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Classification of a Retinal Disease based on Different Supervised Learning Techniques

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Abstract— This paper is based on classification of a retinal disease observed in premature infants named as "Retinopathy of Prematurity" (ROP). According to current market survey very few hospitals are associated in dealing with this disorder and is costly. So, the main aim here is to provide a simple yet effective MATLAB based algorithm for detection and classification of this disease. Here for computational purpose authors have used 30 affected and 30 normal images. These images are pre-processed using various MATLAB functions and commands and blood vessels are extracted. Later the tortuosity of these vessels is estimated and stored. These signals are further given to supervised learning classifiers, accuracy and error rate of the algorithm is estimated using different kernels.

Keywords— Premature, infants, Retinopathy of Prematurity, Supervised Learning, Tortuosity

I. INTRODUCTION

Retinopathy of prematurity (ROP) is an ocular disease of premature infants and it can cause blindness on high threshold stages. It affects development of retina in the eyes of premature babies. It can be mild with no visual defects, or it may become aggressive with new blood vessel formation (neovascularization) and progress to retinal detachment and blindness. All babies who less than 1800g birth weight or younger than 32 weeks' gestational age at birth are at risk of developing ROP.

In any neonatal intensive care unit (NICU), the timing of the first evaluation must be based on the gestational age at birth. (a) If the baby is born at 23-24 weeks' gestational age, the first eye examination should be performed at 27-28 weeks gestational age. (b) If the baby is born at or beyond 25-28 weeks' gestational age, the first examination should occur at the fourth to fifth week of life. (c) Beyond 29 weeks, the first eye examination should probably occur by fourth week life time of baby.
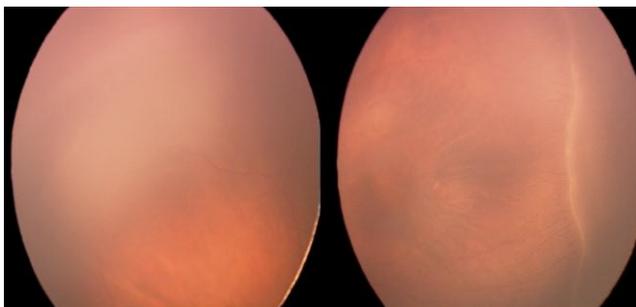

Fig. 1 Unaffected Retina (Left) , ROP affected retina (Right)

Image Courtesy – Dr. H. V. Desai Hosiptal, Hadapsar, Pune

It is essential that those caring for premature infants know who is at risk of retinopathy of prematurity, when screening must begin and how often these infants need to be examined.

It is also important to know when to treat those infants who develop severe retinopathy of prematurity and what long term follow-up is needed to manage other complications of retinopathy of prematurity. The discrimination between normal retinal vessels and diseased vessels plays a vital role to detect the ROP. Indirect ophthalmoscope is the goal standard for ROP screening. But in a big way the indirect ophthalmoscope has been replaced with Retcam in ROP tele screening. Even though Retcam images can be taken by non-ophthalmologist, it is difficult for them to interpret the stages of ROP. Thus, automation of detection of this disease is very important. This will provide the effective time utilization for the ophthalmologists. They can concentrate on infants who suffered with high risk threshold ROP and threshold ROP instead of analysing all ROP images. Depending on various retinal conditions this disease can be classified into six different stages [1,2,3,4].

- Stage 1. Demarcation line: a flat, white, thin line that separates the avascular retina anteriorly (toward the retinal periphery) from the vascularized retina posteriorly.

- Stage 2. Ridge the flat line from stage 1 has grown in height, width, and volume and has become a pink-white ridge.

- Stage 3. Ridge with extra retinal fibro vascular proliferation: proliferating tissue can be continuous with the posterior aspect of the ridge; immediately posterior to the ridge, or extending directly into the vitreous.

- Stage 4. Subtotal retinal detachment: dragging vessels and subtotal traction retinal detachment can be seen. Stage 4A disease does not affect the macula and has a relatively good prognosis for vision; stage 4B disease affects the fovea and usually has a poor prognosis for vision.

- Stage 5. Total retinal detachment: funnel-shaped retinal detachment. Anterior and posterior portions appear open or narrowed on ultra-sonographic scans.

- Plus Disease. The designation "+" is placed after the stage when dilated posterior veins, tortuous retinal arteries, vitreous haze, and pupillary rigidity are observed. If plus disease is observed in the posterior portion of the retina, patients must be monitored closely, as there is high risk of ROP progressing rapidly within a few days and lead to retinal detachment and may cause blindness with high risk ROP.

Supervised learning entails learning a mapping between a set of input variables X and an output variable Y and applying this mapping to predict the outputs for unseen data. Supervised learning is the most important methodology in machine learning and it also has a central importance in the processing of multimedia data. Support vector machines which represent the dominant supervised learning technology these days – particularly in the processing of multimedia data. We also review nearest neighbour classifiers which can (loosely speaking) be considered kernel-based strategy. Nearest neighbour techniques are popular in multimedia because the emphasis on similarity is appropriate for multimedia data where a rich array of similarity assessment techniques is available [5].

The principle underlying nearest neighbour classification is quite straight forward, example sare classified based on the class of their nearest neighbours. It is often useful to take more than one neighbour in to accounts this technique is more commonly referred to as k-nearest neighbour (k-NN) Classification where k nearest neighbours are used in determining the class. Since the training examples are needed at runtime, i.e. they need to be in memory at run-time, it is sometimes also called memory based classification. Because induction is delayed Torun-time, it is considered lazy learning technique. Because classification is based directly entertaining examples it is also called example-based classification or case-based classification [5].

The key idea in ensemble research is in many situations a committee of classifiers will produce better results than a single classifier – better in terms of stability and accuracy. This is particularly the case when the component classifiers are unstable as is the case with neural networks and decision trees. While the use of ensembles in machine learning research is fairly new, the idea that aggregating the opinions of a committee of experts will increase accuracy is not new [5].

Support Vector Machine (SVM) was introduced into the field of machine learning and its related area in 1992 [6]. Since then, it receives widespread attention of researchers and has made great progress in many fields. SVM has a solid theoretical foundation and straightforward mathematical model and has got considerable development in pattern recognition, function estimation, time series forecasting and many other areas. It uses a nonlinear mapping to map original training data into high-dimensional space for finding the optimal classification hyper plane that separates those data into different categories. SVM is based structural risk minimization principle of Statistical Learning Theory (SLT) [7, 8]. Compared with traditional neural networks, SVM gains great enhancement in generalization ability and overcomes some problems existing in feed-forward neural networks, such as local minimum and the curse of dimensionality [9]. Further, the introduction of kernel function greatly simplifies the complexity of dot product operation in SVM for nonlinear data classification, and makes it possible to distinguish and enlarge the useful features by SVM. Generalization ability of SVM relies heavily on the choice of kernel function. Basing on kernel function, SVM is playing more and more powerful role in the field of data mining.

II.   PROPOSED METHOD

Input Images
The images for computational purpose were provided by Dr. H. V. Desai Hospital, Hadapsar, Pune (Normal and Stage 1 images). Whereas the images for plus disease are downloaded.
These colour images are taken as input and are processed accordingly to get proper results.

Pro-processing
As the images are coloured and cannot be used for direct applications it must be pre-processed, the following steps are taken for pre-processing of these images,

The above shown flow graph is the pre-processing algorithm used for detection of blood vessels from the retina, the extracted blood vessels are marked using area properties and thus extraction of such retinal blood vessels and estimation of area covered by the vessels can help in formation of dataset for machine learning algorithms. Normal and Stage 1 affected retina show up less blood vessels and nominal amount of tortuosity whereas for plus disease the amount of blood vessels detected is high and the detected vessels are very tortoise.
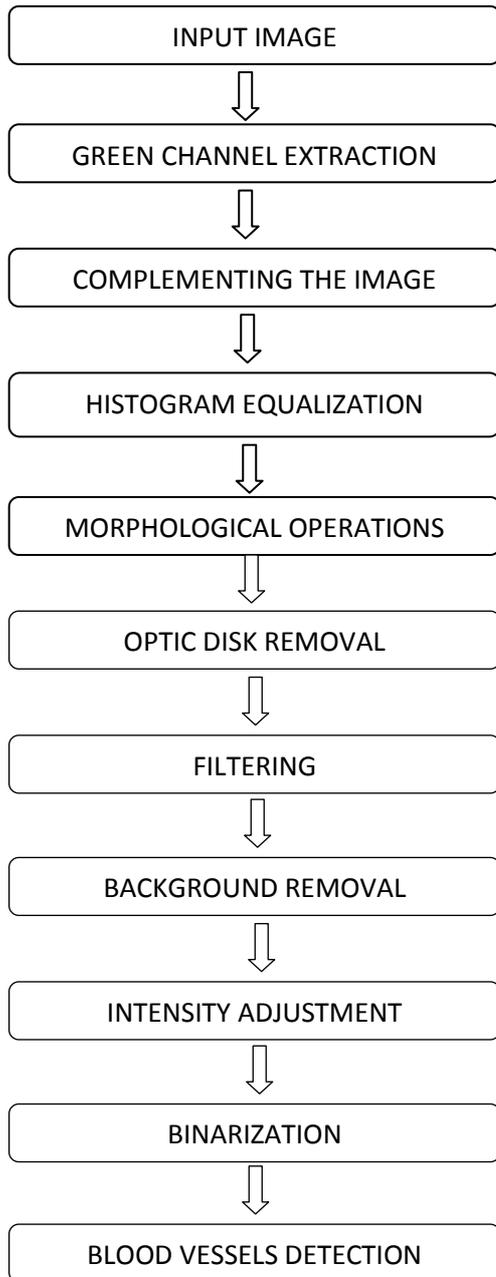
INPUT IMAGE

GREEN CHANNEL EXTRACTION

COMPLEMENTING THE IMAGE

HISTOGRAM EQUALIZATION

MORPHOLOGICAL OPERATIONS

OPTIC DISK REMOVAL

FILTERING

BACKGROUND REMOVAL

INTENSITY ADJUSTMENT

BINARIZATION

BLOOD VESSELS DETECTION

Fig.2: Pre-processing

Feature Extraction and Storage
As said above that the features (blood vessels) are extracted from the given image and the tortuosity is estimated, these results are stored on a excel sheet. Once all the images are processed and whole sheet is formed, this sheet is ready for classification.Here for computational purpose 30 images of affected as well as of normal conditions are considered.

III.   CLASSIFICATION

SVM – Here linear SVM method is used for classification. Linear SVM is the newest extremely fast machine learning (data mining) algorithm for solving multiclass classification problems from ultra large data sets that

implements an original proprietary version of a cutting plane algorithm for designing a linear support vector machine. Linear SVM is a linearly scalable routine meaning that it creates an SVM model in a CPU time which scales linearly with the size of the training data set. Linear SVM accepts data in two standard machine learning formats – sparse and dense one.   Data must be organized as follows, the first column must be the desired (target) vector y and the rest of columns are the columns of the input vector x [10].

$$\begin{bmatrix} y_1 & x_{11} & x_{12} & x_{13} \\ y_2 & x_{21} & x_{22} & x_{23} \\ \vdots & \vdots & \vdots & \vdots \\ y_{1,000} & x_{1,000\ 1} & x_{1,000\ 2} & x_{1,000\ 3} \end{bmatrix}$$
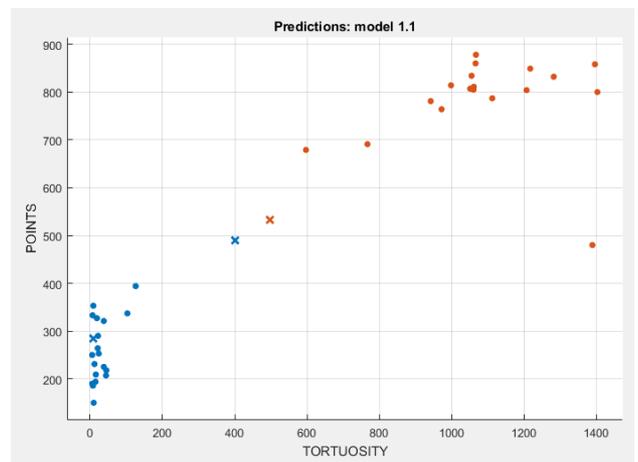
Fig. 3: Scatter plot of Linear SVM

Here by using linear SVM the total accuracy of the system is 92.5%. The above shoe in figure number 2 is the scatter plot and the shown below in figure 3 is the confusion matix.
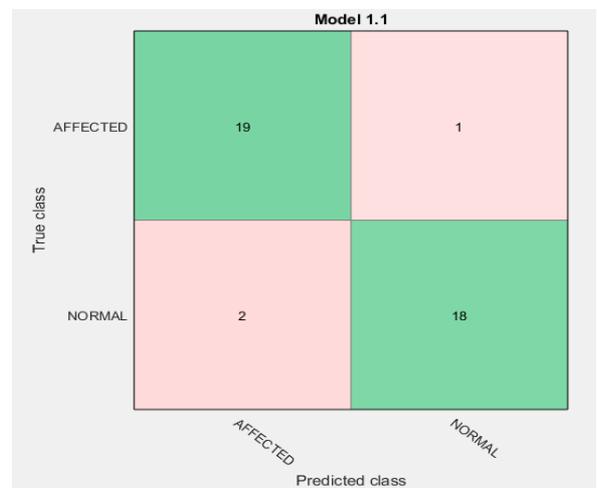
Fig. 4: Confusion Matrix for linear SVM

(k-NN) - The k-means clustering algorithm attempts to

split a given anonymous data set (a set containing no information as to class identity) into a fixed number (k) of clusters. Initially k number of so called centroids are chosen. A centroid is a data point (imaginary or real) at the center of a cluster. Each centroid is an existing data point in the given input data set, picked at random, such that all centroids are unique (that is, for all centroids c_i and c_j, $c_i \neq c_j$). These centroids are used to train a kNN classifier. The resulting classifier is used to classify (using k = 1) the data and thereby produce an initial randomized set of clusters. Each centroid is thereafter set to the arithmetic mean of the cluster it defines. The process of classification and centroid adjustment is repeated until the values of the centroids stabilize. The final centroids will be used to produce the final classification/clustering of the input data, effectively turning the set of initially anonymous data points into a set of data points, each with a class identity [11].

Here Fine K-NN is used by authors. Fine KNN means Finely detailed distinctions between classes. The number of neighbors is set to 1.
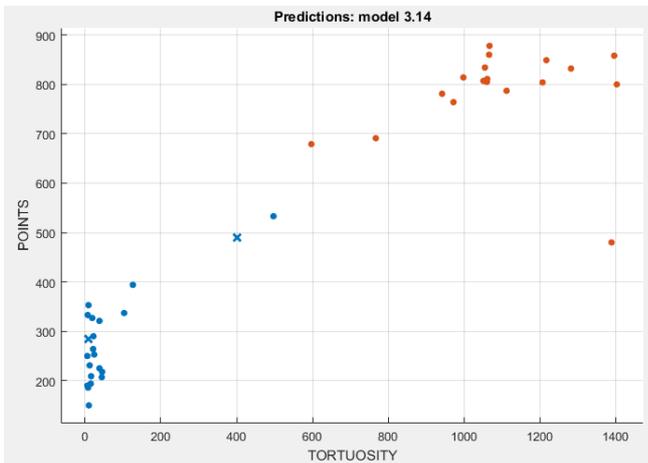

Fig. 5: Scatter plot of Fine k-NN

Here by using Fine k-NN the total accuracy of the system is 95.0%. The above shown in figure number 4 is the scatter plot and the shown below in figure 5 is the confusion matix.
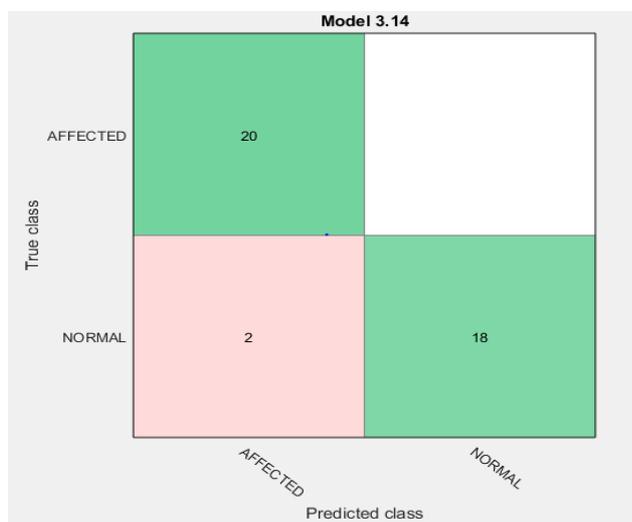

Fig. 6: Confusion Matrix for Fine k-NN

Ensemble - A subspace S of the D-dimensional data space is represented by a vector S = (S1, . . . , SD) ∈ {0, 1} D, where $S_i = 1$, if the ith attribute is an element of the subspace, and $S_i = 0$, otherwise. The number d of 1 entries in S, i.e., d = PD i=1 Si is called the dimensionality of S.

The distance in a subspace S between two points x, y ∈ DB is given by dist S(x, y) = p qPd i=1 Si |xi − yi | p , where xi, yi, and Si denote the values of the ith component of the vectors x, y, and S. Given a query object q and dimensional (d ≤ D) query subspace represented by a corresponding vector S of weights, a subspace k-NN query retrieves the set NN (k, S, q) that contains k objects from DB for which the following condition holds: ∀o ∈ NN (k, S, q), ∀o 0 ∈ DB \ NN (k, S, q) : distS(o, q) ≤ distS(o 0 , q) [12].
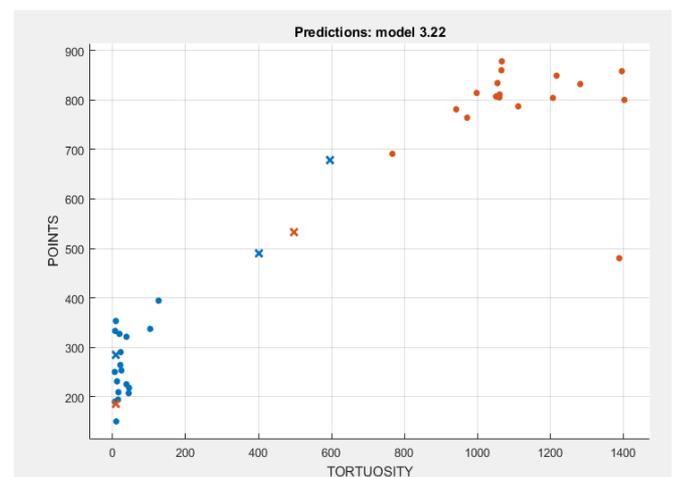

Fig. 7: Scatter plot of Ensemble Subspace k-NN

Here by using Fine Esemble subspace k-NN the total accuracy of the system is 87.5%. The above shown in figure number 6 is the scatter plot and the shown below in figure 7 is the confusion matix.

Fig. 8: Confusion Matrix for Ensemble subspace k-NN

IV.   RESULTS

Above mentioned three methods for classification of data under supervised learning, the accuracy for all the three methods is good but best accuracy is obtained from Ensemble Subspace k-NN.

Sr.no	Classifier Type	Accuracy	Error
1.	SVM	92.5%	7.5%
2.	k-NN	95%	5%
3.	Ensemble	87.5%	12.5%

V.   FUTURE WORK

Since database is constraint, images related to stage1, normal and plus disease are only available thus classification can be done between affected and normal images depending on blood vessels. If in future the images for all stages are available, the main aim will be of developing a system for detection and classification of all stages.

VI.   ACKNOWLEDGEMENT

VII.   REFERENCES

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