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# Diabetic Retinopathy Detection and Severity Classification Using SVM

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**ABSTRACT:**Diabetic Retinopathy (DR) is quite a major threat when complications of diabetes are taken into account which might result in permanent blindness if not treated within a stipulated time. It is more common in working-age people. Research says that close to 4 million people with diabetes get blind each year worldwide by DR. Early diagnosis is considered an effective way to detect and endure such a difficulty. In this paper fundus images containing diabetic retinopathy has been taken into consideration. The idea behind this paper is to propose an automated knowledge model to perform the DR detection and grading. Proposed Model have been trained with SVM, KNN and Naïve Bayes. Performance evaluation using GLCM and Gabor features is done. The proposed models are capable of quantifying the features as Gabor, statistical features into different DR grading. As the performance is evaluated in terms of Precision, Recall, F measure and Accuracy, SVM classification with Gabor features gives better accuracy. The model will be helpful to identify the proper class of severity of diabetic retinopathy images.

**KEYWORDS:**Diabetic Retinopathy, SVM, KNN, Naïve Bayes, Gabor, Statistical

## I. INTRODUCTION

Diabetic Retinopathy is one of the leading disabling chronic diseases, and one of the leading causes of preventable blindness in the world [1]. Early diagnosis of diabetic retinopathy enables timely treatment and in order to achieve it a major effort will have to be invested into screening programs and especially into automated screening programs. For automated screening programs to work robustly efficient image processing and analysis algorithms have to be developed [3]. It was found to be the fourth most frequently managed chronic disease in general practice in 2009, and the projections go as high as the second most frequent disease by the year 2030. The global burden of diabetic patients is expected to rise from 171 million in 2000 to 366 million in 2030. In Europe more than 52.8 million people are diagnosed with diabetes with the number expected to rise to 64 million by 2030. In Croatia about 300 thousand people are estimated to have diabetes and of those only 190 thousand are registered [1]. Early diagnosis of diabetic retinopathy enables timely treatment that can ease the burden of the disease on the patients and their families by maintaining a sufficient quality of vision and preventing severe vision loss and blindness. In addition to the obvious medical benefits, significant positive economic effects are achieved by maintaining patient's workability and self-sustainability. In order to achieve early diagnosis of diabetic retinopathy a major effort will have to be invested into screening programs. Screening is important as up to one third of people with diabetes may have progressive DR changes without symptoms of reduced vision, thus allowing the disease to progress and making treatment difficult. Systematic screening programs for diabetic eye disease have been developed in many countries. In the UK, the NHS Diabetic Screening Program offers annual fundus photography for all patients with diabetes over the age of 12, regardless of their socio-economic status.

## II. TECHNIQUES FOR KEYWORD BASED SEARCH

Diabetes and Cataract are the key causes of retinal blindness for millions of people. Current detection of diabetes and Cataract from retinal images using low cost Smartphone based intelligent system integrated with microscopic lens that allows patients in remote and isolated areas for regular eye examinations and disease diagnosis. This mobile diagnosis system uses an artificial Neural Network algorithm to analyse the retinal images captured by the microscopic lens to identify retinal disease conditions. The evaluation results indicate that the system shows competitive retinal disease

detection accuracy rates (N87%). It also offers early detection of retinal diseases and shows great potential to be further developed to identify skin cancer [2].

In the framework of computer assisted diagnosis of diabetic retinopathy, a new algorithm for detection of exudates is presented and discussed. The presence of exudates within the macular region is a main hallmark of diabetic macular enema and allows its detection with a high sensitivity. Hence, diagnostic task, in which computer assistance may play a major role. Exudates are found using their high grey level variation, and their contours are determined by means of morphological reconstruction techniques. The detection of the optic disc is indispensable for this approach. The detection of the optic disc is done means of morphological filtering techniques and the watershed transformation [3].

The Fundus images of retina of human eye can provide valuable information about human health and open up a window of unforeseeable opportunities. In this respect, one can systematically assess digital retinal photographs, to predict chronic diseases. This eliminates the need for manual assessment of ophthalmic images in diagnostic practices. It is also possible to detect certain type of cancers and cataract in their early stages in addition to diseases like hypertension, stroke and serious organ malfunctioning in diabetic patients. The facility to maintain a database of the retinal photographs and associated data of any patient, taken on a regular basis, scrutinized for the prediction of the diseases may easily be incorporated [8].

Hence it can be concluded from above literature survey, that in the earlier part of the research, authors have classified fundus images based on two or three features. Then subsequently, more features were introduced to improve the classification efficiency. The algorithms involving four features namely, area of blood vessel, exudates, haemorrhages and micro aneurysms coupled with support vector machine were used to classify fundus images into five classes (normal, mild DR, moderate DR, severe DR and prolific DR) with an efficiency of 86%, sensitivity and specificity of 82% and 86% respectively.

### III. PROBLEM DEFINITION

Diabetes is a well-known disease and may cause abnormalities in the retina (diabetic retinopathy), kidneys (diabetic nephropathy), nervous system (diabetic neuropathy) and is known to be a major risk for cardiovascular diseases. Diabetic retinopathy is a microvascular complication caused by diabetes which can lead to blindness. In early stages of diabetic retinopathy typically there are no visible signs but the number and severity of abnormalities increase during the time. Diabetic retinopathy typically starts with small changes in retinal capillaries. The first detectable abnormalities are micro aneurysms which represent local enlargements of the retinal capillaries. The ruptured microaneurysms can cause haemorrhages. After a period of time, hard exudates may appear. The hard exudates are lipid formations leaking from wakened blood vessels. As the retinopathy advances, the blood vessels may become obstructed which causes icroinfarcts in the retina. These microinfarcts are called soft exudates. Extensive lack of oxygen caused by microinfarcts causes the development of new fragile vessels. This phenomenon is called ovascularization which is a serious eyesight threatening state and may cause sudden loss in visual acuity or even permanent blindness.

Fundus imaging has an important role in diabetic retinopathy detection and monitoring because eye fundus is sensitive to vascular diseases and we can consider fundus imaging as a candidate for non-invasive screening. The success of this type of screening approach depends on accurate fundus image capture and especially on accurate and robust image processing and analysis algorithms for detection of of abnormalities. Many algorithms have been proposed for fundus image analysis using different methods and approaches.

The main contribution of this work is to present an overview of algorithms for early detection of diabetic retinopathy in fundus photographs.

#### OBJECTIVES:

1. Detecting and grading of diabetic retinopathy (DR) by means of digital retinal images taken for diagnosis purpose of live images taken from Hospital.
2. To improve efficiency in diagnosis by using robust algorithm.
3. To help in saving sight of diabetic patient by timely monitoring the status of retinopathy.

#### IV. IDRiD DATASET FOR DR GRADING

In this paper, IDRiD (Indian Diabetic Retinopathy Image Dataset [9]) is used for detection and grading of diabetic retinopathy. This database is the representative of an Indian population. Moreover, it is the only dataset constituting typical diabetic retinopathy lesions and also normal retinal structures annotated at a pixel level. This dataset provides information on the disease severity of diabetic retinopathy, and diabetic macular edema for each image. This makes it perfect for development and evaluation of image analysis algorithms for early detection of diabetic retinopathy.

There may be a presence of venous beading, retinal neovascularization which can be utilized to classify DR retinopathy in one of the two phases known as non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR) as shown in Figure 1a and 1b. DME is a complication associated with DR in which retinal thickening or accumulation of fluid can occur at any stage of DR. The risk of having DME is classified into no risk and two probable risks (illustrated in Figure 1c and 1d respectively). The determination of DR and DME severity based on criteria given in Table 1. It is essential to decide the need for treatment and follow-up recommendations.

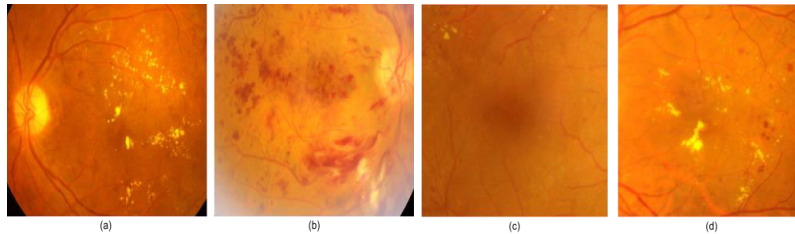


Figure1: Phases of Diabetic Retinopathy

The dataset for Diabetic Grading consists of it consists of

1. Original color fundus images (516 images divided into train set (413 images) and test set (103 images) - JPG Files)
2. Ground truth Labels for Diabetic Retinopathy and Diabetic Macular Edema Severity Grade (Divided into train and test set - CSV File)

Disease Severity Level	Findings
Grade – 0: No apparent retinopathy	No visible sign of abnormalities
Grade – 1: Mild – NPDR	Presence of Microaneurysms only
Grade – 2: Moderate– NPDR	More than just microaneurysms but less than severe NPDR
Grade – 3: Severe – NPDR	Any of the following: > 20 intraretinal haemorrhages Venous beading Intraretinal microvascular abnormalities no signs of PDR
Grade – 4: PDR	Either or both of the following: Neovascularization Vitreous/pre-retinal haemorrhage

Table I. Diabetic Retinopathy Grading

#### V. METHODOLOGY

The proposed methodology for detection and grading of Diabetic Retinopathy is depicted below:

1. Select Training Image Directory
2. Training Preprocessing : Median Filtering for Noise Removal
3. GLCM Statistical and Gabor features are computed for all training images.
4. KNN, Naïve Bayes and SVM classifiers are trained using features vector matrices.
5. After preprocessing and feature extraction of test images, performance of KNN, Naïve Bayes and SVM classifiers is evaluated for detection and grading of diabetic retinopathy.

*A. Gabor Features Extraction*

In image processing, a Gabor filter, named after Dennis Gabor, is a linear filter used for texture analysis, which means that it basically analyzes whether there are any specific frequency content in the image in specific directions in a localized region around the point or region of analysis. Frequency and orientation representations of Gabor filters are claimed by many contemporary vision scientists to be similar to those of the human visual system, though there is no empirical evidence and no functional rationale to support the idea. They have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave.

*B. GLCM Statistical Features*

stats = graycoprops (glcm, properties) calculates the statistics specified in properties from the gray-level co-occurrence matrix glcm. glcm is an m-by-n-by-p array of valid gray-level co-occurrence matrices. If glcm is an array of GLCMs, stats are an array of statistics for each glcm.

graycoprops normalizes the gray-level co-occurrence matrix (GLCM) so that the sum of its elements is equal to 1. Each element (r,c) in the normalized GLCM is the joint probability occurrence of pixel pairs with a defined spatial relationship having gray level values r and c in the image. graycoprops uses the normalized GLCM to calculate properties

Different statistical features considered here are contrast, correlation, Energy and Homogeneity

*C. Support Vector Machines*

In machine learning, support-vector machines (SVMs, also support-vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier (although methods such as Platt scaling exist to use SVM in a probabilistic classification setting). An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on the side of the gap on which they fall.

In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

When data are unlabelled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups.

**VI. EXPERIMENTAL RESULTS**

Matlab-based GUI-driven tool is developed for effective detection and grading of diabetic retinopathy. Figure 2 shows graphical user interface(GUI) developed for proposed algorithm before execution

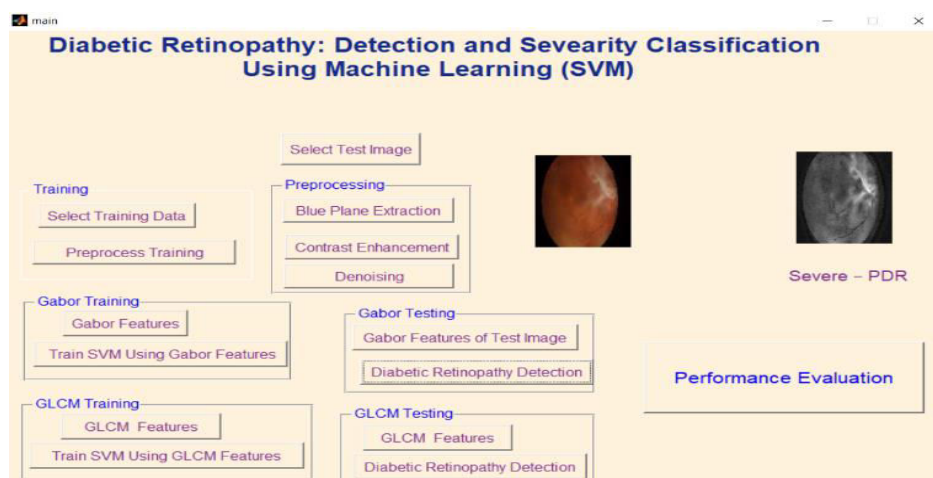


Figure 2: MATLAB based proposed system

GUI for this software is divided into number of subgroups according to their functionality. This software module not only detects diabetic retinopathy but also helpful in grading DR images for analysis and classification of diabetic retinopathy.

*A. Database Selection and Preprocessing:*

DR image training database is selected. Then for preprocessing, median filter is used for noise removal.

*B. Features Extraction*

From the pre-processed training images Gabor and statistical features (GLCM) are extracted.

*C. KNN, Naïve Bayes and SVM for Training and Classification*

KNN, Naïve Bayes and SVM are trained with various features for diabetic retinopathy detection and grading. This module deals with DR disease detection and grading: if the patient is suffering with disease or not, if yes then what is the severity of diabetic retinopathy he's suffering with, can be found by "Diabetic Retinopathy Detection" push.

The performance of KNN, Naïve Bayes and SVM classifiers have been evaluated by considering different number of training images. Four parameters are used for evaluating performance of the algorithm. Those are accuracy, precision, recall and F measure.

These parameters are defined using 4 measures True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN)

True Positive: DR detection coincides with actual labelled data

True Negative: both classifier and actually labelled absence of DR

False Positive: system labels a healthy case as an DR one

False Negative: system labels DR image as healthy

Accuracy: Accuracy is the ratio of number of correctly classified cases, and is given by

$$\text{Accuracy} = \frac{TP+TN}{N}$$

Total number of cases are N

Precision is the fraction of retrieved images that are relevant to the query. Precision takes all retrieved images into account, but it can also be evaluated at a given cut-off rank, considering only the results returned by the system

Precision is defined as

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

Recall is the fraction of the relevant images that are successfully retrieved. In binary classification, recall is called sensitivity. It can be viewed as the probability that a relevant document is retrieved by the query.

It is trivial to achieve recall of 100% by returning all documents in response to any query. Therefore, recall alone is not enough but one needs to measure the number of non-relevant documents also, for example by also computing the precision.

Recall is defined as

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

F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F1 is usually more useful than accuracy, especially if you have an uneven class distribution. Accuracy works best if false positives and false negatives have similar cost. If the cost of false positives and false negatives are very different, it's better to look at both Precision and Recall. In our case, F1 score is 0.701.

$$\text{F1 Score} = \frac{2 * (\text{Recall} * \text{Precision})}{(\text{Recall} + \text{Precision})}$$

We have evaluated the performance of diabetic retinopathy detection and grading on IDRiD (Indian Diabetic Retinopathy Image Dataset [9]).

The DR images are labelled in five categories as

Grade – 0: No apparent retinopathy

Grade – 1: Mild – NPDR

Grade – 2: Moderate – NPDR  
 Grade – 3: Severe – NPDR  
 Grade – 4: PDR

We have considered 70% training data for evaluating the performance. Tables II to V depicts the results obtained.

TABLE II. ACCURACY WITH 70% TRAINING DATA

Accuracy	SVM	KNN	NB
GLCM	54.6099	75.1773	51.0638
Gabor	80.8511	72.3404	77.1429

Gabor features with SVM gives the better accuracy of 80.8511% as compared to KNN, Naïve Bayes and GLCM features extraction techniques.

Figure 3 depicts the accuracy with SVM classification using Gabor features

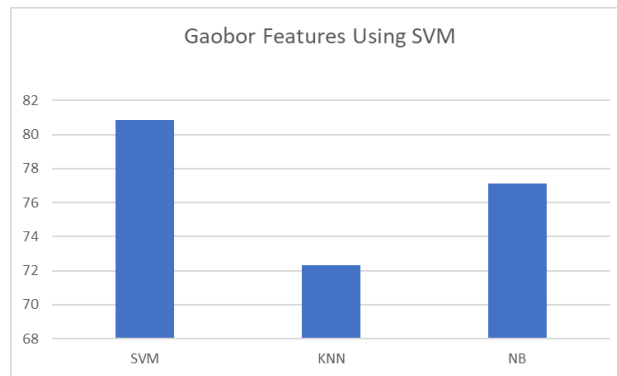


Figure 3: Accuracy Using Gabor features.

Performance measured using precision, recall and F measure for Gabor features is depicted in table III.

TABLE III. PERFORMANCE MEASUREMENT USING GLCM

GLCM	SVM	KNN	NB
Precision	0.5961	0.7544	0.5316
Recall	0.5577	0.8155	0.5158
F Measure	0.5763	0.7837	0.5236

Performance measured using precision, recall and F measure for Gabor features is depicted in table IV.

TABLE IV. PERFORMANCE MEASUREMENT USING GLCM

Gabor	SVM	KNN	NB
Precision	0.839	0.7344	0.7786
Recall	0.8538	0.7899	0.8234
F Measure	0.8464	0.7611	0.8004

Figure 4 depicts the performance comparison of SVM, KNN and Naïve Bayes classifiers using Gabor features.

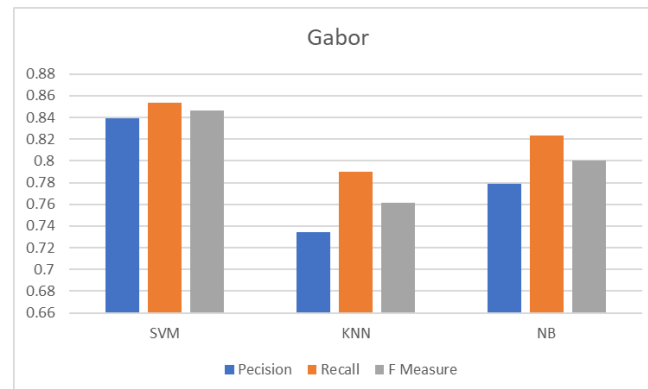


Figure 4: Performance Using Gabor Features

## VII. CONCLUSION

In this paper, SVM classification framework with gabor features is used for detection and grading of diabetic retinopathy images into different severity types. Different features like Statistical and Gabor are used. The SVM, KNN and Naïve Bayes classifiers are trained to carry out the final DR detection and grading. Main focus of this study is to preprocess the DR images for noise removal. After preprocessing and features extraction, classification of the selected five different DR severity conditions is performed. For IDRiD data SVM with Gabor features gives better accuracy in terms of precision, recall and F measure. The experimental results have demonstrated the effectiveness of our proposed algorithm to be good enough to be employed in clinical applications

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