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# An Analysis of Diabetic Retinopathy Prediction Using Efficient Retinopathy Prediction Algorithm

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***Abstract :*** Prediction of diabetic retinopathy on early stage is an interesting task in medical image diagnosis system. In this approach, we proposed a novel Efficient Retinopathy Prediction Algorithm (ERPA) for efficiently classify and predict the various stages of retinopathy. We proposed an algorithm, which combines the Convolutional Neural Network (CNN) and Support vector machine (SVM) to predict the retinopathy in digital image. The novelty of the work is that we use the CNN for feature extraction and SVM for classification to predict with more accuracy. The analysis results shows that the proposed ERPA provides the high results compare than various learning-based methods. The experimental results are verified with the google colab tool and the Kaggle dataset is tested**.**

***IndexTerms*** **- Retinopathy Prediction, Convolutional Neural Network, Support Vector Machine, Machine Learning, Digital Image Processing**

## I. INTRODUCTION

Diabetic Retinopathy (DR) is an Eye Disease that can cause vision loss and blindness in people whose blood vessels in the Retina may swell. Many physical tests are there to detect the DR but those are time consuming and affect the patients as well. By using machine learning techniques in DR, it automatically detects the early symptoms.

In order to improve the early detection and monitoring of DR, numerous authors have classified the causes using learning approaches. The Artificial Neural Network (ANN) approach was first presented by May Phu Paing et.al. [1]. The algorithm removed the blood vessels, exudates, and microaneurysms and measured the lesions' diameter, length, and number. Sammy et al. [2] proposed a learning algorithm to classify the plant diseases. Enrique et.al. [3] Classify the non-proliferative diabetic retinopathy grade automatically with Support Vector Machines (SVM). Feature extraction using Histogram of Oriented Gradients (HOG) and classification using Shallow Learning Techniques (SLT) was proposed by Devi sarwinda et al. [4]. By employing retinal pictures and CNN classification, Mobeen-ur-Rehman et al. [5] were able to detect diabetic retinopathy early and achieve high accuracy using pre-trained models (AlexNet, VGG-116, SqueezeNet). Aruna et al. [6] analyzes the DR models of Probabilistic Neural Network (PNN), Bayesian Classification, and Support Vector Machine (SVM), which is tested in fundus images. Deep Convolutional Neural Networks (DCNNs) with a Region scoring map (RSM) attention mechanism were proposed in Junjun Pan et al. [7], for automated retinopathy detection technique. Retinal microaneurysms and exudates were identified with the use of SVM and KNN classifiers in Jaykumar Lachure et al.'s [8] DR screening. Nihel et.al. [9] proposed a difficult exudate detection technique for the early diagnosis of diabetic retinopathy. With retinal images after optical disk removal, this technique uses Random Forest to achieve high accuracy. Johin et. al. [10] proposed an algorithm to classy the DR aimed to achieve high accuracy with CNN, KNN, and Soft-max Classifier. Navoneel Chakrabarty et. al. [11] proposed a deep learning approach using CNN to classify the diabetic retinopathy in high resolution fundus images. The rest of the paper is organized as follows.

The detailed discussion of the proposed novel ERPLA is in section 2. Performance evaluation and comprehensive comparisons with earlier approaches are given in Section 3. Finally, a brief conclusion of the work done is presented in Section 4.

## II. PROPOSED WORK

This section briefs the design of the proposed ERPA design that uses CNN for feature extraction and SVM for classification. Figure 2.1 shows the block diagram of the proposed ERPA. The various blocks of ERPA are preprocessing, feature extraction and classification. A brief discussion on the various blocks is given in following subsections. The abnormalities associated with fundus image processed through various stages of processing. The input images were taken from the dataset and preprocessed to enhance the quality of the image. The various DR severity levels, such as no DR, mild DR, moderate DR, severe DR, and proliferative DR, are then classified using these features using SVM classifiers. By using this innovative method, we combine the advantages of SVM-based classification with CNN-based feature extraction to identify DR with high sensitivity, specificity, and accuracy.

**2.1 Block Diagram**

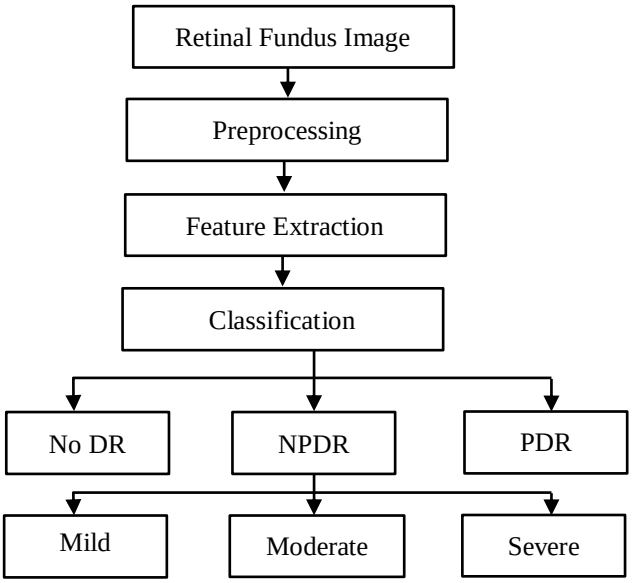


Figure 2.1 Block diagram of ERPLA

**2.1.1 Data Set**

The EyePACS dataset, which can be downloaded for free from Kaggle.com, was used [12]. Every image is taken of a different person with a different camera, at different sizes.

The dataset contains 35,126 images for training and testing. There is a perceptible class imbalance in the dataset, which makes training the model difficult. More specifically, 73.47% of the entire dataset is made up of class 0 (No DR). Data augmentation approaches are used to balance the classes in order to address this problem. The detailed number of images for each class is given in table 2.1.

Table 2.1: Various classes of images in dataset taken for training and testing.

| Class | Count |
|---|---|
| No_DR | 25810 |
| Mild NPDR | 2443 |
| Moderate NPDR | 5292 |
| Severe NPDR | 873 |
| Proliferative | 708 |
| Total | 35126 |

**2.1.2 Pre-processing**

During image acquisition and transferring, the image details may be corrupted due to various types of noises. In this preprocessing stage, we reconstruct the original image details using the mid-point filter to provide the better results, even though at high density noise images.

**2.1.3 Feature Extraction**

In this approach, the backbone of every learning algorithm is explained. Every learning algorithm works better if the feature extraction performed better. We use one of the best learning algorithm, known as Convolutional Neural Netwok (CNN). CNNs are particularly well-suited for DR classification tasks because they can automatically learn and extract appropriate features from the input images, including vascular anomalies, exudates, hemorrhages, and microaneurysms that are indicative of the severity of DR.

In machine learning a feature map for data is created and the classifier is applied on this to solve the problem. Each problem has a distinct set of facts, and the approaches taken to solve it vary depending on the issue. In order to get around this, features are automatically generated by CNN and combined with the classifier. The CNN has several advantages, that it has the smallest list of layers among all algorithms for converting input to output. A deep network will require more time for each training step.

Layers Rescaling (1./255):

Rescales pixel values of input images to the range [0,1] to standardize input data.

Layers. Conv2D(16,3, padding=’same’,activation=’relu’):

Creates a convolutional layer with 16 filters (also known as kernels) of size 3x3. The 'same' padding ensures that the spatial dimensions of the output feature maps remain the same as the input. The Rectified Linear Unit (ReLU) activation function is applied element-wise to introduce non-linearity.

MidPooling Layers:

Mid-pooling involves applying pooling operations at intermediate convolutional layers, between convolutional and fully connected layers. The main purpose of Mid-pooling helps in reducing the spatial dimensions of feature maps while preserving important

spatial information, which is beneficial for capturing localized features in fundus images. It enables the network to focus on relevant features at different scales and spatial locations, enhancing discriminative power.

Feature Map:

Let X represent the input feature map, Y denote the output feature map after mid-pooling, and P be the pooling operation. Then, the formula for mid-pooling can be represented as: Y=P(X)

Flattening Layer:

Layers.Flatten():Flattens the 2D feature maps into a 1D vector to feed into the dense layers.

Dense(Fully Connected)Layers:

Layers.Dense(128,activation='relu'): Fully connected layer with 128 neurons and ReLU activation function.

Output = ReLU(input×weight+bias)

Layers.Dense(len(data_train.class_names)): Output layer with the number of neurons equal to the number of classes in the dataset(in this case, the length of data_train.class_names). No activation function is specified, implying a linear activation function for classification tasks.

Output = Softmax(input × weights+bias)

**2.1.4 Classification**

From the previous approach on feature extraction, the final approach in ERPLA is classification. In ERPLA, SVM classifier is implemented to classify the different stages of the retinopathy. Retinal images are used as training examples, and SVM efficiently maps them into feature spaces using supervised learning techniques. As important data points in the feature space, these images depict different phases of diabetic retinopathy. Similar mapping is applied to test samples, which consist of extra retinal images, in order to categorize them into distinct classes and help with the precise diagnosis of the illness. Minimizing classification mistakes and accurately identifying the stages of diabetic retinopathy are made possible by SVM's capacity to create a maximal splitting hyperplane between two classes. Moreover, SVM creates high-dimensional feature spaces from input data, which is represented by retinal images. This makes it easier to classify datasets that are linearly inseparable and frequently used in the detection of diabetic retinopathy. By efficiently projecting data into these high-dimensional feature spaces, the use of kernel functions improves the performance of SVM. Non-linear classification is made possible by SVM by utilizing non-linear kernel functions, which permits more in-depth examination of retinal images and the attributes that go along with them. To effectively categorize retinal pictures in the context of diabetic retinopathy diagnosis, SVM functions as a binary classifier, differentiating between two values: +1 and -1. SVM, in fact, uses a straight-line equation (wx+b=0) in two-dimensional spaces to distinguish between various retinal image classes; positive and negative classes are indicated, respectively, by specific conditions (wx+b>0 and wx+b<0). The accurate classification of diabetic retinopathy phases is made possible by this methodical approach, which also makes it easier for those who are affected to receive early diagnosis and treatment.

**III.RESULT ANALYSIS**

The performance of the proposed method ERPA is compared with the state-of-the-art techniques. The results are analyzed in terms of accuracy, sensitivity, specificity and precision, that shown in table 3.1.

Table 3.1:Performance comparison of the proposed ERPA with other prior methods

| METHODS | | ACCURACY | SENSITIVITY | SPECIFICITY | PRECISION |
|---|---|---|---|---|---|
| FEATURE EXTRACTION | CLASSIFIER | | | | |
| HOG | SVM | 85.00% | 80.00% | 90.00% | 88.89% |
| SIFT | SVM | 81.67% | 83.33% | 80.00% | 88.65% |
| SIFT | CNN | 86.11% | 84.21% | 88.24% | 88.89% |
| HOG | CNN | 90.00% | 87.80% | 92.31% | 92.31 |
| ERPA | | 93.75% | 92.50% | 95.00% | 94.87 |

**3.1 Metrics**

For diabetic retinopathy detection, we can adapt the classification problem to utilize sensitivity and precision as evaluation measures. Sensitivity, also known as recall, measures the proportion of actual positive cases that were correctly identified by the model, while precision measures the proportion of positive identifications that were actually correct.

Here's how we can modify the parameters for diabetic retinopathy detection:

True Positive (TP): Number of instances classified as having diabetic retinopathy correctly.

True Negative (TN): Number of instances classified as not having diabetic retinopathy correctly.

False Positive (FP): Number of instances classified as having diabetic retinopathy incorrectly (false alarm).

False Negative (FN): Number of instances classified as not having diabetic retinopathy incorrectly (missed diagnosis).

With these definitions, we can compute sensitivity and precision as follows:

### 3.1.1 Accuracy

Accuracy (AC) is given by the percentage of the total number of predictions that were accurate and is given by,
Accuracy = (TP + TN) / (TP + TN + FP + FN).

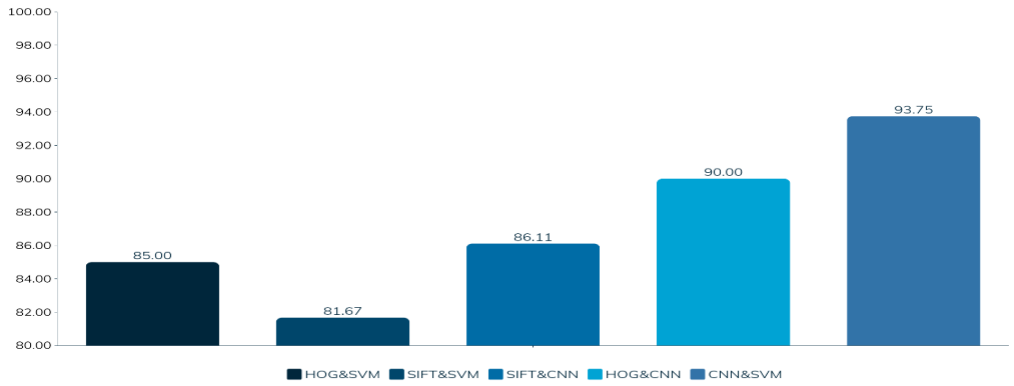


Figure 3.1 Comparison of proposed ERPA in terms of accuracy

The Figure 3.1 shows the accuracy of proposed ERPA compared with the other state of the art algorithms designs. The proposed method ERPA shows 10.3%, 14.8%, 8.8%, 4.2% higher accuracy compare than the methods shown in table 3.1.

### 3.1.2 Sensitivity

Sensitivity is defined as the quantity of the cases that are actually positive and that also got predicted as positive. Mathematically, sensitivity can be calculated as
Sensitivity = (TP) / (TP + FN).

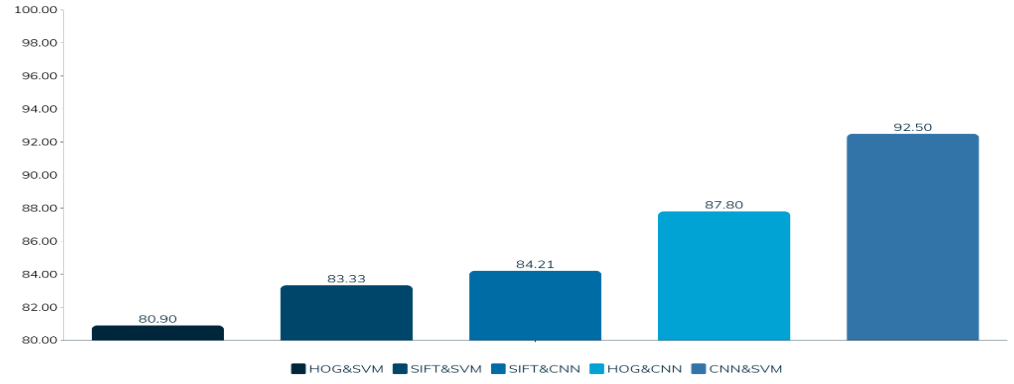


Figure 3.2 Comparison of proposed ERPA in terms of sensitivity

The Figure 3.2 shows the sensitivity of proposed ERPA compared with the other learning algorithms. The proposed algorithm ERPA shows 17.2%, 12.5%, 11.33%, 6.8% higher sensitivity compare than the methods shown in table 3.1.

### 3.1.3 Specificity

Specificity is described as the positive cases that are negative and which also got predicted as the negative (or true negative). Mathematically, the specificity is computed as the following:

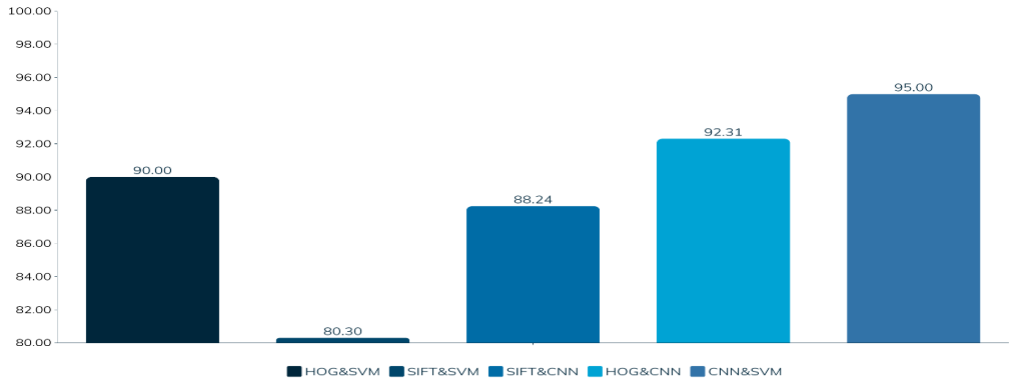


Figure 3.3 Comparison of proposed ERPA in terms of specificity

Specificity = (TN) / (TN + F) The Figure 3.3 shows the Specificity of proposed ERPA compared with the other algorithms designs. The proposed method ERPA shows 4.2%, 17.2%, 6.2%, 1.6% higher accuracy compare than the methods shown in table

3.1.

**3.1.4 Precision**

Precision is the proportion of total positive predictions that are actually correct.

Precision = (TP) / (TP + FP)

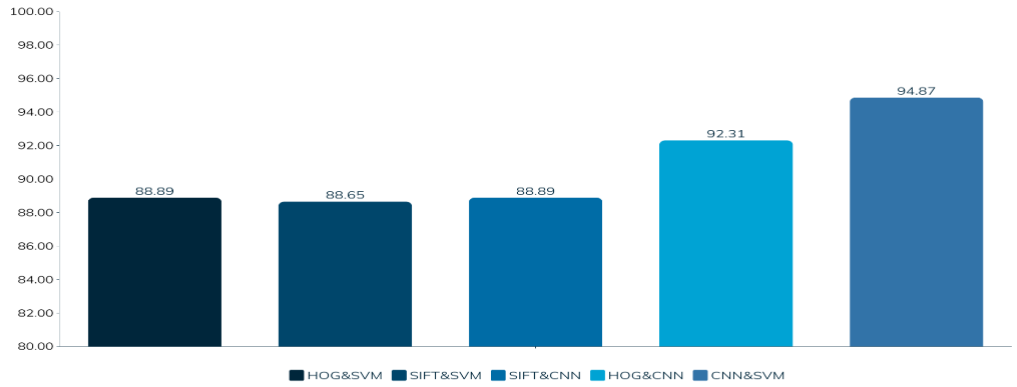


Figure 3.4 Comparison of proposed ERPA in terms of precision

The Figure 3.4 shows the precision of proposed ERPA compared with the other algorithms. The proposed method ERPA shows 5.5%, 5.8%, 5.5%, 9.9% higher precision compare than the methods shown in table 3.1.

## IV.CONCLUTION

In this brief, Efficient Retinopathy Prediction Algorithm (ERPA) for diabetic retinopathy prediction is proposed and tested in image application. Hybrid combinations of CNN and SVM boost the performances compare than the other state of the art designs. Overall, the results underscore the efficacy of utilizing CNN feature extraction and SVM classification for DR classification and emphasize the importance of continued refinement and augmentation of datasets and features to enhance model performance. the SVM classifier achieves a classification accuracy of 93.5% in determining the level of DR. The findings suggest that this approach holds significant promise for accurately classifying DR levels. The testing of dataset images using various designs the ERPA provides the high accuracy, sensitivity, specificity, and precision.

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