# Detection of Diabetic Retinopathy Using Principal Component Analysis and Deep Neural Networks

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***Abstract*—** Diabetic Retinopathy (DR) is a common problem of diabetes mellitus, which causes lesions on the retina that effect vision. If it is not identified early, it can lead to blindness. Early detection of DR and treatment can significantly reduce the risk of vision loss. In this paper, Principal component analysis technique is used for selecting the best features and deep neural network is used for classifying the presence and absence of DR.

***Keywords*—** Diabetic Retinopathy, optimization, feature selection.

## I. INTRODUCTION

Diabetic Retinopathy is a human-eye disease in diabetes patients that affects the eye's retina and can cause in complete blindness eventually. Identification of early stage diabetic retinopathy is necessary to avoid full blindness. Successful DR treatments are available while initial detection and continuous assessment of diabetic patients are needed. This could improve disease management before contributing to infection by administering the same medications and providing the physicians health advice. In implementing Particle swarm optimization in optimization and also in conjunction with several other popular techniques was already extended to various regions. This technique works the analysis for the global optimal by entities, called particles, the oscillations of which are modified by an analytical and numerical variable. The identified functions are then categorized to use the appropriate Decision Tree algorithms, Random Forest, Support Vector Machine. Proposed methodology performance is evaluated by the evaluation methods: accuracy, sensitivity and specificity. Thus the method examines the Diabetic retinopathy using PSO feature selection technique on three miscellaneous Classifiers SVM Classifier accuracy (98), sensitivity (96.6) and specificity (96.5). SVM Classification algorithm has the highest number of metrics for the selection method for the PSO feature.

The number of diabetic retinopathy patients is increasing in present day. It predicted that the population will rise from 125.8 million to 190 million on 2030 and that if no appropriate action is taken, the percentage of vision-threatening diabetic retinopathy will rise from 36.3 million to 55.3 million people. Increasing evidence shows documenting routines DR treatment efficacy and advanced diagnosis, it still contributes to impaired virtual performance and reflects the high incidence of blindness. This has been largely ignored in education and in many low-income countries due to insufficient health care.

According to the report published in 2017 by the IAPB (International Blindness Prevention Agency) 422 million people were diagnosed with diabetes. 1 in 3 people diagnosed with diabetes will have diabetic retinopathy to some degree and 1 in 10 will have vision loss. A new CDC study found high prevalence of diabetic retinopathy, affecting about one-third of adults over 40 years of age with diabetes, and more than one-third of African-Americans and Mexican-Americans.Machine learning plays a crucial part in detection of diabetics retinopathy. Machine Learning's aim is to understand the data structure and fit the data into a model. Feature Selection is one of Machine Learning's core concepts that impacts the model's efficiency.

We get inspired to work with this subject while learning about these causes. Since there are inadequate approaches to diagnose diabetic retinopathy, we 're going to develop a framework that will estimate diabetic retinopathy. So we chose to use Machine Learning algorithms to detect this situation.

There are about 94 million people globally with DR, 18 million people with proliferative DR, 20 million people with diabetic macular edema and 28 million with VTDR. Larger period of diabetics and impaired regulation of glycemic and blood pressure are heavily connected with DR. Such findings DR's significant global health burden and the role of identifying risk factors in its incidence. The data collected was at vary time point from the studies, with different techniques and attributes of population.

Diabetic retinopathy is the undergoing changes that take place in blood sugar levels throughout the capillary of the retinal system. Some vessels may swell up in some

cases, and fluid leaks into the back of the eye. These could swell and drop in the capillary. Or they could close, blocking the flow of blood. Anomalous new capillary often grows up on the retina. All these improvements will rob your eyesight. DR was not leading symptoms initially, just low vision complications. Ultimately, that it will lead blindness. Whoever also type 1 and type 2 diabetic can develop the condition. The you have far more diabetes, and the less sugar on your blood regulated, the greater the probability that you will experience this eye complication. In other cases, abnormal arteries will grow on the ground of the retina. Over time, too much blood sugar will contribute to blocking the tiny capillary that feed the retina and sever blood supply. As a consequence, the eye looks for new capillary development

***A. Types of diabetic retinopathy***

There are two types of diabetic retinopathy (DR):

Early diabetic*retinopathy: Commonly known as non-proliferative diabetic retinopathy (NPDR) which will occur when there isn't growth/proliferating of new capillary. That is the initial phase of Diabetes eye disease. The walls of the capillary within the retina weaken when you have NPDR. Smaller bulges (microaneurysms) extend down from the edges of the smaller vessels, frequently withering fluid and plasma blood into another retina.

Greater retinal shafts, too, may start dilating and radius is abnormal. NPDR can switch from minimum to severe, as more siege capillary. Capillary within the eye can also close off with NPDR. This is called ischemia macular. When this occurs, the macula cannot be penetrated by blood. Occasionally, small particles, termed exudates, could perhaps form in the retina. Nerve fibers in the retina can start swelling. Central segment of the retina (macula) sometimes starts swelling (macular edema), an ailment which needs medical attention.

Advanced! diabetic retinopathy: known as proliferative diabetic8retinopathy, can progress to this serious type. In this case, damaged capillary narrow off, brings new prosperity, irregular capillary of retina, and may dip into the transparent, fliud-like fluid that filling your (vitreous) middle of eye.

PDR is the one most advanced stage of eye disease for diabetics. It occurs when new capillary start to grow in the retina. Neovascularization is called this. Often those delicate bleeding current vessels into the pigment particles. You might see some gloomy gnats, when they bleed a little. When it spills a lot, then all vision could be blocked. Finally scar tissue, eventually aroused by the development of new capillary, can induce the retina to divide from either the rear in your eye.

Unless the new capillary interacts with ordinary fluid flow out from the eye, stress in the eye ball will accumulate. This can disrupt the nerves that brings stimuli (optic nerve) of your eye to your brain, contributing to macular degeneration.

The body's effort to save its retina is proliferative retinopathy, but it can often lead to retina scarring and can cause the retina to detach itself, leading to blindness. Modern eye care can help prevent blindness from arising as a result of proliferative retinopathy.

***B. Complications of DR***

Diabetic retinopathy includes the development of irregular blood vessels within that retina. Abnormalities can cause major problems regarding vision:

1. ***Vitreous! haemorrhage.*** The fresh capillary can bleed into the fresh, creamy-like stuff, covering the middle of your eye. Where the rate of leakage is low, you can only see some dark spots (floaters). Blood will fills the vitreous cavity in more severe cases and effectively block your vision. If the vitreous humor shrinks, these capillary can be weakened, causing them to bleed, which can contribute to the appearance of cobwebs in your eyes and make it harder to see. Blood from a vitreous haemorrhage can dissipate, but any complications would require medical attention.
2. ***Retinal! tightening.*** The enlarged capillary correlated with macular degeneration facilitates the development of the scar tissue may remove the retina from the back side of the eye.
3. ***Glaucoma.*** New capillary must develop at the front of of your eye and collide to your eye's ordinary fluid flow, allowing pressure to build up in your eye (glaucoma). The above pressure may disrupt the nerves, which carry images of your naked eye in your nervous system (antenna nerve).
4. ***Blindness.*** Diabetic retinal detachments, cataracts or both ultimately result in total vision lost.

***C. Stages of Diabetic Retinopathy***

The four stages of diabetic retinopathy is described in table1.

***Table 1:*** *Stages of Diabetic retinopathy*

| | STAGES | DESCRIPTION | IMAGE |
|---|---|---|---|
| 1 | Mild Nonproliferative Retinopathy | Microaneurysms occur at this stage. These are small pockets of globular swelling in the relatively small capillary of the eye. |  |
| 2 | Moderate Nonproliferative Retinopathy | This is the phase where blocking of capillary occur. |  |
| 3 | Severe Nonproliferative Retinopathy | The capillary which helps for the nourishment of eye are blocked thus signaling the retina to grow new capillary. |  |
| 4 | Proliferative Retinopathy | Fresh capillary were proliferating, expanding within the retina, and into the vitreous gel. |  |

## II. RELATED WORK

This research paper focuses primarily on the application of deep learning in the classification of the stage of diabetic*retinopathy and the identification of naked eye laterality utilizes funduscopic images. Diabetic*retinopathy is a chronic disease of the eye blood vessels that is progressive and sight-threatening. Ophthalmologists use early Funduscopic imaging to diagnose diabetic retinopathy. This is usually a time late in detection and action, apart from the financial payments and the associated with risk of blindness. We equipped the estimation network mostly on readily viewable Kaggle dataset and use a convolutionary neural network-based method for diabetic*retinopathy automatic diagnosis which showed a sensitivity of 80.28% and a specificity of 92.29% , accuracy of 93.28%

Their thesis focuses on making a Statement on the nature of diabetic*retinopathy using a machine learning technique ensemble that categorizes algorithms on features extracted from the output of retinal objects. Actions to predict diabetic retinopathy are made using K-Nearest*Neighbor, Random Forest, Help Support Vector Machine, and Neural Networks which showed the highest accuracy of 75%.

To automate the DR diagnosis and provide DR patients with the appropriate suggestions, we formed a Diabetic*Retinopathy fundus image set of data which was classified with both the appropriate treatment option necessary. we instructed deeply convolutionary methods of neural networks to evaluate the severity of Diabetic*Retinopathy fundus images using this dataset.

We are capable of achieving an accuracy of 89.72 per cent for a four-degree classification method throughout the tests. We implemented our prototypes on a cloud computing platform and provided pilot DR patient care over several clinics, the design produced a 92.8 percent accuracy rate with ophthalmologists in the clinical assessment, demonstrating the efficacy of our research.

In this research, we represented a system known as SLDR to identify five stage severity levels of diabetic*retinopathy by the use of visual features and neural*deep-learning (DLNN) model. On the recognition of five severity levels on retinal fundus images not performing preprocessing and post-processing steps. Although there are a few studies

devoted to DR gravity level identification, anyone of them centered of the experts ' five classes commonly used in observation by the experts. In addition, literature techniques were represent to the detection of specific DR lesions seeking to categorized the images based on the parameters of regions so obtained. This showed about 92.18% sensitivity,94.5% specificity and 92.4% accuracy.

In this study fundus photos including retinopathy for diabetic were Factored into the equation, The concept behind such an article is to suggest a computerized method of data to define appropriate origins of DR. The developed framework was equipped with three forms of back propagation, Deep Neural*Network (DNN) and Convolutionary*Neural Neural Network (CNN) after evaluating systems with CPU equipped Neural Network shows the minimum accuracy due to one hidden layer while the deep learning methods are all out-performing. The deep learning methods can measure features of various groups, including blood vessels, fluid flow, exudates, hemorrhages and micro aneurysms. Model measures the masses of that give patient's eye severity level. This has about 86.3% accuracy.

Recently, deep convolutionary neural networks has shown superior image classification performance compared with previous handcrafted methods for image classification based on characteristics. In this research, we identified the using of deep convolutionary neural*network methodology to instantaneously classify diabetic*retinopathy with a fundus images, and 94.5 percent accuracy in our dataset, surpassing the data achieved through the use of classical techniques.

In this examine research, we are attempting to establish a computer*assisted system for recognizing clinical data of the retina within order to diagnose diabetic retinopathy rapidly and accurately. A neural network with*CNN architecture, via learning with labelled data supported by EyePACS, a free retinopathy identification tool, identifies exudates, micro-aneurysms and hemorrhages in the retina picture. The array consists of 35566 high-resolution retinal images which are taken under various conditions. After testing, the network shows a 94.65 percent precision and 85.68 percent accuracy in the testing process.

An automated Diabetic*Retinopathy recognition system known as Deep*DR is executed in this report. Deep*DR detects DR's having and intensity directly through transfer and ensemble learning from fundus images. It includes a set of state of the art neural*networks on basis combined of popular convolutionary neural networks and deep*neural networks with customized standards. We test the models using nine metrics, based on validity and reliability. Analysis show that the techique performs best with 97.5% sensitivity, 97.7% specificity and 97.7% curve area. In the meantime, the grading model achieves 98.1 percent sensitivity and 98.9 percent specificity.

This research paper adopts deep convolutionary neural*network (CNN) to get pixel-wise notified of the exudate. The CNN model is primarily trained with expertly labeled pictures patches of exudates and then noticed as offline classification. To obtain pixel-level accuracy though the computing time, the potential exudate member points are first retrieved with morphological absolute open method. The regional immediately near the initiatives to promote (64 section 64) will then be transferred to the appropriate CNN model for recognition / detection. The suggested proposed system on the testing dataset achieves 92.91% pixel-wise accuracy, 89.6% sensitivity and 95.7% specificity.

## III. PROPOSED WORK

Principal component analysis technique is used for selecting the best features and deep neural network is used for classifying the presence and absence of DR.

### *A. Data Set Information:*

We used Debrecen Dataset Diabetic Retinopathy, retrieved from UCI*Machine Learning Repository. The utilized dataset includes the functions derived from the early images from the Messidor. The photographs are using to predict or not they show any symptoms of Diabetic* Retinopathy. The data contains 20 attributes. The explanations about the attributes are given below.

***Attribute 0:*** A*binary value {0,*1} determines the measurements are of higher quality or of lower quality.

***Attribute 1:*** A*binary value {0, 1} where 1 represents extreme retinal abnormality and 0 represents no shortcomings.

***Attributes 2-7:*** MA*detection tests having with alpha= 0.5... 1 confidence rates respectively.

***Attributes 8-15:*** The exudate tests for MA detection.

***Attribute 16:*** The Euclidean distance to the midpoint of the macula between centers of the optic disc. This feature is a critical and ROI centralized feature.

***Attribute 17:*** Diameter of the optical disk.

***Attribute 18:*** *The binary values {0, 1} describes a category AM or FM

***Attribute 19:*** *This component contains data about the class mark. These are two different class labels. Class mark 1 reflects DR signals, and 0 is natural pupil.

***B. Feature Detection:***

To determine NPDR automatically we have introduced three key processes to retrieve those important features. In addition, the edge of the retina was previously separated from the picture using each retinal image's red part.

***1) Blood vessels:***

The beginning process is evaluated to recognize the density of the blood vessel in a retinal image. To end, the RGB pictures is converted into its CMY classification and segregated from the magenta attribute. Morphological operations on the magenta portion cover blood vessels. After a matching histogram which increases its contrast, the difference between the magenta portion and the experimental morphological processing image is maintenance manual. Dilation and erosion processes reduce the noise presented in the binarized image. In the last frame, the density*of white pixels is measured at the top.

***2) Microaneurysms:***

Microaneurysm* are tiny lesions in the blood vessels, occurring around tiny blood vessels as small, circular shaped dots. The green portion is collected to calculate the number of microaneurysms, and the blood vessels are covered having the noise*reduced picture of the earlier method. This pixels belonging to the blood vessels are generally painted with the normal retina color. Next, the microaneurysms are illuminated using a disc-based dilation process. This image is then treated with algorithms for edge-detection and hole filling to knead the possible microaneurysms together. To finally remove those edges, it's necessary to find the difference between the resulting image and the edge image. Using morphological processes and a large number of pixels to have the actual*microaneurysms, the potential microaneurysms are eventually sorted by shape and scale.

***C. Principal Component Analysis:***

Reduce the data to n dimensions from m-dimensions. Primary Component Analysis (PCA) is a method that reduces the dimension of the data of such datasets, improves accuracy while minimizing loss of information at the same time. It does this by producing new negatively correlated parameters, which subsequently increase the variance. Finding these additional variables lessens the primary features to solve an issue of own value / self-vector, and the new variable are determined by the data at hand, not a priori, making the algorithm an integrative machine learning technique. This is also versatile in other way, because variations of the approach have been created which are adapted to different types and data formats. In PCA Selection function, we use two types of objectives, one is standard scalar and the other is minmax scalar, which is close to feature scaling, and the normalization that is used to locate the parameter range by encoding into a limit that makes the algorithm work faster. In this, the data are processed with the pca.fit and transforms the features later.

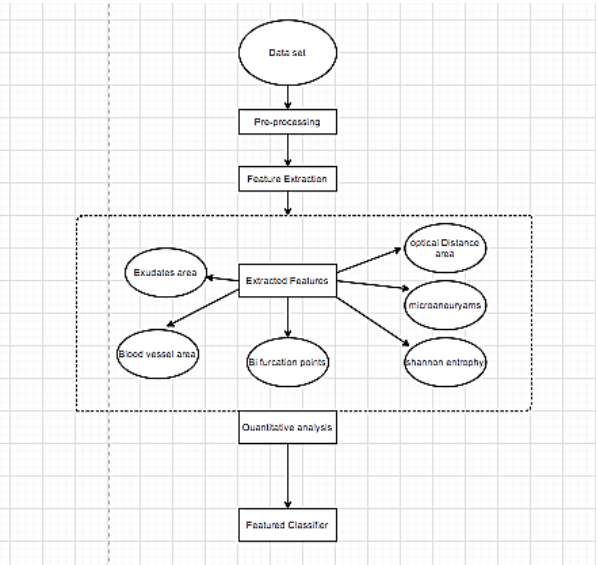


***Figure 2:*** *Feature selection process*

***D. Classification Algorithms:***

Various distinct classification algorithms (classifiers) had been developed in machine learning. This report outlines four most commonly used classifiers to be used in this analysis. They are Random Forest (RF), Support Vector Machines (SVM) and deep neural networks classifiers.

**Random Forest**: Though one point to mention is that constructing the forest isn't just about building the decision mostly with technique of gaining information or index gain. Random decision forest or random forest is an example of supervised, regression and some other activities that operates by creating a wide array of decision trees at training time and delivering the category that is the class mode (classification) or mean prediction (regression) of the tree branches. Random forest is appropriate for the inclination of decision tree to overfit to their set of training.

**Support Vector Machine**: The purpose of the SVM algorithm is to find a decision boundary in an N-dimensional space (N - number of attributes) which categorizes the data sets individually. SVM

is supervised deep learning models, with related learning algorithms analyzing data used for regression and classification metrics. Based on the set of training images, most of which are classified as corresponding to either one of 2 groups, an SVM training model computes a method that allocates new examples to one or another category, trying to make it a non - probability binary linear classification model (although methodologies such as Platt scaling exist to be using SVM in probabilistic classification). SVM design is a description of the cases as spatial points, represented in certain way so as to split the cases of the multiple classes by a simple gap as large as possible.

## IV. RESULTS AND DISCUSSION

The result of the presented work should be measured with the following parameters: precision, accuracy and sensitivity.

$$\boldsymbol{Sensitivity} = \frac{True\ Positive}{(True\ Positive + Falsee\ Negative)} * 100$$

$$\boldsymbol{Accuracy} = \frac{Number\ of\ instances\ classifed\ correctly}{total\ number\ of\ instances} * 100$$

$$\boldsymbol{Precision} = \frac{True\ Positive}{(True\ Positive + False\ Positive)} * 100$$

Performance is determined using the metrics: sensitivity, accuracy and specificity.

***Table 2**: Comparison of accuracy, sensitivity and precision of various classifiers*

| Classifiers | Accuracy | Sensitivity | Precision |
|---|---|---|---|
| **SVM** | 84.6 | 84.1 | 84 |
| **Random Forest** | 86.3 | 85.7 | 87.1 |
| **DNN** | 89.8 | 89.1 | 88.7 |

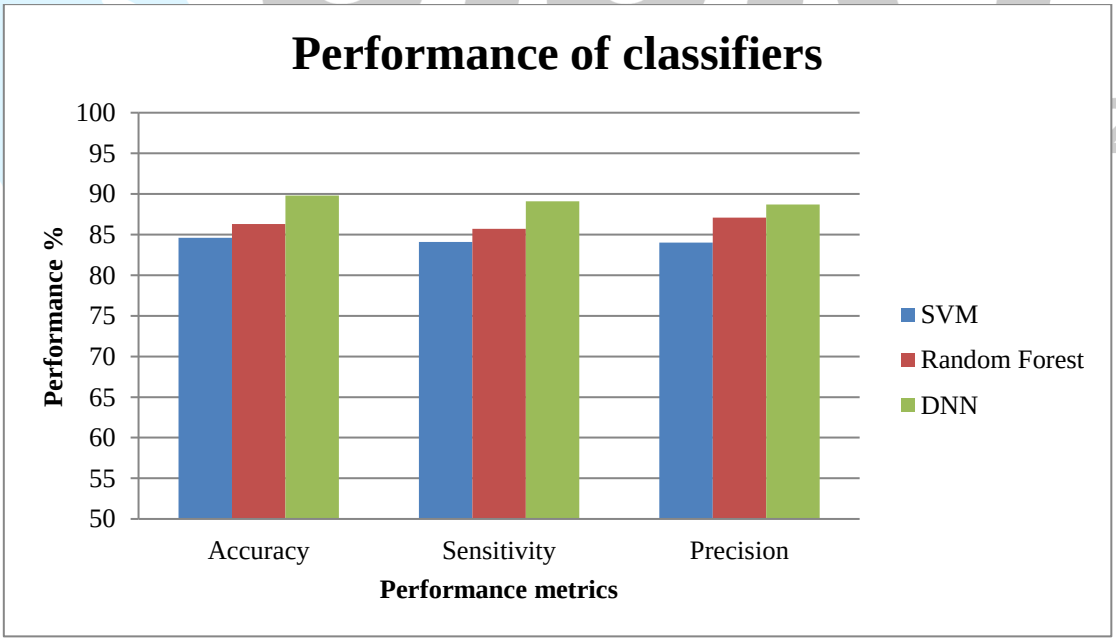


***Figure 3:** Comparison of accuracy, sensitivity and precision of various classifiers*

## V. CONCLUSION AND SUMMARY

The result shows that PCA selects best features which contributes more for diabetic retinopathy classification and deep neural network performs better than random forest and support vector machine algorithms.

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