related complications will be 693 million. Another nearly half (49.7%) of people with diabetes remain undiagnosed for long periods of time because they have no symptoms [3]. Long-lasting high level of blood sugar damage small nerves and blood vessels causing serious health problems such as heart disease, penetrating pain and loss of eyesight. In today’s world, there are an estimated 537 million people who suffer from diabetes, causing about 6.7 million deaths each year. With these figures steadily rising, early detection and management have become as urgent as ever.

In recent years, machine learning and deep learning technologies have gained popularity in the medical field due to their capability for early detection and diagnosis of various illnesses. Using textual data like electronic health records and graphical data like medical images, these methods extract underlying patterns and relationships which are not detected by human beings. [4], [5]. Deep learning, especially using a convolutional neural network (CNN), is equally effective in carrying out image-based tasks involving diagnosis as it automatically extracts features from images without requiring human intervention or hardcoding. Unlike earlier ML models which relied on manual feature learning, CNNs can use raw images and learn the complex spatial relationship important for classification.

we propose CNN model helps in diabetes detection from retinal fundus images (RGB) taken from Indian Diabetic Retinopathy Image dataset (IDRiD). The architecture of the CNN under consideration has an I\p layer, three convolutional layers, three pooling layers, two fully connected layers and an O\p layer with two neurons for classification. Proposed model was trained by using 512 retinal fundus images while tested on 128 fundus images while cross-validation for generalization.

2- Related Work

Computer-Aided Diagnosis (CAD) systems leverage image processing technologies to assist in the detection and diagnosis of various medical conditions. One of the most promising applications of image processing is the mechanical detection of DR from images of retinal fundus, where structural and textural features are analyzed to classify disease severity and identify early pathological changes.

ML and DL algorithms recently have played an increasingly essential role in medical diagnostics, particularly in the early detection of diabetes. Numerous studies have explored different algorithmic approaches and datasets to improve diagnostic accuracy. For instance, Nimmagadda et.al. [1] proposed a diabetes detection system that performs noise removal before classification using a SVM, reaching a achievement rate of 96.71%. Similarly, Kaviani et.al. [2] developed a diabetes classification model based on an ANN with 9 hidden nerve cells, obtaining 91.6% accuracy. Kumar et.al. [3] proposed a fuzzy hierarchical model which achieved an accuracy of 87.46%, while Jafarnezhad et.al. [4] introduced a Gaussian Process (GP)-based classifier that reached 81.97% performance.

Further relative analysis of numerous ML algorithms was shown in [5], including Random Forest (RF), SVM, k-Nearest Neighbors (k-NN), Classification and Regression Trees (CART), and Linear Discriminant Analysis (LDA), where RF algorithm demonstrated superior performance. In [6], a Random Forest-based model designed for early diabetes detection yielded an accuracy of 82%, reinforcing its reliability. Another study [8] tested multiple algorithms—linear and radial SVM, k-NN, ANN, and dimensionality reduction methods—and found that linear SVM achieved the best results. Commonly, these models used the Pima Indian Diabetes Dataset, which consists of structured medical record data rather than imaging data, achieving high predictive performance but limited visual diagnostic capability.

The focus of more recent research has switched to image-based diabetes detection, especially using fundus pictures like those found in the DIARETDB1 dataset [9]. For instance, [10] tested 200 retinal images using statistical and texture-based feature extraction and normalization methods, then used Random Forest, AdaBoost, SVM, and neural networks for classification. At 89.66%, the RF classifier had the greatest accuracy. Di Vaio et.al. [11] evaluated Alex Net, VGG16, and Inception Net using convolutional neural networks (CNNs) on 166 high-resolution Kaggle photos classified into five DR severity levels. The latter had the greatest performance at 66% accuracy.

The majority of these research show limitations relating to short datasets, middling accuracy, or reliance on conventional feature extraction techniques, despite the fact that they show notable advancements in the identification of diabetes and DR. More reliable and effective solutions are now possible because to the quick development of deep learning and image processing techniques. Inspired by these advancements, the current study suggests a CNN-based method for diabetes detection utilizing retinal fundus photos with the goal of achieving better diagnostic reliability and accuracy when compared to traditional ML techniques.

3- Methodology

Our method has four steps, from image capture to pattern assessment. The methodology stages are shown in figure 1.The next describes our steps of the approach that was employed.

First stage- Image acquisition: This involves choosing a collection of reliable photographs that contain data from both diabetic and non-diabetic patients. Two images' sets are needed for training and validation.

Second Stage- Pre-processing: Data rescaling, size reduction, and conversion to a three-dimensional array are among the many picture analysis and processing techniques used. for both the training and validation images.

Third Stage- Pattern training: In addition to the Convolutional Neural Network pattern, training photos are applied to ML - based patterns including RF, Extra Trees, Support Vector Machine, and AdaBoost. The performance of each design is assessed to choose the pattern to improve.

Fourth Stage- *analysis of patterns*. The trained pattern makes pattern predictions using the validation photos to confirm and correctly categorize each case. The patterns are then evaluated using the accuracy metrics. Patients' photos, both with and without diabetes, are added to the pattern.

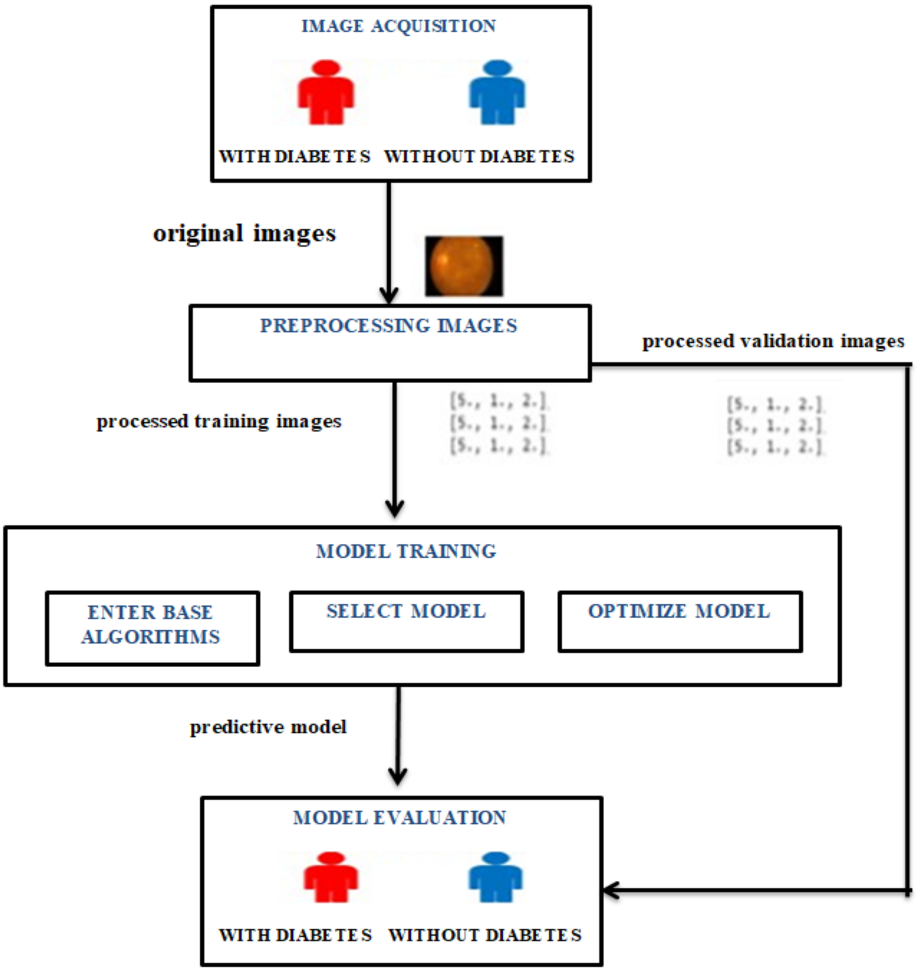

Figure 1. Proposed Method

4- Results

Each step is built using the suggested process, and the outcomes are explained below.

4.1. Data set

The need for improved methods of diagnosing retinal illnesses in the experimental training of eye care has been better understood because of recent research. In the studies done by Chaki et.al [9] and Lindroth et.al. [10], imaging tests were carried out to diagnose diabetes using a series of fundus pictures.

516 retinal fundus images are included in the publicly accessible IDRiD dataset [17], which is divided into two categories diabetes-related retinal images versus normal or diabetes-free retinal imaging. as seen in Figure 2.

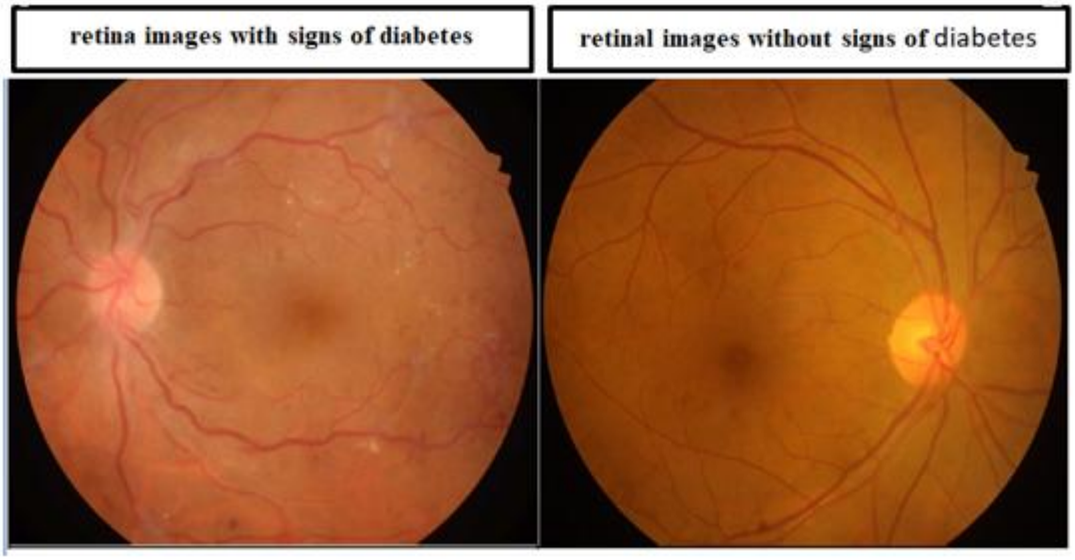

Figure 2. Images of the retina with and without diabetes

Images are categorized based on degrees of diabetic macular edema (DME) and diabetic retinopathy (DR) that have been previously diagnosed. Levels 0 (no DR) and 4 (1: mild DR, 2: moderate DR, 3: severe DR, and 4: severe DR) are the different levels of DR. The color photos are separated into two folders, one for training and the other for validation, and have a resolution of 4288 by 2848 pixels.

Table 1 illustrates that there are 516 images in the image set, of which 413 (80%) are used for training and 103 (20%) are used for validation. Furthermore, 348 photos match class 1, with DR (with symptoms of diabetic retinopathy), and 168 images match class 0, without DR (without symptoms of diabetic retinopathy).

Table 1. IDRiD image set

IDRiD Images	Total	Percentage	Classes	
			Without RD	*With RD*
Training	413	80%	134	279
Validation	103	20%	34	69
Total	516		168	384

4.2 Data processing

High memory and processing hardware capabilities are needed because the photos have a high resolution. Furthermore, since the images are colored, it is necessary to preserve the colors' three dimensions. The established procedure involves reducing the image size to 150x150 pixels, converting it into a 3D array, and then separating the labels from the features.

Five processed training photos are shown in Figure 3, with the class label at the top of each image. The first image is then shown in 3D array format (150x150x3).


```
<tf.Tensor: shape=(150, 150, 3), dtype=float32, numpy=
array([[[5., 1., 2.],
        [5., 1., 2.],
        [5., 1., 2.],
        ...,
        [0., 0., 0.],
        [0., 0., 0.],
        [0., 0., 0.]],
```

Figure 3. Training images

4.3. Pattern training

In order to choose the Random Forest (RF), Extra Trees (ET), SVM, AdaBoost (AB), and Network Neural Convolution (CNN) approaches, we evaluated machine and deep learning algorithms that had been employed in previous studies. We then conducted a performance evaluation taking into account cross-validation with ten iterations.

The median accuracy generated by CNN (82.90%), RF (78.90%), ET (78.63%), SVM (73.81%), and AB (76.72%) is shown in Table 2. Along with the expected standard deviation for each pattern, the lowest and maximum accuracy generated during the iterations are also displayed.

Table 2. Accuracy results

pattern	median	Deviation	Maximum	Minimum
RF	78.90	5.24	87.10	67.29
ET	78.63	5.96	89.48	67.29
SVM	73.81	5.63	84.37	62.41
AB	76.72	4.97	84.71	65.67
CNN	82.90	2.73	91.02	80.61

The CNN pattern is optimized to make predictions with new images for the pattern because it yields the best results when compared to the other patterns used. Since the median precision is regarded as a performance indicator, this pattern is deemed suitable for the research's objectives. The CNN pattern for diabetes diagnosis is depicted in Figure 4.

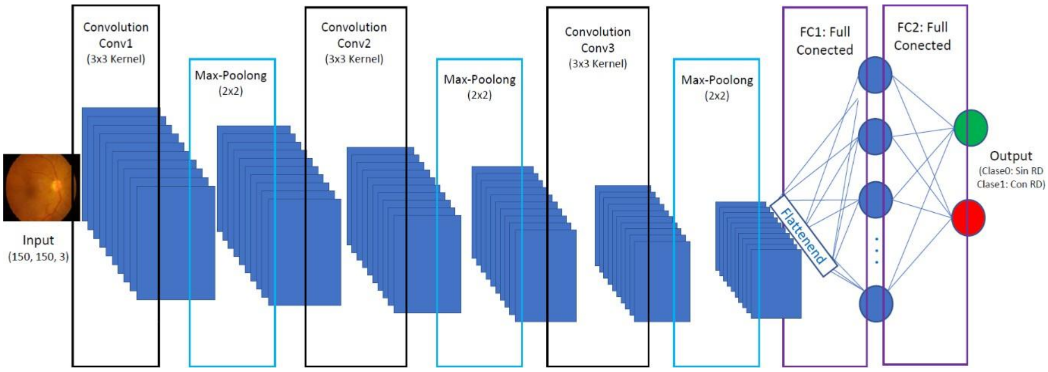

Figure 4. CNN pattern

An input layer, three convolutional layers, three pooling layers, two fully connected layers, and an output layer with two neurons make up the produced CNN pattern, as seen in Figure 4.

An image in the form of a 3D array that has previously been scaled to 150x150 pixels is supported by the input layer. The activation function is relu, and the convolutional layers have a 3x3 kernel with the same padding. The 2x2 max pooling function is used by the pooling layers.

In order to predict whether or not the input image corresponds to a patient with symptoms of diabetic retinopathy, the fully connected layers first use the flatten layer to reduce the three-dimensional images to a single one, followed by two dense layers with the relu activation function and an output layer with two classes. The CNN pattern's summary following execution of its implementation code is displayed in Figure 5. Convolutional layers, pooling layers, flattening layers, the input layer with a rescaling of the data, and the output layer with its various features and functions are all displayed.

When the calculated value and the correct value differ as little as possible, the CNN pattern is optimized for maximum accuracy. The process of the algorithm traveling back and modifying weights and biases is referred to as "backpropagation" in neural networks; each cycle of backpropagation and forward propagation adjustment to lower the loss is referred to as an epoch. 120 epochs are used in the evaluation, and each epoch's accuracy from the training and validation phases is measured. As seen in Figure 6, stable results are acquired starting at epoch 100, leading to the final pattern that is ultimately saved for use in generating predictions.

```
Layer (type)                 Output Shape              Param #
=================================================================
rescaling_5 (Rescaling)      (None, 150, 150, 3)       0

conv2d_24 (Conv2D)           (None, 150, 150, 32)      896

max_pooling2d_15 (MaxPooling (None, 75, 75, 32)        0

conv2d_25 (Conv2D)           (None, 75, 75, 64)        18496

max_pooling2d_16 (MaxPooling (None, 37, 37, 64)        0

conv2d_26 (Conv2D)           (None, 37, 37, 128)       73856

dropout_14 (Dropout)         (None, 37, 37, 128)       0

max_pooling2d_17 (MaxPooling (None, 18, 18, 128)       0

flatten_5 (Flatten)          (None, 41472)             0

dense_11 (Dense)             (None, 1024)              42468352

dense_12 (Dense)             (None, 512)               524800

dropout_15 (Dropout)         (None, 512)               0

dense_13 (Dense)             (None, 2)                 1026
=================================================================
Total params: 43,087,426
Trainable params: 43,087,426
Non-trainable params: 0
```

Figure 5. Summary of the CNN pattern implementation

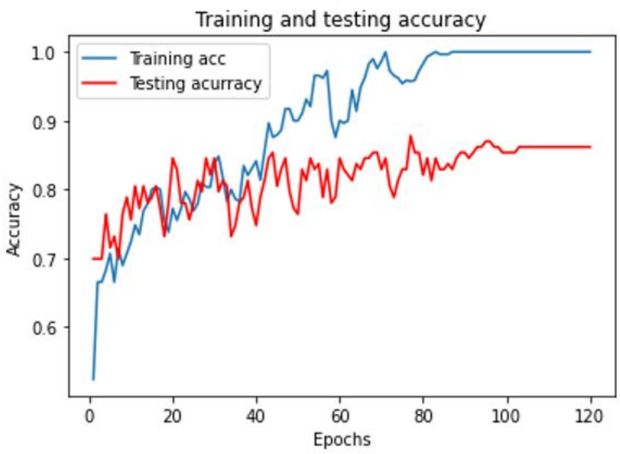

Figure 6. Epochs vs accuracy of the CNN pattern

5- Evaluations and Discussion

Using the validation images from the IDRiD dataset, we assess the final pattern's performance. An output of the CCN pattern evaluation using ten photos is displayed in Figure 7. Each image has a real label on the left and a pattern prediction label on the right at the top. If the labels match, the pattern correctly classified the input image and turned it blue; if they do not match, the pattern has not classified correctly and is shown in red.

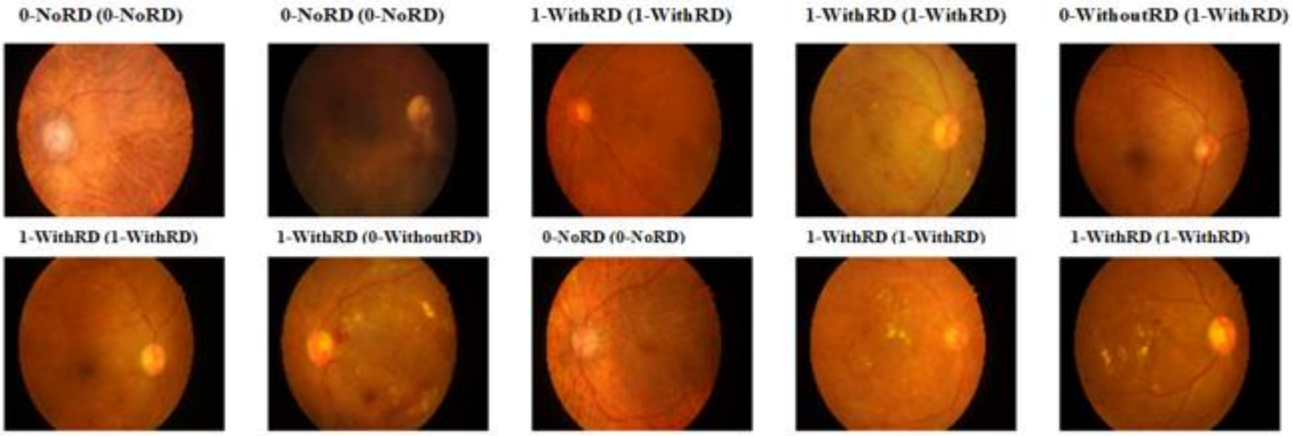

Figure 7. Visualization of Diabetes prediction with images

We employ the confusion matrix [19] to evaluate the CNN pattern using the 103 pictures from the IDRiD data set. True positives and true negatives are instances that the pattern correctly classified; false positives are images that the pattern labeled as belonging to the class "With RD," but which actually belong to the class "Without RD," and false negatives are images that the pattern labeled as belonging to the class "Without RD," but which actually belong to the class "With RD."

Table 3 illustrates that the pattern properly identifies 59 of the 69 photos in the "With RD" class, resulting in 86% True Positives (TP). Additionally, it is demonstrated that the pattern accurately identifies 27 of the 34 photos in the "No RD" class, resulting in 79% True Negatives (VN).

Table 3. Diabetes classification confusion matrix

	Classes	Predictive Labeling with CNN		
		With RD	***Without RD***	***Total***
Royal Labeling	With RD	59	10	69
		VP	FN	
	Without RD	7	27	34
		FP	VN	

We compute the performance measures using the confusion matrix results [13], [14], [18]. Sensitivity (recall) is the metric that allows determining the percentage of positive cases "with DR" that were correctly classified by the pattern; specificity is the metric that allows evaluating the negative cases "No DR" that are correctly classified by the pattern; and accuracy is the metric that has been used the most in earlier works to assess the effectiveness of the pattern.

With an accuracy of 83.50%, sensitivity of 85.50%, and specificity of 79.41%, as seen in Table 4, the pattern achieves higher prediction outcomes with the class "With RD," that is, the pattern Be more precise when using pictures of diabetes symptoms.

Table 4. Accuracy, sensitivity and specificity results of the CNN pattern

Evaluated Metric	Formula	Result
Accuracy	Accuracy = (VP+VN) /(VP+VN+FP+FN)	83.50%
Sensitivity	recall = (VP)/(VP+FN)	85.50%
Specificity	Specificity = (VN)/(VN+FP)	79.41%

6- Conclusion

413 photos were utilized for training and 103 images were used for evaluation from the IDRiD image set. The fundus photos were processed by scaling them to 150x150 pixels and turning them to a 3D array. A convolutional neural network, Random Forest, Extra Trees, Support Vector Machine, AdaBoost, and other machine learning and deep learning patterns were tested; the latter produced higher performance outcomes. An input layer, three convolutional layers, three pooling layers, two fully connected layers, and an output layer containing two neurons to identify if the picture has diabetes or not make up the convolutional neural network that produced the best results. An accuracy of 83.50% is achieved in the assessment of the convolutional neural network's effectiveness in identifying diabetes using fundus pictures. In comparison to other patterns found in earlier research, the results show improved performance.

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