CHAPTER 4
CLASSIFICATION AND SEVERITY GRADING OF DIABETIC RETINOPATHY

4.1 INTRODUCTION

Diabetic Retinopathy (DR) is a sight-threatening risk inflicting disorder diabetic patients. It occurs due to damage in the retina as a result of diabetes mellitus. Early diagnosis and treatment have been shown to prevent visual loss and blindness. Retinal images obtained by the fundus camera are used to diagnose DR. Automated methods of DR screening help to save time, cost and vision of patients compared to the manual methods of diagnosis.

Retinal image classification has been done by various methods. Vijaya Kumari et al. (2010) used MDD classifiers for classifying retinal images where propagation through radii method is used for OD detection. Zohra et al. (2009) performed a computer-based approach for the detection of diabetic retinopathy stage using SVM where the features are extracted from the raw images using image processing techniques. Retinal Grading Algorithm was used by Singh et al. (2010) to automatically classify the DR intensity based on distribution of exudate, count, size and the distribution of the hemorrhages and microaneurysms. Classification using fractal measures and clustering techniques was done by Jebarani et al. (2009). Multiple classifiers were used by Jonathan et al. (2009) for the classification of retinal images.

In Section 4.2, the classification of normal and abnormal images is proposed using two types of classifiers and different input features. The classification process is carried out considering only the anatomical structures of
optic disc and blood vessels. The features such as mean, variance, entropy, area extracted from the segmented optic disc and mean, variance, entropy, area, diameter and number of regions extracted from segmented blood vessels are given as input to the Feed Forward Neural Network (FFNN) classifier. The next classification process has been carried out by considering blood vessel anatomical structure, hard exudate and microaneurysms pathological structures with extracted features such as vessel pixel intensity, microaneurysm area, exudate area and textural features (contrast, homogeneity, correlation and energy). The machine learning technique used is the SVM classifier where the different combinations of the above features have been done.

In Section 4.3, the severity grading of diabetic retinopathy is discussed. Wahyudi Setiawan et al. (2016) studied the classification of DR fundus images into four stages respectively. In this work, the severity classification of diabetic retinopathy in fundus images has been proposed and graded considering the features as region area and intensity level of hard exudate and hemorrhages. The multiclass SVM classifier categorizes the abnormal fundus images into four stages as mild NPDR, moderate NPDR, severe NPDR and PDR.

4.2 ABNORMALITY CLASSIFICATION

4.2.1 Classification Phase - I

The framework for the first phase of abnormality classification is shown in Figure 4.1. The input retinal images undergo segmentation of anatomical structures: optic disc and blood vessels. The RGB fundus image is processed for pre-processing for noise removal using median filtering. Then, the anatomical structures, optic disc and blood vessels segmented as described in Section 3.3 and 3.4, are utilized for further processing of feature extraction and classification of fundus images.
4.2.1.1 Feature Extraction from Optic Disc

From the segmented optic disc of retinal images, the features mean, variance, entropy and area are extracted. Pixel values in these images are represented as $p_i$, and the features such as mean, variance and entropy are calculated for these pixels in the image. Features are calculated by using Equation (4.1) to Equation (4.3).

Mean

$$M_k = \frac{1}{n} \sum_{i=1}^{n} p_i \quad (4.1)$$
Variance

\[ V_k = \left( \frac{1}{n} \left( \sum_{i=1}^{n} (p_i - M_k)^2 \right) \right) \]  (4.2)

Entropy

\[ E_k = -\sum_i p_i \log_2 p_i \]  (4.3)

In the above equations, \( k \) represents R or G or B components, separately in the RGB format image. Mean, variance and entropy are calculated for each RGB component of the images separately.

Area: Area (\( A \)) is a quantity that says the size of a 2-D surface or shape in the plane. In this work, area of the image can be found out by finding the total number of pixels in the region. Suppose \( N \) number of pixels are present in the segmented region, and then the area (\( A \)) is calculated as \( N \).

Thus, totally ten features are extracted from the segmented optic discs of retinal images, and the features are represented as \( \{ M_k, V_k, E_k, A \} \).

4.2.1.2 Feature Extraction from Blood Vessels

From the segmented blood vessel images of retinal images, the features mean, variance, entropy, area, diameter and number of regions are extracted. The first four features mean, variance, entropy and area are extracted as discussed in Section 4.2.1.1. The features diameter and number of regions are extracted as follows.

Diameter (\( D \)): Diameter of an image is calculated by using Equation (4.4)

\[ D = \sqrt{\frac{4 \times A}{\pi}} \]  (4.4)
where, $A$ denotes the area of the image.

Number of regions (NR): From the segmented blood vessel retinal images, one can find regions. The number of segmented regions in these segmented images is also considered as one of the features for the process.

Thus, totally twelve features are extracted from the segmented blood vessels of retinal images, and the features are represented as $\{M_k, V_k, E_k, A, D, NR\}$. Hence totally 22 features, 10 features from optic disc segmented image and 12 features from blood vessel segmented image are extracted for further classification process.

**4.2.1.3 Normal and Abnormal Classification**

The features extracted from the anatomical structures are further utilized for the classification of fundus images into normal and abnormal. One of the accepted classification methods using Feed Forward Back Propagation Neural Network classifier (FFBNN) is used in this work. The neural network is a three-layer standard classifier with $I_u$ input nodes, $HU_{a,u}$ hidden nodes and $O_u$ output nodes. It is examined that if the two hidden layers are used, the first hidden layer is to associate every pair in one important unit and the second is regarded as the real hidden layer after classifying the input data in the first hidden layer. For the proposed work, the input layers are the twenty two features extracted from the segmented optic disc and blood vessels $\{M_k, V_k, E_k, A, M'_k, V'_k, E'_k, A', D, NR\}$, $HU_u$ Hidden Units (20 hidden nodes are set for the work based on the classification accuracy) and one output unit, $O$. The structure of the FFBNN classifier is shown in Figure 4.2.
4.2.1.4 Results and Discussion

The classification effectiveness for the normal and abnormal retinal images is also computed by the evaluation metrics FPR, FNR, sensitivity, specificity and accuracy using Equations (3.5) to Equation (3.9) as described in Chapter 3. The description of TP, TN, FP and FN is given in Table 4.1. The features of five normal images and five abnormal images from STARE datasets are given for retinal image classification in which, among five normal images, one image is incorrectly classified as abnormal and the five abnormal images are correctly classified as abnormal. The accuracy results have reached 90% value with 80% of sensitivity and 100% of specificity values. The proposed work gives very good classification accuracy results by extracting the features of retinal images effectively as shown in Table 4.2. The graph results of normal-abnormal image classification are represented in Figure 4.3.

**Figure 4.2 FFBNN classifier structure for the proposed work**
Table 4.1 Description of normal/abnormal classification

<table>
<thead>
<tr>
<th>Description</th>
<th>Classified as Normal image</th>
<th>Classified as Abnormal image</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actually Normal image</td>
<td>TP</td>
<td>FN</td>
</tr>
<tr>
<td>Actually Abnormal image</td>
<td>FP</td>
<td>TN</td>
</tr>
</tbody>
</table>

Table 4.2 Classification results of FFBNN

<table>
<thead>
<tr>
<th>Evaluation metrics</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>True Positive</td>
<td>4</td>
</tr>
<tr>
<td>True Negative</td>
<td>5</td>
</tr>
<tr>
<td>False Positive</td>
<td>0</td>
</tr>
<tr>
<td>False Negative</td>
<td>1</td>
</tr>
<tr>
<td>False Positive Rate</td>
<td>0</td>
</tr>
<tr>
<td>False Negative Rate</td>
<td>0.2</td>
</tr>
<tr>
<td>Sensitivity (in %)</td>
<td>80</td>
</tr>
<tr>
<td>Specificity (in %)</td>
<td>100</td>
</tr>
<tr>
<td>Accuracy (in %)</td>
<td>90</td>
</tr>
</tbody>
</table>

Figure 4.3 Graphical plot of normal-abnormal classification results
As the retinal disease diabetic retinopathy advances, the changes in the anatomical structure optic disc and blood vessels also advance. Early stage of identifying the changes in the structure becomes of prime importance for the classification of images into normal and abnormal. Many of the previous studies have addressed the abnormality classification based on blood vessels. However, features from the anatomical structures optic disc and blood vessel are considered and implemented in this work. The results obtained are better and the scope of improvement in the accuracy of abnormality classification with the combination of pathological features and anatomical features is implemented and discussed in the forthcoming sections.

4.2.2 Classification Phase - II

In this work, the anatomical structure blood vessels, pathological features exudate and microaneurysms (MA) are taken into consideration for abnormality classification. The block diagram in Figure 4.4 represents the proposed classification method. The segmentation of blood vessels, exudate and microaneurysms is described in Chapter 3 is taken into consideration and features were extracted from the retinal image of DRIVE, DIARETDB1 and MESSIDOR datasets. The features specified to the classifier include the areas of these segmented structures and textural features obtained from GLCM. The SVM classifier classifies the input image as normal (not affected by DR) or abnormal (DR images) based on the trained sample features.
4.2.2.1 Feature Extraction

The feature vector used for classification consists of seven features obtained from segmentation of retinal structures and texture analysis. These features are the area of blood vessels, area of exudate, area of microaneurysm, contrast, homogeneity, correlation and energy. Area of blood vessels is determined by finding the total number of white (vessel) pixels in the vessel-segmented image. Similarly area of exudate and area of MA are determined by finding the number of white pixels in the exudate image and MA image respectively.

Contrast is a measure of the intensity contrast between a pixel and its neighbor over the whole image, and is given by Equation (4.5)

$$\text{Contrast} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i - j)^2 P_{ij} \quad (4.5)$$

where $P_{ij}$ are the elements of the GLCM.
Homogeneity measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal and can be mathematically written as in Equation (4.6)

\[
\text{Homogeneity} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{P_{ij}}{1+|i-j|}
\]  

(4.6)

Correlation calculates the linear dependency of the gray level values in the co-occurrence matrix. It is represented mathematically as in Equation (4.7)

\[
\text{Correlation} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{(i-\mu_i)(j-\mu_j)P_{ij}}{\sigma_i \sigma_j}
\]  

(4.7)

where \(\mu_i, \mu_j, \sigma_i\) and \(\sigma_j\) are the mean and standard deviations of \(P_i\) and \(P_j\).

Energy is the sum of squared elements in the co-occurrence matrix calculated using Equation (4.8)

\[
\text{Energy} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P_{ij}^2
\]  

(4.8)

4.2.2.2 Texture Analysis

Texture means repeating patterns of local variation of pixel intensities. It gives information about the arrangement of surface pixels and their relationship with the surrounding pixels (Robert et al. 1973). Statistical texture analysis is based on Gray Level Co-occurrence Matrix (GLCM). It is a tabulation of how often different combinations of pixel gray levels occur in an image. For a 2-dimensional image \(f(x,y)\) with \(N\) gray levels, the GLCM \(P(d, \phi)\) for each \(d\) and \(\phi\) is given by Equation (4.9)

\[
P(d, \phi) = \begin{bmatrix}
p_{0,0} & p_{0,1} & \cdots & p_{0,N-1} 
p_{1,0} & p_{1,1} & \cdots & p_{1,N-1} 
\vdots & \vdots & \ddots & \vdots 
p_{N-1,0} & p_{N-1,1} & \cdots & p_{N-1,N-1}
\end{bmatrix}
\]  

(4.9)
where

\[ p_{ij} = \frac{\text{number of pixel pairs with intensity } (i,j)}{\text{total number of pairs considered}} \]

\( p_{ij} \) is defined as the relative number of times gray level pair \((i,j)\) occurs when pixels separated by the distance \(d\) along the angle \(\phi\) are compared. Each element is normalized by the total number of occurrences to form the GLCM. The commonly extracted textural features from GLCM are contrast, homogeneity, correlation and energy.

### 4.2.2.3 Classification

In this work, classification based on the extracted features is done by using SVM classifier (Vojislav et al. 2001). For training, fifty images (25 normal and 25 DR images) along with their corresponding ground truths are used. For testing, a set of one hundred and fifty images (75 normal images and 75 DR images) are taken and their features are calculated. Then, these features are used by the SVM for classifying the images into normal and DR (abnormal) images.

### 4.2.2.4 Results and Discussion

The results for classification process are discussed in this section. From the segmented retinal structures, the area of blood vessels, exudate and MA are calculated by finding the total number of blood vessels, exudate and MA respectively. The textural features such as contrast, homogeneity, correlation and energy are also calculated from the GLCM. All these seven features together form a feature vector of an image.
The features of 25 normal images and 25 DR images are given for training the SVM classifier. For testing, the features extracted from 75 normal images and 75 DR images are fed to the SVM. The analysis is done with different combinations of features as input to the classifier. The comparison of classification performance using different combinations of features is given in Table 4.3, and its graphical representation is shown in Figure 4.5.

### Table 4.3 Classification results for combination of different features

<table>
<thead>
<tr>
<th>Feature</th>
<th>Classification Accuracy in (%) Using SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Textural</td>
<td>71.33</td>
</tr>
<tr>
<td>BV + Exudate</td>
<td>66.67</td>
</tr>
<tr>
<td>Exudate + MA</td>
<td>67.4</td>
</tr>
<tr>
<td>BV + MA</td>
<td>69.33</td>
</tr>
<tr>
<td>Textural + BV</td>
<td>72.62</td>
</tr>
<tr>
<td>Textural + Exudate</td>
<td>67.33</td>
</tr>
<tr>
<td>Textural + MA</td>
<td>74.13</td>
</tr>
<tr>
<td>Textural + BV + Exudate</td>
<td>72.67</td>
</tr>
<tr>
<td>Textural + Exudate + MA</td>
<td>84.33</td>
</tr>
<tr>
<td>Textural + BV + MA</td>
<td>86.7</td>
</tr>
<tr>
<td>Textural + BV + Exudate + MA</td>
<td>93</td>
</tr>
</tbody>
</table>
It is observed from the results obtained that classification using all the seven features including the textural features, areas of blood vessels, exudate and MA by the SVM classifier yields the highest classification accuracy compared to all other combinations of features. The details about the classification results with all the features are tabulated in Table 4.4. The table characterizes that 91% classification accuracy has been obtained for normal images whereas the DR images give an accuracy of 95%, giving 93% average accuracy.
Table 4.4 Classification Results using all seven features

<table>
<thead>
<tr>
<th>Classes</th>
<th>No. of Training Images</th>
<th>No. of Testing Images</th>
<th>No. of Correctly Classified Images</th>
<th>Classification Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>25</td>
<td>75</td>
<td>68</td>
<td>91</td>
</tr>
<tr>
<td>DR</td>
<td>25</td>
<td>75</td>
<td>71</td>
<td>95</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Average Accuracy</td>
<td>93</td>
</tr>
</tbody>
</table>

Therefore, the abnormality detection is done with higher accuracy rate and the comparison of classification considering anatomical features and the combination of anatomical and pathological structures are shown in Figure 4.6. From the yielded results, it is inferred that the classification accuracy improves while considering all the input features of RBV, Ex and MA.
4.3 SEVERITY GRADING OF DIABETIC RETINOPATHY

Medical image analysis is an area of research that drives the researchers’ enthusiasm to concentrate on computerized images with the target of providing computation tools which will help the quantification and verification of pathology and anatomical structures. Physicians have produced analytic tools to screen patients and to supervise the growth in different forms of management. However, this is a multidisciplinary task and requires knowledge in disciplines such as image processing, computer vision, machine learning, pattern recognition and expert systems. Diabetic retinopathy is a complication of diabetes which leads to vision loss. Hence early screening and recognizing the retinopathy patients will help to prevent loss of vision. In this section, the DR severity classification with the four level stages has been presented and discussed using the SVM classifier.

4.3.1 The Proposed Methodology

The severity classification of diabetic retinopathy in fundus images has been graded considering the features as region area and intensity level of hard exudate and hemorrhages. The framework of the proposed method is shown in Figure 4.7.

![Figure 4.7 The Proposed DR severity grading framework](image_url)
The results of phase–I classification obtained from Section 4.2 have been used for further analysis of diabetic retinopathy severity in this work. The image abnormality is defined in terms of Diabetic Retinopathy (DR). The classified abnormal image obtained from phase–I have been trained with the intensity and region area features using multiclass SVM classifier which categorizes the abnormal fundus images into four stages as mild NPDR, moderate NPDR, severe NPDR and PDR.

4.3.2 Feature Extraction

To differentiate the stages of diabetic retinopathy, an attempt is made to mimic ophthalmologist expertise by extracting the relevant and significant features. In this work, intensity level and the region area features for the pathology symptom hemorrhages and exudates have been considered. Four features are computed and used as input for the SVM classifier.

4.3.2.1 Intensity Feature Extraction

The contrast is the measure of the amount of intensity level in the hemorrhages and exudate segmented image that has been computed using Equation (4.10)

\[ \text{Contrast} = \sum_{l=0}^{N-1} \sum_{j=0}^{N-1} (i - j)^2 P_{ij} \] (4.10)

where \( P_{ij} \) is the elements of the co-occurrence matrix.

The intensity value for NPDR is inferior to normal and PDR images due to the presence of more exudate. In PDR the intensity variation is higher compared to the NPDR due to the presence of more blood vessels and hemorrhages.
4.3.2.2 Region Area Feature Extraction

The feature region area refers to the number of neighboring white pixels of the resulting segmented image exudate and hemorrhages, and these neighboring pixels are counted to form the feature vector for the classifier. The feature vector has been calculated using Equation (4.11)

\[
\text{Region area} = 4\pi \frac{\text{area}}{\left(\text{perimeter}\right)^2}
\]  

(4.11)

where area is the number of pixels in the region, and perimeter is the total number of pixels around the boundary of each region.

4.3.3 Classification Using SVM Method

SVMs are related to the simplified linear classifier’s family. SVMs are also viewed as a unique case of Tikhonov regularization. A strange property is that they minimize the practical classification error and boost the geometric margin at the same time. Therefore, they are named as maximum margin classifiers. Equation (4.12) given below is the SVMs’ objective function, which may recognize the support vector for the classification,

\[
OF = \sum_{i} w_i * K(SV_i, PR) + b_i
\]  

(4.12)

where \(i\) = index of summation, \(w_i\) – weight, \(K\) – Kernel function, \(SV_i\) – Support Vectors, \(PR\) – Vectors for classification, \(b_i\) - bias

The above equation is the objective function that operates an optimization method to find the support vectors, weights and bias for classifying the vector \(PR\), where \(K\) is a kernel function. In case of a linear kernel, \(K\) will be a dot product. In this work, \(PR\) vector is used for training process that discovers the severity level of Diabetic Retinopathy and classifies it according to the level. This vector uses the region area and intensity level of hard exudate and
hemorrhage in the abnormal retinal images. Based on this area and intensity level, one can set threshold for each mild, moderate, severe and proliferate and according to the threshold values, the severity of DR in every retinal image is classified as mild, moderate, severe and proliferate retinal images.

Support Vector Machine contains error, and the following error minimization function is used for the minimization of this error that is given as follows.

$$\arg \min \left\{ \sum_{x=0}^{n-1} v_x + 0.5\lambda^T \lambda \right\}$$  \hspace{1cm} (4.13)$$

with the following constraints,

$$CL_x (\lambda^T K(\hat{PR}_x) + c) \geq 1 - v_x$$  \hspace{1cm} (4.14)$$

$$v_x \geq 0$$  \hspace{1cm} (4.15)$$

In Equation (4.13), $PC$ is the penalty constant, $\nu$ is a parameter that handles the image, and $\lambda$ is a matrix of coefficients. In the constraints given in Equation (4.14) and Equation (4.15), $CL_x$ is the class label of the $x^{th}$ image, $c$ is a constant, and $K$ is the kernel that transforms the input image to the feature space. Hence by minimizing the error function, the SVM gains knowledge of the training images $\hat{PR}$, well so that it can classify the vector that is similar to the training set. Once the errors are minimized to a minimum value the classification of the retinal images is made as mild, moderate, severe and proliferative stages of Diabetic Retinopathy.

**4.3.4 Results and Discussion**

The abnormal retinal images have been classified into mild, moderate, severe and proliferative by means of the severity level of diabetic retinopathy.
The classification effectiveness for the severity level of retinal images is also computed by the evaluation metrics sensitivity, specificity and accuracy using Equation (3.7) to Equation (3.9). The description of TP, TN, FP and FN is given in the Table 4.5.

Table 4.5 Description of TP, TN, FP, FN mild DR severity classification

<table>
<thead>
<tr>
<th>Description</th>
<th>Mild image</th>
<th>Non-Mild image</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mild image</td>
<td>TP</td>
<td>FN</td>
</tr>
<tr>
<td>Non-Mild image</td>
<td>FP</td>
<td>TN</td>
</tr>
</tbody>
</table>

Similarly, the TP, TN, FP, FN descriptions for the other three severity stages moderate, severe and proliferative are given in Table 4.6. The abnormal images obtained from former classification applied on STARE datasets are used in the severity classification. In addition, real-time database collected from Bejan Singh Eye Hospital, Nagercoil is also used for testing. So, the obtained six abnormal images from the normal-abnormal classification phase are used for training purpose, and ten abnormal images with one normal image to a total of eleven images are used for testing purpose. For checking out the efficiency of the proposed work, one normal image is added to the ten abnormal images in the testing phase. The results of the severity classification are given in the Table 4.6.

Table 4.6 DR severity classification results

<table>
<thead>
<tr>
<th>Severity stages</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
<th>FPR</th>
<th>FNR</th>
<th>Se (%)</th>
<th>Sp (%)</th>
<th>Ac (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mild NPDR</td>
<td>5</td>
<td>5</td>
<td>1</td>
<td>0</td>
<td>0.17</td>
<td>0</td>
<td>100</td>
<td>83.33</td>
<td>90.91</td>
</tr>
<tr>
<td>Moderate NPDR</td>
<td>1</td>
<td>10</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Severe NPDR</td>
<td>1</td>
<td>9</td>
<td>0</td>
<td>1</td>
<td>0.5</td>
<td>50</td>
<td>100</td>
<td>100</td>
<td>90.91</td>
</tr>
<tr>
<td>PDR</td>
<td>2</td>
<td>9</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>
The confusion matrix for the tested abnormal images is given in the following Table 4.7. The graph results for this severity classification are represented in Figure 4.8.

**Table 4.7 Confusion matrix for tested abnormal images**

<table>
<thead>
<tr>
<th>Images taken</th>
<th>Mild NPDR</th>
<th>Moderate NPDR</th>
<th>Severe NPDR</th>
<th>PDR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mild NPDR</td>
<td>5</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Moderate NPDR</td>
<td>-</td>
<td>1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Severe NPDR</td>
<td>1</td>
<td>-</td>
<td>1</td>
<td>-</td>
</tr>
<tr>
<td>PDR</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>2</td>
</tr>
</tbody>
</table>

![Graphical plot for DR severity classification results](image)

**Figure 4.8 Graphical plot for DR severity classification results**

The severity stages moderate and proliferative provide accurate classification results with 100% values of sensitivity, specificity and accuracy and 0 values for the False Positive and False Negative rates. But in the classification of mild stage, among 5 mild images, 5 of the mild images are correctly classified as mild image and one of the non-mild images is incorrectly classified as mild, which results in 0.17% of False Positive Rate with 100% of sensitivity value, 83.33% of specificity value and 90.91% of accuracy value.
Further in the classification of severe stage image, among 2 non-severe stage retinal images, one of the images is incorrectly classified as severe stage image and where also, the classification accuracy is 90.91% with 0.5 of FNR, 50% of sensitivity and 100% of specificity values. From the results of mild and severe stage classification, one can observe that if any one of the images is classified as wrong class means, nearly 10% of accuracy is reduced. The severity stage classification results give 95.45% of accuracy on average proves that SVM classifier facilitates good classification results.

The proposed severity-based diabetic retinopathy classification results are obtained using SVM classifier. These results are compared with the existing classifiers and the results are given in the following Table 4.8.

### Table 4.8 DR severity comparison results

<table>
<thead>
<tr>
<th>Severity stages</th>
<th>Classification Accuracy (in %)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NN</td>
</tr>
<tr>
<td>Mild NPDR</td>
<td>77.65</td>
</tr>
<tr>
<td>Moderate NPDR</td>
<td>85.70</td>
</tr>
<tr>
<td>Severe NPDR</td>
<td>77.65</td>
</tr>
<tr>
<td>PDR</td>
<td>85.70</td>
</tr>
</tbody>
</table>

The proposed work with SVM-based severity in retinal image classification gets very good accuracy results compared with the existing classifiers; proves that the proposed work is better. The proposed work (SVM classifier) is compared with other two existing classifiers Neural Network (NN) and Artificial Neuro-Fuzzy Inference System (ANFIS). NN provides 77.65% of accuracy for the mild and severe stage classification and also 85.7% of accuracy for the stages moderate and proliferative retinal images. These accuracy values of NN are very low compared with the ANFIS classifier, in which, 86.5% of accuracy is gained for the mild and severe stages, and 91% of accuracy is
obtained for the moderate and proliferative stages of diabetic retinopathy images. Even though the ANFIS classifier acquires better classification results than the NN classifier, SVM classifier used in the proposed work facilitates very accurate classification of severity stages in abnormal retinal images.

4.4 SUMMARY

In Section 4.2, the proposed methods to classify the fundus image into normal and abnormal using two different classifiers are carried out in this work. The phase-I classification considering the features extracted from anatomical features yield lower results compared to the phase-II classification considering the features from the anatomical and pathological features. In Section 4.3, the proposed method to automate fundus image classification into different level of stages has been implemented. The features extracted from the hemorrhages and exudate such as intensity level and the region area are utilized for DR severity grading. The performance analysis of the various classifiers has been made, and it is observed that the SVM classifier outperforms the other classifiers. This system intends to help the medical practitioner in diabetic retinopathy screening process.