Constructive Analysis on Prediction and Detection of Diabetic Retinopathy (DR) Using Machine Learning Algorithms - A Generic Survey

*Abstract*—Diabetic retinopathy is an eye disorder that affects people with diabetes. When high blood sugar levels harm the retina's blood vessels, the blood vessels may enlarge and leak or they may block the flow of blood. All these alterations may cause visual loss. In the current era, machine learning is very useful and plays a key role in medical applications. In this research, investigate the effectiveness and capability of different types of machine learning based diabetic retinopathy detection systems. The authors tested large quantities of retinal fundus images & gray scale pictures from Kaggle, Messidor, IEMRC and multiple available datasets. The application of an ensemble of machine learning classification algorithms to characteristics taken from the results of various retinal image processing algorithms is used to determine the presence of disease. Our goal is to anticipate the DR before it results in the worst scenario and prevent the patient from losing their visual acuity. The method we propose uses both supervised algorithms like support vector machine (SVM), ResNet and DensNet, naive bayes, nearest neighbors, and Neural Networks, as well as unsupervised algorithms like k-means clustering, hierarchical clustering, and Markov chains to classify a variety of characteristics in the DR. The best overall result is displayed by ResNet and DensNet with the accuracy of 96.22%.

Keywords—Machine Learning, Diabetic retinopathy, Supervised and Unsupervised Learning Techniques.

# Introduction

A class of conditions that have an impact on how the body uses blood sugar (glucose) often known as diabetes, which causes diabetic retinopathy (eye disease). This set of metabolic illnesses is distinguished by persistently elevated blood sugar levels. It is a frequent cause of vision loss in diabetics. Based on a survey, 35 to 60 percent of those who have diabetic retinopathy (DR) have a history of the disease. One of the common reasons of blindness and visual impairment (It is impossible to restore someone's vision to "normal" levels.) in persons between the ages of 24-74 years is DR. Therefore, the goal of this research is to provide an automated method for identifying DR-related retinal abnormalities such microaneurysms. Data classification offers a tremendous potential for unsupervised learning. As far as we are aware, the suggested system is the first to identify DR utilizing a combination of deep learning and unsupervised learning techniques. With the suggested system, the accuracy rate was improved to 98.6%. When the blood vessels in the retina are impacted by DR, it makes them haemorrhage or drip of fluid, and then leads to distorting vision. This study examines parameters such as the diameter of the optic disc, lesion specificity and image quality that is used to detect diabetic retinopathy automatically with computer assistance. These elements are then applied to a machine learning ensemble system that utilizes several different learning algorithms, such as ResNet & DensNet, naive bayes, nearest neighbors, and neural networks, k-means clustering, hierarchical clustering.

Fig. 1. Normal retina and diabetic retinopathy of damaged bloodvessels & leakage of fluids in blood in the retina

*Table. 1. Symptoms of diabetic retinopathy*

| *S.no* | *Symptoms* |
| --- | --- |
| 1 | Readness or eye pain |
| 2 | Partchy / distored pain |
| 3 | Color blindness |
| 4 | Small spots within the vision (floaters) |
| 5 | Night blindness |
| 6 | Difficulty in reading or seeing objects at a distance |
| 7 | Sudden vission loss |

# Review of literature

According to a review, numerous studies have been done in the field of medical science to forecast the course of a disease from datasets using statistical techniques, artificial neural networks, and other techniques. Due to the diversity and robustness of a patient's clinical features, clinical diagnosis becomes extremely important. It becomes a tiresome effort for the doctors to manually investigate, diagnose, and determine the best course of treatment. There are numerous methods to help medical professionals deal with medical issues on a scenario basis.

To make the photographs compatible for the network being used, many researchers shrunk the images to a fixed resolution. Data normalization was utilized to normalize the photos into a comparable distribution after the excess parts of the image were removed using cropped photographs. Due to its strong contrast, only the green channel of photographs was recovered in some works, resulting in the grayscale conversion of the photos [10].

Fig. 2.

***Reference:*** Harry Pratt, Frans Coenen, Deborah M. Broadbent [13].

**Fundus images:** Samples of left side and right side of the retina’s fundus images from Kaggle. The visual cortex, or Centre of the macula, is the area of the human eye that provides clear vision. Vision loss may result from macula lesions. With a supervised classifier, the images were analyzed to determine whether they were of high enough quality to yield a trustworthy conclusion and whether the box count values from the discovered vessel system served as features. For vessel segmentation, a method based on Markov Random Fields was employed.

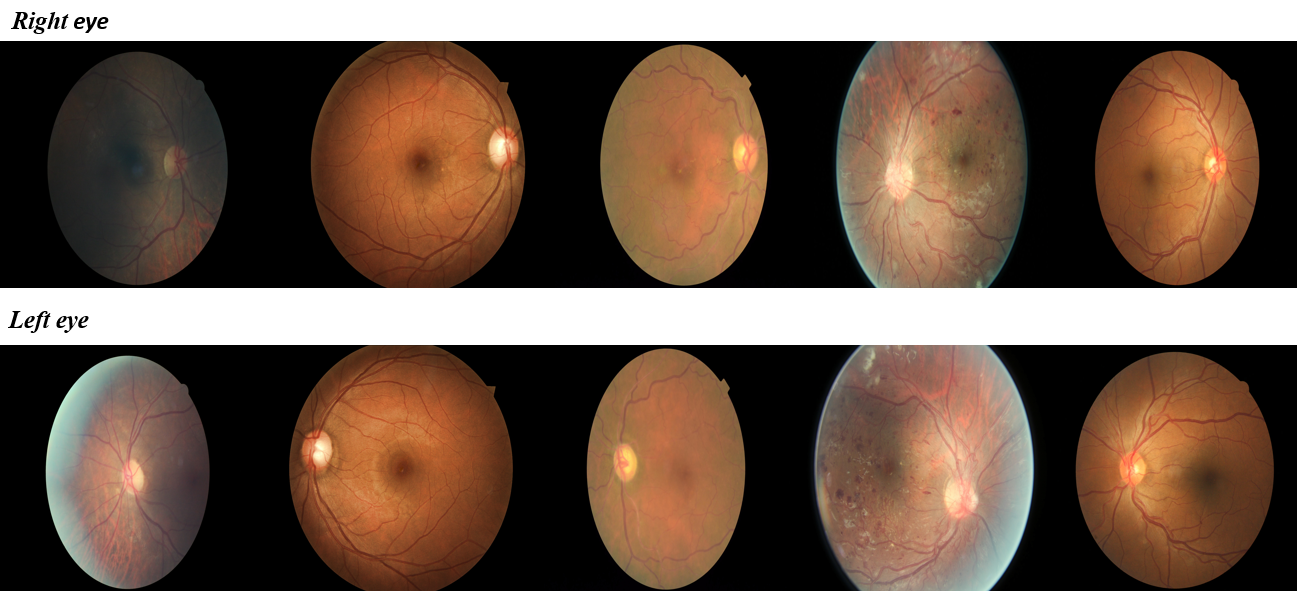


Fig. 3. DR's affected eyes from various perspectives

**Pre-processing:** The photos were categorized during the pre-screening test as either having a severe disease (abnormal) or to be forwarded for additional processing. The separated portions of each image are extracted to yield a straightforward texture descriptor. The photos are then classified using a classifier algorithm that has been trained using these attributes [10][12].

**Feature extraction:** The Amplitude Modulation Frequency-Modulation (AM/FM) approach is used to extract visual data. Using signal processing techniques like amplitude- and frequency-modulation, the green channels of the images are divided into various representations that reflect the structure's intensity, geometry, and texture. The extracted data is used to create the various representations of the image [7][18].

**Classification:** During the prediction stage, it assigns categorization to a fresh instance based on a similarity metric from the training stage. Based on a distance measure, it calculates the distance between the new example and all other training examples [10][12][18].

# Algorithms

This analysis study focused on the supervised and unsupervised learning component of machine learning techniques. The goal function, which is an expression of a model explaining the data, is created during the learning process in supervised learning. The objective function is used to predict a variable's value throughout the learning process. The algorithm must be given a sizable amount of labelled training data. When the algorithm analyses the output and iteratively alters the weights' values to generate the desired results, the classification model is created (classifier). The classifier then forecasts future data to categorize each input value according to the proper class (label). Tasks involving classification and regression are a part of supervised learning.

The images are categorized as No diabetic retinopathy stage, non-proliferative diabetic retinopathy (mild, moderate, and severe cases), proliferative diabetic retinopathy, and advanced diabetic eye disease are included in the second categorization, which consists of four stages. The first categorization divides the images into two classes, no diabetic retinopathy and diabetic retinopathy. The ten stages of retinopathy are included in the third classification, which is the final one.

**ResNet:**Deep learning architectures are frequently used as a starting point together with the weights from the pre-trained models. Tasks involving computer vision and image processing primarily use this idea. The develop model approach and the pre-trained model approach are the two most used methods. To classify diabetic retinopathy, the suggested work used two hybrid models, CNN with ResNet and CNN with DenseNet. Every succeeding successful design uses a deep-neural network with more layers to lower the error rate. This works well for less levels, but as we increase the number of layers, a common deep learning problem known as the Vanishing/Exploding gradient appears. The gradient thus either reaches zero or increases substantially. As a result, the training and test error rates increase as the number of layers increases. To overcome the issue of vanishing gradients, Residual Network uses the skip connection to arbitrary allow some input to the layer to absorb the flow of information and to avoid its loss (which also suppresses the generation of some noise). To maintain the balance between generalization and precision while lowering noise, the models are averaged. The structure of ResNet and the vast training data sets allow for faster and more accurate training of ultra-deep neural networks [12][19].

Formula: F(*x*) = H(*x*) – x 🡪 H(*x*) = F(*x*) + x.

**Diagram

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Fig 4: ResNet Working

**DenseNet:** For the dataset annotations needed for model training, we produce them. To compute the representative collection of key points, DenseNet is then introduced at the Faster-RCNN feature extraction level. The Faster RCNN then localizes and divides the input sample into several classes. Extensive testing on a dataset of photos from Kaggle demonstrates that the proposed methodology outperforms with an accuracy of 97%. To demonstrate our technique's stability in terms of DR localization and classification, we compared it to cutting-edge methodologies. The Kaggle datasets were also used for cross-dataset validation, and the results were outstanding in both the training and testing phases [18].

**Neural Networks:** On the test data set with a few chosen parameters, the performance of the remaining algorithms was generally mediocre. Regarding the quantity of attributes employed and how the attributes were expressed, the approach had certain drawbacks. Instead of extracting features and displaying them as numbers, more research can be done using an image dataset with deep neural networks. The learning algorithm that imitates the human brain is called a neural network. The sigmoid activation function is employed to stimulate the artificial neuron units found in each layer. A parameter matrix is utilized between any two layers to perform function connected from one layer to the other layer. The neural network is trained using both forward propagation and backward propagation [4][12][18].

Fig. 5. Neural networks

Based on the input image's color attributes, the training set is created. The system can refine itself till network error is minimal. The point at which error is reduced is the point at which the system is deemed to have received the most training. The test image is used as input for the detection of diabetes retinopathy. The training image will be compared to the test image to determine [1].

**Decision Tree:** It continuously divided the incoming data into classification and regression issues using a set of parameters. The data is divided into nodes, and the leaves refer to the decisions. In a classification tree, the decision variable is typically continuous, whereas in a regression tree, it is typically categorical Yes/No [1][12].

**KNN:** The KNN classifier is used to categorize images of people with diabetes and those without diabetes. A well-known machine learning algorithm is K-Nearest Neighbors. The classification task is completed satisfactorily by this method. This method is referred to as unsupervised machine learning. Numerous tasks, including as intrusion detection, data mining, and pattern identification, can be accomplished using this method. This approach cannot be used to real-world circumstances since it is nonparametric. This demonstrates that the method's assumptions about the distribution of the data are unfounded. The data used by this method are some preexisting data. The relevant data are training data. The split of coordinates into groups that can be identified by a feature is carried out using this data. This algorithm determines the separation between the data points [2][3].

**Naïve Bayes:** This is a classification algorithm based on probability theory, unlike other classifiers. Simple but effective, naive bayes has been utilized extensively in a variety of domains, including the identification of cardiovascular disease risk levels, the selection and categorization of biomarkers from genome-wide SNP data, the diagnosis of Parkinson's disease, the management of glaucoma, and others. Furthermore, early-stage signs of DR, such as retinal hard exudates, microaneurysms, and cotton version, are extremely rare and difficult to detect macroscopically. Some patients might receive a false diagnosis, missing the opportunity to halt the progression. But as we all know, DR can be prevented if laser photocoagulation is used early on [1][3][5].

P(*c | x*) = P(*x | c*)P(c)

P(x)

P(*c | X*) = P(*x1 | c*) *\** P(*x2 | c*) *\*……..\** P(*xn | c*) *\**P(*c*)

P(*c | X*): Posterior Probability

P(*x | c*) Likelihood

P(*c*): Class Prior Probability

P(*x*): Predictor Prior Probability

**Random Forest:** The deep properties of a refined ResNet-50's pooling layer are used in the suggested method for the diagnosis and grading of diabetic retinopathy. As opposed to the conventional method of using the fully connected layer, the classification is carried out using the Random Forest (RF) classifier. On the Eye Pac’s and Messidor-2 datasets for the identification and grading of diabetic retinopathy, the proposed feature extraction and classification approach surpasses existing deep architectures in terms of execution time and classification accuracy.

On the two datasets indicated above, the suggested method outperforms the existing methods in terms of detection and grading of diabetic retinopathy [5][11][17].

Chart, scatter chart

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Graphical user interface, application

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Fig. 6. Model prediction and Random Guessing

In the above graph an ROC curve for healthy (severity == 0) and sick (severity>0) to see how well the model works at just identifying the disease.

The results are evaluated by loading the best version of the model and seeing how the predictions look on the results. Then the author visualized the specification of data.

**Support Vector Machine (SVM):** This algorithm is used as a classification and regression technique model to distinguish between real and fake vessels. Clinical eye examination and ocular fundus imaging are required for the diagnosis of diabetic retinopathy. To maximize the margin of separation between the classes, SVM creates a perfect hyperplane [1][17].

Fig. 7. support vector machine

The data spans from +1 to -1, and feature scaling is necessary for the SVM classifier. Depending on which side of the decision boundary it lies on, the support vector machine generates a real-valued output that is either negative or positive. A confidence indication can be created using the hyperplane distance. The classification is more accurate the farther away an observation is from the plane. Hinge loss, a kind of cost function that establishes the cost based on a hyperplane margin, is the loss function used by the SVM classifier [9].

**K-means clustering:** K-means clustering, N’th observation are divided into K clusters and each observation is assigned on clusters that has closest mean value. K-means clustering is then used to color compress the image. In this study, we condense the colors to highlight the hues that exude while also speeding up computation. Then, using thresholding and the information of the histogram of the color-compressed image, exudates are segregated. In order to identify, locate, and count the number of hemorrhages and exudates, de-correlation stretch, and areas attributes parameter bounds are utilized. To suggest possible illness conditions, ten acceptable features from the exudates are collected and used to classify them using a fuzzy classifier [18].

**Diagram

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Fig. 8. flow chart of k-means clustering*.*

**Hierarchical clustering**: This research suggests using hierarchical clustering using Siamese network with pre-trained CNN to choose clusters with more discriminative patches. Larger image patches' global-level characteristics are extracted using CNN's fine-tuned Exception model. The overall image-wise classification accuracy is increased by combining local and global characteristics.

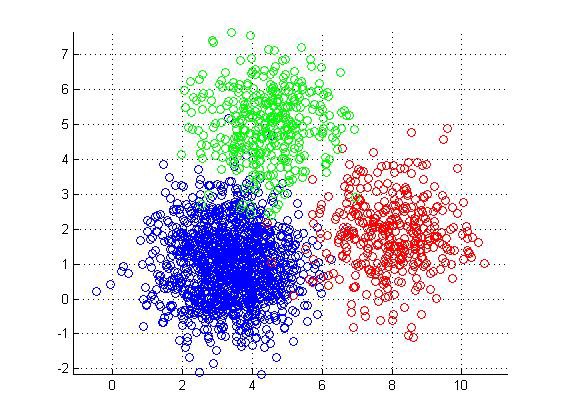
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Fig. 9. Hierarchical clustering

**Markov chains:** A patient's history of DR might be portrayed as progressing through multiple different degrees of severity, like the course of many chronic diseases. A useful technique for describing random processes that change over time is the Markov process. Markov Chains have been utilized successfully in earlier investigations to model DR. It was decided to employ a homogeneous discrete-time Markov Chain model to represent the yearly progression. While the WESDR contained between-observation intervals of four and six years and three observations each patient. It is only considered for patients with young-onset insulin dependence, and only the right eye. Typically, a Markov chain has a finite number of states and a probability that is known. The probability of transitioning to other states are determined within a predetermined time, or Markov cycle, after which patients are first placed in one of the states. The core of the Markov model is the Markov Property, which asserts that, given the subject's whole history, the present state simply depends on the most recent previous state. Due to its memoryless quality, the model may be described in terms of a single-cycle transition matrix.

Equation generated Latex:

P(Xn = Sn | Xn-1 = sn-1) = P(Xn = C | Xn-1 = B)

# Results & Datasets

The results of those actions functions are utilized for ensemble selection [4]:

* Sensitivity: TP / TP + FN
* Accuracy: TP + TN / TP + FP + TN + FN
* F-score: 2TP / 2TP + FN + FP

Table

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Fig. 10. Precision and F-score

Machine learning analysis of diabetic retinopathy the computer-aided screening system described in this study uses machine learning to classify the severity of DR based on the analysis of fundus images with different lighting and fields of vision. The two key outcomes are the identification of DRNPs and the grading of DRNPs. The authors employed 301 retinal pictures for detection, of which 152 had a grade of 0 and 149 the other had a grade of 3. We used all the features from these photos to train a ResNet, which was then put to the test using a 10-fold cross-validation procedure. Additionally, the performance was enhanced by choosing the most essential features and ResNet parameters. 400 retinal pictures were utilized for grade classification. Except for controls due to its high precision, ResNet and DenseNet are used as bioinformatics tools in most cases. It can identify and handle highly dimensional data, for instance, and is flexible in how it displays data from many sources. ResNet and DenseNet fit within a modern classification known as component structures. This portion of the framework is an estimation that is based on data obtained primarily from spot things. In this case, a section limit can take the place of the spot problem.

| S.no | Name of the algorithm | Learning  algorithm  techniques | Accuracy |
| --- | --- | --- | --- |
|  | ResNet And DensNet[19] | Supervised | 96.22% |
| 2 | K-means clustering[18] | Unsupervised | 93.29% |
| 3 | Decision Tree[5] | Supervised | 89% |
| 4 | Support Vector Machine[3] | Supervised | 88.8% |
| 5 | Neural Networks[8] | Supervised | 88.3% |
| 6 | K-nearest neighbor[2] | Supervised | 87.8% |
| 7 | Random Forest[11] | Supervised | 75% |
| 8 | Naïve Bayes[10] | Supervised | 65.97% |

Table. 2.***Accuracy of reference algorithms***

Chart

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Fig. 11. Graphical analysis of Accuracy

Fig. 12. Graphical analysis of Sensitivity and Specificity

To extract the properties of the eye for efficient categorization, deep learning architectures including CNN with ResNet, and CNN with DenseNet 2.1 are proposed. The models' respective levels of accuracy were 96.22%, 93.29%, and 75.61%. A fully automated & extremely accurate DR detection is a feature of this technology. As a result, our model has an accuracy of up to 96.35% to 97% in ResNet & DenseNet for predicting the signs of diabetic retinopathy. K-means clustering, which had a lower accuracy than ResNet & DenseNet at 92.3%, was also utilized to gain a general understanding of the dataset.

# Conclusion

A common side effect of diabetes is Diabetic Retinopathy, which stands for retinal blood vessel explosion. Patients are saved from going blind by the accurate and early detection of DR. These algorithms develop categorization and detection methods for fundus pictures of Diabetic Retinopathy. The examination models showed that they were capable of correctly categorizing both healthy and DR cases in retinal images. Additionally, few algorithms locate the DR severity level of the fundus picture. The major objective of this study is to develop an automated system model that can correctly recognize the early most common form of Diabetic Retinopathy (DR) indication in diabetes patients. The disease known as DR is fatal. The retina is harmed by optical laser examination, yet it frequently succeeds in averting irreversible eyesight loss. Screening is crucial for the first finding because severe symptoms do not appear until the disease has become irreversible. Deep learning techniques were used in most of the studies that were reviewed because of their ability to reliably extract useful characteristics. ResNet capacity to extensively extract useful information from fundus images made it the most successful algorithm for detecting and classifying DR cases. However, the requirement to obtain and work with updated datasets hurts the field's researchers. Additionally, using these datasets for processing to attain good accuracy results in longer execution times.

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