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Research paper

Performance Evaluation of Multiple Classifiers for Hemorrhage Severity in Diabetic Retinal Fundus Images

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Abstract

Diabetic retinopathy is one of the major diseases caused by diabetes. Diseases considered under diabetic retinopathy are problem in Optic Disc, Blood Vessels, Microaneurysms, exudates and fovea. Among these haemorrhages is one of the dangerous diseases which make vision loss speedily. Hence most of the recent research works are focusing on detecting the availability and analyzing the severity of haemorrhages in retinal images. But the accuracy of the haemorrhages analysis is less and not up to the market. This paper is motivated to provide a best classification approach by comparing the performance among different classification approaches to make use of it in medical industry. It helps to diagnose the severity of the haemorrhages for applying proper treatment in the earlier stage itself and avoid major surgery. Image preprocessing, image enhancement, haemorrhages segmentation, feature extraction and classification are the main steps followed in the proposed approach. KNN, Random Forest, Naïve Bayes and Multi-Class Support Vector Machine are the four different classifiers used in this paper. The experimental results is verified and the performance is evaluated among the above said classification approaches where it increases the accuracy of haemorrhages detection and classification on Diabetic Retinopathy Fundus Images.

Keywords: *Diabetic Retinopathy Fundus Images, Diabetes, Retinal Diseases, Haemorrhages, Classification Algorithms.*

1. Introduction

Diabetic Retinopathy(DR) is a disease of the human retina caused by diabetes. Two different kinds of defects on the retina are: (1) Micro-aneurysms are amongst the first signs of the presence of diabetic retinopathy. But, it is important to note that, while a critical component of any DR screening system, detection of Microan-eurysms is not equivalent to detection of DR. (2) The haemorrhage detection is yet another important aspect in the early detection of Diabetic Retinopathy. DR or hypertensive retinopathy can be easily detected by daignosing haemorrhages using the classification scheme. Even though micro-aneurysms are detected, it is difficult for ophthalmologists to find haemorrhages in fundus images having low contrast. The contrast of a fundus image used to observe micro-aneurysm is very low; therefore, ophthalmologists usually detect micro-aneurysms using fluorescein angiograms. However, it is difficult to use fluorescein angiograms as a contrast medium for diagnosing since all the medical examiners are subjected to mass screening. Detecting DR lesions is often accomplished by supervised classi-fication that involves training of classifiers using expert labelled target objects at pixel level .The probability that indicates the pixel being one or part of a target object, features are extracted from each pixel and soft labels are assigned. Objects are formed through abnormal pixels. For training and estimate which is exclusive and flat to error, it is costly to obtain expert labelled
Reference standards. The information provided by individual sam-ples overlaps as smaller as possible as perfectly preparation samples are planned to be both informative to the classification model and varied. Without accompanying other signs of DR, such as micro-aneurysms or small haemorrhages, larger haemorrhages occur rarely and have non regular shape. To detect the regular DR lesions, they will thus be missed by systems designed. Using different technique, several approaches have been already presented for this purpose. In these issues, they all have some deviations or drawbacks. Elimination of more severe false negatives leads large haemorrhages indicate more severe disease, and improved detection of such lesions.

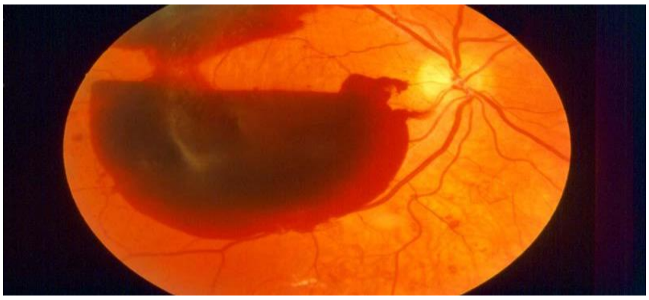

Figure 1: Fundus Image Showing Retinal Haemorrhages

2. Literature Review

The main objective of this paper is to evaluate the performance of various classification approaches to finalize the best classification method for improving the predictive accuracy and effectiveness of the classification. This proposed model utilizes various classification algorithms based on the various attributes. This section provides the information about various studies focused on diagnosing diabetic retinal images. For example, Lagares et al. [3] examined the numerous grading scales for calculating the result of subarachnoid haemorrhages (SAH). Modified Massachusetts General Hospital (MGH) scale was based on the features which are applicable for every patient suffering from subarachnoid haemorrhages was presented and equated with world federation of neurological surgeon scale (WFNS), Glasgow coma scale (GCS) and MGH scale for subarachnoid haemorrhages. Yet, the analytical accuracy was less and composite to take in clinical situations.

Li et al.[2] modelled a neural network system for surgical verdicts on traumatic brain injury patients. This prototype was modelled for huge TBI patient database. The model was realized and compared to the scientific models in order to obtain a traumatic brain injury medical decision support system. The logistic regression method, multi-layer perceptron neural network model (MLP) and radial basis function (RBF) models were related. However, the accuracy of this model provides was identical to logistic regression.

Mobley et al.[4] modelled another neural network predictions of coronary artery stenosis found in adults. The neural network prototype was presented to predict coronary stenosis. The clinical figures from male cardio patients were gathered from national cardiac catheterization (NCC) database. The input to the neural network was the patient variables. Coronary stenosis was identified and determined using the degree of stenosis. Even then the model's performance was not better than SVM and decision trees.

Buscema et al.[5] modelled an augmented procedure based on Neuro-evolutionary algorithms for classification of dyspeptic patients and forecast their treatment. The specific augmented experimental protocol was defined for classification and prediction. The applications of Neuro-evolutionary algorithms were modelled based on two parameters. The prediction was achieved based on the two dissimilar dependent variables. Here also, it does not outperform other techniques.

Germanson et al. [1] examined about risk after aneurysmal subarachnoid haemorrhages. The predictive degree of two multi-variant methods was assessed for risk classification. Classification and Regression Trees (CART) and multiple logistic regressions were related based on outcome and level of perception from best single predictor. However, the predictive accuracy rate was less.

Takahashi et al. [6] examined about risk stratification for mortality in impulsive intra-cerebral haemorrhages. The impulsive ICH patient's data were gathered and the variables from data were combined. The calculation method for mortality was improved with the help of classification and regression tree technique. ROC curve was used for the predictive accuracy.

Balasooriya et al. [8] modelled intelligent brain haemorrhages detection by watershed segmentation method on CT images. The CT images of brain were altered into suitable format and passed on for pre-processing. The objects of the brain images were detached and the features were mined from every object by exploiting watershed segmentation technique. Artificial neural network model was constructed by extracted features. Here also, the cost of computation was high and over-fitting problem could not be avoided.

Sharma et al. [10] examined the haemorrhages in brain with the help of brain CT images - automatic segmentation method. Pre-processed images were partitioned by using histogram based centroids initialization and k-means clustering algorithm relating to pixel intensity values. Histogram analysis was executed to detect the centre of the clusters and haemorrhages were predicted. However, this technique was subtle to noise or repeated data.

Choi et al. [11] advanced a prediction model for rats in hemorrhagic shock by using random forest classifier. The input variables were ranked by means of Breiman's method. The average accuracy by backward elimination process was assessed by repeating 5-fold cross validation. The uppermost variables were sorted and cross confirmed accuracy was chosen as optimal variable and used for creating prediction model. The prediction is slow when compared with similar techniques.

Shahangian et al. [12] studied prediction performance of brain haemorrhages using automatic detection and classification technique. Primarily, the skull and brain ventricles were removed from the images and haemorrhages were secluded with the help of thresholding method. The features selection was done using genetic algorithm and features were extracted from every haemorrhage region. Multilayer neural network and k-nearest neighbor classification based methods was used to predict haemorrhages. Comparatively, the convergence rate was less for obtaining the better results.

3. Existing Approaches

There are several research works that focus on diagnosing diabetic retinopathy fundus images using various classification methods. Some of the efficient methods are mentioned above. But the accuracy of the above said existing methods are not high. Hence this paper is motivated to verify and evaluate the performance of five different efficient classifiers and find out the best one among them. It helps to use the best classifier for future diabetic retinal analyzation. In the existing systems Nisha et al. [13], Labhade et al. [14], Choi et al. [15] and Lin et al. [9] only one classifier is discussed with the experimental results based on various data sets. But this paper focused on using all the four classification algorithms for the same dataset and the results are compared for choosing the best performed one.

4. Proposed Approach

The entire process of the proposed approach given in this paper is illustrated in Figure-3. There are six main steps are carried out here, they are reading the input image, remove the noise, enhance the image, haemorrhages detection, feature extraction and classification. Finally compare the classification accuracy among all the classifiers. In order to increase the efficiency in terms accuracy and applied for medical images, this paper motivated to provide a novel content based image retrieval system with various classifiers including Multi Class SVM method. With entire feature information available in the images, the novelty of this paper chooses the common features selected using all the classifiers and classified from the feature labels for comparing the images. Among the medical experts in online, the medical applications are tremendously growing based on cloud, and the medical information (especially medical images) are shared. This paper provides an effective CBIR system especially for medical dataset to effectively retrieve relevant medical images. Two main stages such as training stage and testing stage comprises the proposed work. For efficient comparison with the testing stage, the training stage provides an optimal feature subset. By various classification algorithms in the testing stage, the query image is preprocessed, enhanced, GLCM feature extracted and features selected. In Figure-3, the entire process of the proposed system used in this paper is shown.

4.1. Dataset

In this paper, diabetic retinal images are the image used having various diseases like exudates, haemorrhages, Microaneurysms and other damages on the surface of the retinal images. From benchmark dataset DRIVE which is publically available in http://www.isi.uu.nl/Research/Databases/DRIVE/download.php, the entire dataset is taken. From a screening program in Netherlands, the images in the DRIVE dataset are taken. Along with 7 signs, it comprises of 400 images. The patient's age group is from 25 years to 90 years. Using a CANON CR5 NON-

MYDRIATIC 3 CCD camera, all the images are acquired. It has high resolution of pixels. Hence the image processing results can be perfect.

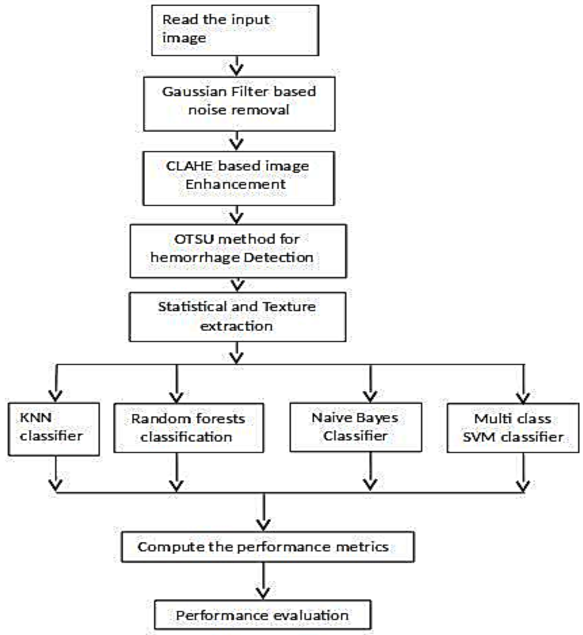

Figure-2: Proposed Method

4.2. Training Stage

Around 30% of the images are taken for training purpose. For selecting an optimal set of features, the extracted features form GLCM feature extraction method is feed as input into PS-classifier, ANN-Classifier and Association rules –Classifier. The common features are selected as the final feature subset for comparing and retrieval from the three obtained optimal feature set. Using a multi class SVM classifier with four classes such as “Normal”, “Mild”, “Moderate”, and “Sever”, the final feature subset is classified. To compare with the test images and the relevant image is retrieved; this optimal feature subset and the four classes are used.

4.3. Testing Stage

The remaining 70% of the images in the DRIVE dataset is considered as the test images/query images in the testing stage. According to the feature subset and classes, any image can be selected as the query image and the relevant images are retrieved from the database. For improving the efficiency of the CBIR, a two-fold comparison is applied. The first fold comparison considers the comparison of the optimal feature subset and the second-fold comparison considers the comparison of the classes. Classes obtained from MSVM method the final retrieved image in accordance to the query image is more accurate since the final feature set is optimal obtained using various feature selection method.

5. Image Preprocessing

To acquire a digital image from the image database is the first step of the process. Based on the user range and choice, the image database consists of the collection of n number of images. It is the process of improving the image in its appearance and efficient representation. Extraction, analysis, and recognition of image coding, filtering, normalization, segmentation, and object identification is involved along with this. The process of dividing an image into multiple parts is image segmentation. A set of significant regions and objects is the output of this stage [12]. By the filter parameter “h”, the noise occurred in the image I is removed whereas this parameter is estimated based on the noise variation σ^2. The output images is noise removed image which can be represented by$DIhv + n(DIh, v)$ where, denoised image is represented as DIh, and $n(DIh, v)$ is noise predicted and v is the decomposed image.

6. Image Enhancement

Enhancing the images for effective image processing is more essential. The output of the image processing steps gets degraded by the poor quality of the image. Histogram equalization, contrast equalization and etc., are the image processing methods used. It modifies the brightness of the image and it affect the original look of the images and it does not suit for all kind of images which is the main drawback in histogram equalization. This paper used Contrast Limited Adaptive Histogram Equalization (CLAHE) method for enhancing the image in order to overcome this issue. Using the mean value of brightness, wiener filter is used to sharpen the image and minimize the variations among the input image and the processed image. Hence CLAHE control the level of contrast in the image which is enhanced image.

7. OTSU Threshold based Haemorrhages Segmentation

Modified Otsu’s approach [5] was applied in a way to subdue the unwanted noise and geometrical objects based on vessel structure. Generally Otsu’s approach is used locally or totally on the complete image to find an inception for classification of blood vessel pixels and non-blood-vessel pixels. Applying Otsu threshold on the whole image at once does not give a productive mark. This is the reason why it was applied distinctly on varied and thin blood-vessel images. Global threshold on wide blood-vessel enhanced image was used and fused the output image into thin vessel enhanced image. So both thin and thick vessels will become prominent. A single enhanced image was obtained and further local thresholding applied. Vessel based thresholding was used for local thresholding that truly depends upon vessel locality and a new threshold is defined. Some offsets were added in the global threshold to subdue the noise more efficiently for vessels in the neighbourhood of wide vessels. For regions which were distant from wide vessels, a lower threshold was set than the global threshold by subtracting some offset from it to extract the small or thin vessels from the background having low intensity. Final segmented image was obtained by performing further, postprocessing steps.

7.1. Postprocessing Steps

We have used pixel/area based thresholding to eliminate unconnected non-vessel pixels. The segmentation results usually consist of some small isolated regions caused by noise, and these regions are sometimes wrongly detected as vessels. Based on the connectivity of the retinal vessels, we removed less than or equal to 30 unconnected pixels considered as a non-vessel or apart of the background noise.

8. Feature Extraction

To examine texture of spatial image, GLCM is a method used. With defined values, it compares and coordinates the pair of pixels. A texture property includes contrast between the pixels stored in matrix, correlation, homogeneity and energy. For an Image G, matrix P is defined as,

$$P(i,j) = \sum_{x=1}^{R}\sum_{y=1}^{C}\begin{cases}1 & \text{if } I(x,y) = i \text{ and } I(x+\Delta x, y+\Delta y) = j \\ 0 & \text{else}\end{cases}$$

$$\text{Energy} = \sum_{i=1}^{R}\sum_{j=1}^{C} P(i,j)^2$$

Contrast of texture is given as,

$$\text{Contrast} = \frac{1}{N^2}\sum_{i=1}^{R}\sum_{j=1}^{C} P(i,j)\,(i - j)^2$$

Correlation deals with the grey level of surrounding pixels and defined as,

$$\text{Correlation} = \frac{\sum_{m=1}^{R}\sum_{n=1}^{C} mnp(m,n) - \mu_x \times \mu_y}{\sigma_x \sigma_y}$$

In different samples, GLCM is a statistical approach which quantizes the matrix levels. Based on intensity levels the matrix is adjusted, image description consists of all the features described above. To consider the probability of relationship, GLCM updates relationship from i to j in the matrix. By using proper mean function the mean intensity obtained.

9. Classification based on Various Classifiers

9.1. KNN Classifier Algorithm

This paper utilizes KNN classifier for evaluating the performance among various classifiers and it is referred from Nisha et al.[13]. The K-NN is a non-parametric method used for classification and regression in pattern recognition. In the feature space, the input consists of the k-closest training examples. Whether K-NN is used for classification or regression decides the output. Each with a class labels, training examples are vectors in a multidimensional feature space. Storing the feature vectors and class labels of the training samples exists in training phase of the algorithm. To reduce the computational load, the KNN classifier is used. With the practical exploitation of the power of the K-NN approach, there are two difficulties. First, while there is no time required to estimate parameters from the training data, the time to find the nearest neighbours in a large training set can be prohibitive. To overcome the difficulties,

- Reduce the time taken to compute distances by working in a reduced dimension using dimension reduction techniques such as principal components.
- Use sophisticated data structures such as search trees to speed up identification of the nearest neighbor. This approach often settles for an almost neighbor to improve speed.

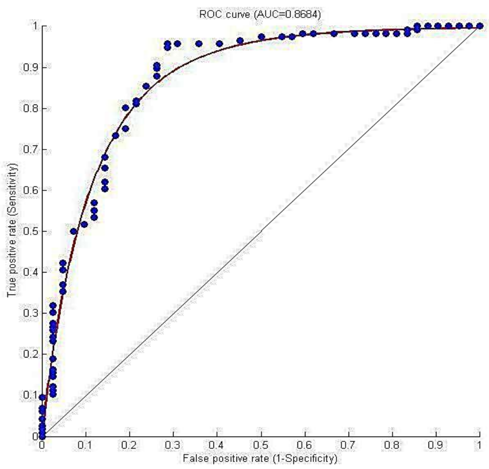

Figure-3: KNN Classifier Algorithm

- Edit the training data to remove redundant or almost redundant points in the training set to speed up the search for the nearest neighbor.
- To remove the samples in the training data set that has no effect on the classification because they are surrounded by samples that all belong to the same class.

An n-dimensional vector is formed by combining n attributes by each sample in the data in this project.

$X = \{X_1, X_2, \dots, X_n\}$

Where, n attributes are considered to be variables. Another attributes are denoted by y. The value depends on other n attributes X. The value y defined as,

$y = f(X)$

f is a scalar function and y is a categorical variable the probability of splat from haemorrhages itself. The probability value p was determined by,

$p = n/k$

The distance of the nearest neighbor can be measured by using Euclidean metric in the optimized feature space,

$$d\,(x,u) = \sqrt{\sum_{i=1}^{n}(x_i - u_i)^2}$$

Where, d(x,u) is to measure the distance between the points in the space of independent predictor variables. Finally it classifies the splat features such as splat size, splat orientation, splat area, splat solidity and texture features. The main goal of the splat feature classification is to develop a haemorrhages detector for indicating whether the image was in normal condition or abnormal conditions. To eliminate the haemorrhages map h, the low probability values are suppressed by using,

$$h(x,y) = \begin{cases}h(x,y) & \text{if } h(x,y) \geq h_0 \\ 0 & \text{if } h(x,y) < h_0\end{cases}$$

Where, h_0 is a pre-defined threshold. The appropriate value can be chosen according to the training set by collecting the probabilities of both haemorrhages and non-haemorrhages splat and then the relevant objects are detected. Here the two groups of splat probabilities are sorted by using the ROC curve which ranges from 0 to 1 in Figure 3 (ROC curve). The non-haemorrhages splats are classified with very low probabilities, the threshold value $h_0 = 0.2$ in this the false positives would be suppressed.

9.2. Random Forest Classification

The Random Forests algorithm is one of the best among classification algorithms able to classify large amounts of data with accuracy. It is referred from Labhade et al. [14] to simply the work. To classify large amounts of data with accuracy, the Random Forests algorithm is one of the best among classification algorithms. For classification and regression that construct a number of decision trees at training time and outputting the class that is the mode of the classes output by individual trees, random Forests are an ensemble learning method (also thought of as a form of nearest neighbor predictor). In the forest, random Forests are a combination of tree predictors where each tree depends on the values of a random vector sampled independently with the same distribution for all trees. A group of “weak learners” can come together to form a “strong learner” which is the basic principle. Because of the law of large numbers, random Forests are a wonderful tool for making predictions considering they do not over fit. Introducing the right kind of randomness makes them accurate classifiers and repressors.

Single decision trees often have high variance or high bias. By averaging to find a natural balance between the two extremes, random Forests attempts to mitigate the problems of high variance and high bias. Using simply with default parameter settings, random Forests have few parameters to tune and they are a simple tool to use without having a model or to produce a reasonable model fast and efficiently. Random Forests grows many classification trees. Each tree is grown as follows:

1. If the number of cases in the training set is *N*, sample *N* cases at random but with replacement, from the original data. This sample will be the training set for growing the tree.
2. If there are *M* input variables, a number *mM* is specified such that at each node, m variables are selected at random out of the *M* and the best split on this *m* is used to split the node. The value of *m* is held constant during the forest growing.
3. Each tree is grown to the largest extent possible. There is no pruning.
4. The entire process of the random forest method is implemented in a computer programming language and the results are verified for evaluating the performance.

9.3 Naive Bayes Classifier

A naive Bayes classifier corresponds to a Bayesian network, as in Figure-4 and it is referred from Choi et al. (2016). Naïve Bayes algorithm is implemented and verified for performance evaluation. As in Figure-4, a naive Bayes classifier corresponds to a Bayesian network. A single class variable C andm attribute variables $\boldsymbol{x_i}$ (for simplicity of exposition, weassume that attributes are discrete) is present. A value of an attribute $\boldsymbol{x_i}$ is denoted by $\boldsymbol{x_i}$ and a class label is denoted by $\boldsymbol{c}$. Thus, Bayes classifier induces a distribution:

$$\Pr(c, x_1, x_2, \dots, x_m) = \Pr(c) \cdot \prod_{i=1}^{m} \Pr(x_i|c)$$

where, we have a class prior $\Pr(\boldsymbol{c})$ and conditional distributions Pr(Xi j C). We can estimate these parameters from (labeled) data, using maximum likelihood or MAP estimation. Once we have learned a naive Bayes classifier from data, we can label new instances by selecting the class label$\boldsymbol{c^*}$ ***that*** has maximum posterior probability given observations$\boldsymbol{x_1, \dots, x_m}$. That is, we select

$$c^* = \operatorname*{argmax}_{c} \Pr(c|x_1, \dots, x_m)$$

Similar to the Naive Bayes classifier of Figure 4, the Structured Naive Bayes (SNB) classifier has a structure. As they can also be Sentential Decision Diagram (SDD), the one exception is that the attributes $\boldsymbol{x_i}$ do not need to be discrete (or continuous) variables.

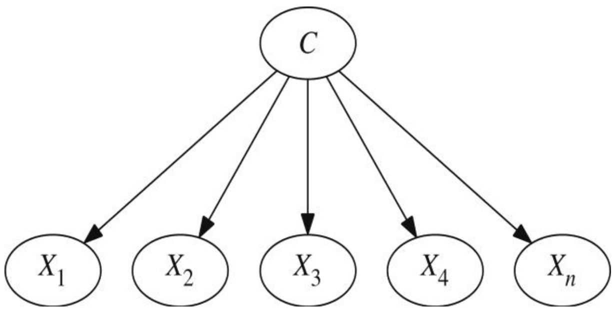

Figure-4: Naive Bayes Algorithm

To define these SDDs, the domain specific investment uses an SNB classifier.

By a class variable C, a classical NB classifier is defined and attributes$\boldsymbol{x_i}$. For the class variable C, and a set of conditional distributions *Pr(X i jc)*, one for each class label c and attribute $\boldsymbol{x_i}$, its parameters include a prior distribution Pr(C). Each $\boldsymbol{x_i}$ is an observed attribute value and one estimates these parameters from labeled data, corresponding to a set of examples of the form c; x1;:::; xm, where c is a class label Except that one can also have structured attributes that are represented by SDDs and whose conditional distributions are represented by Probabilistic Sentential Decision Diagram (PSDD), the SNB classifier is defined similarly. We only include structured attributes in the following definition for simplicity of exposition.

Structured Naive Bayes Classifier Algorithm

- One of the class denoted as *C*, it is a discrete variable
- $\boldsymbol{SDDs, S_1, S_2, \dots, S_n}$ are the attributes used for structuring
- Some of the parameters used to represent the SNB classifier is:
  - for the class variable *C*, there is a class prior $\boldsymbol{\theta_C}$,
  - $\boldsymbol{\theta_{j,c}}$ is the set of parameters created from labels *c* and attributes *j* for SDD *Sj* which will be distributed under certain conditions is called as distribution index PSDD.

In order to interpret the meaning of the SNB classifier the distribution index PSDD is used. PSDD is created from SDD *Sj*, and the parameters$\boldsymbol{\theta_{j,c}}$. Then it provides,

$$\Pr(c, S_1, \dots, S_n) = \theta_c \cdot \prod_{j=1}^{n} P_{j,c}(S_j)$$

The number of PSDD is $k \times n$, when the number of class variable is *k*. Only the simple attributes are included

It is straightforward to also include simple attributes represented by discrete and continuous variables. For example, if we include m discrete attributesX_i with parameters $\boldsymbol{\theta_{(x_i|c)} = Pr(x_i|c)}$,we obtain the following distribution:

$$\boldsymbol{Pr(c, x_1, \dots, x_m, S_1, \dots, S_n) = \theta_c \cdot \prod_{j=1}^{m} \theta_{x_i|c}(S_j) \cdot \prod_{j=1}^{n} P_{j,c}(S_j)}$$

9.4. Multi-Class SVM Approach

Under the label of 0 and 1, support Vector Machine classifies the entire input data into two different classes. It can be said as positive or negative or lower or upper classes in other words. It is essential to use Multi-Class Support Vector Machine algorithm in order to classify the dataset under more than two classes. SVM and Multi-Class SVM are belongs to machine learning approaches and without any external technical support, it is able to learn any

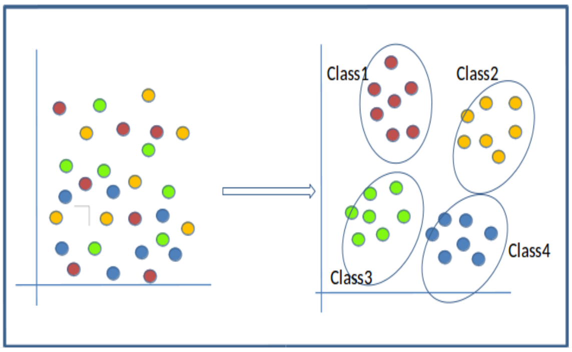

Figure-5: Multi Class SVM Classifier

Kind of data by itself. Among two different objects such as trained object and test object, both approaches have in-built mechanisms to verify the similarities, distance and matching score. But the user requires Multi-class SVM that classifies the data under various classes. In Figure-5, the classification method used in MSVM is illustrated

Two different classes as -1 and +1 is the classification of the entire data which is classified by SVM. But according to the user defined classes like {-1, 0, +1...}, the multi-class SVM classifier classifies the entire data into various classes. Multi SVM classifier classifies the data linearly as:

$$f^k: X^d \rightarrow \{-1, 0, +1, \dots\}$$

Here multi-class SVM is applied for classification due to various classes available in the input data. In Table-5, a sample stage wise result of our proposed approach is given.

10. Results and Discussions

The entire proposed approach discussed above is programmed in MATLAB software and the results are verified. In order to do that there are 500 number of images are taken for experiment whereas 25% of the overall images are taken for training process and remaining 75% of the overall images are taken for testing process. The performance analysis in terms of classification accuracy is verified only for 100 images in order to reduce the computational complexity and time.

Table 1: Performance Metrics Values using KNN Classifier

Images	**Normal**	**Haemorrhages**	**Total Number Of Images**
Existing In Database	60	40	100
Observations By KNN Classifier	59	39	-

- True positives =The number of cases correctly identified as haemorrhages = 39
- False positives = the number of cases incorrectly identified as haemorrhages = 1
- True negatives =the number of cases correctly identified as healthy = 59
- False negative = the number of cases incorrectly identified as healthy = 1
- Sensitivity = TP/(TP+FN) = 39/(39+1)= 0.975
- Specificity= TN/(TN+FP) = 59/(59+1)= 0.983
- Accuracy = (TP+TN)/TP+FP+TN+FN) =98/100=0.9 8

From the above calculation, in terms of percentage, the obtained sensitivity, specificity and accuracy are 97.5%, 98.3% and 98% respectively.

Table 2: Performance Metrics Values using Random forest Classifier

Images	**Normal**	**Haemorrhages**	**Total Number Of Images**
Existing In Database	60	40	100
Observations By Random Forest Classifier	58	38	-

- True positives =The number of cases correctly identified as haemorrhages = 38
- False positives = the number of cases incorrectly identified as haemorrhages = 2
- True negatives =the number of cases correctly identified as healthy = 58
- False negative = the number of cases incorrectly identified as healthy = 2
- Sensitivity = TP/(TP+FN) = 38/(38+2)= 0.95
- Specificity= TN/(TN+FP) = 58/(59+1)= 0.965
- Accuracy = (TP+TN)/TP+FP+TN+FN) =96/100=0.96

From the above calculation, in terms of percentage, the obtained sensitivity, specificity and accuracy are 95%, 96.5% and 95% respectively.

Table 3: Performance Metrics Values using Naive Bayes Classifier

Images	**Normal**	**Haemorrhages**	**Total Number Of Images**
Existing In Database	60	40	100
Observations By Naïve Bayes Classifier	59	38	-

- True positives =The number of cases correctly identified as haemorrhages = 38
- False positives = the number of cases incorrectly identified as haemorrhages = 1
- True negatives =the number of cases correctly identified as healthy = 59
- False negative = the number of cases incorrectly identified as healthy = 2
- Sensitivity = TP/(TP+FN) = 38/(38+2)= 0.95
- Specificity= TN/(TN+FP) = 59/(59+1)= 0.983
- Accuracy = (TP+TN)/TP+FP+TN+FN) =97/100=0.97

From the above calculation, in terms of percentage, the obtained sensitivity, specificity and accuracy are 95%, 98.3% and 97% respectively.

Table 4: Performance Metrics Values using Multi-Class SVM Classifier

Images	**Normal**	**Haemorrhages**	**Total Number Of Images**
Existing In Database	60	40	100
Observations By Multi Class SVM Classifier	59	38	-

- True positives =The number of cases correctly identified as haemorrhages = 38
- False positives = the number of cases incorrectly identified as haemorrhages = 1
- True negatives =the number of cases correctly identified as healthy = 59
- False negative = the number of cases incorrectly identified as healthy = 2
- Sensitivity = TP/(TP+FN) = 38/(38+2)= 0.95
- Specificity= TN/(TN+FP) = 59/(59+1)= 0.983
- Accuracy = (TP+TN)/TP+FP+TN+FN) =97/100=0.97

From the above calculation, in terms of percentage, the obtained sensitivity, specificity and accuracy are 95%, 98.3% and 97% respectively.

Table 5: Comparison of Performance Matrix of Various Classifiers

Algorithm	**No. of Images**	**Sensitivity**	**Specificity**	**Accuracy**
KNN	100	97.5	98.3	98
Random Forest	100	95	96.5	96
Naive Bayes	100	95	98.3	97
Multi-Class SVM	100	95	98.3	97

11. Conclusion

KNN, Random Forest, Naive Bayes and Multi-Class Support Vector Machine are the four different classifiers compared in this paper. The performance matrix shows competitive results of classification. Comparitively, more accuracy is obtained using KNN Classifier.

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