Original Research Article

EVALUATION OF PERFORMANCE OF DECISION TREE, SUPPORT VECTOR MACHINE AND PROBABILISTIC NEURAL NETWORK CLASSIFIERS IN A MOBILE BASED DIABETES RETINOPATHY DETECTION SYSTEM

Abstract: Diabetic Retinopathy (DR) is a medical condition where the retina is damaged because fluid leaks from blood vessels into the retina. Ophthalmologists recognize diabetic retinopathy based on features, such as blood vessel area, exudes, hemorrhages, microaneurysms and texture. The focus of this paper is to evaluate the performance of Decision Tree (DT), Support Vector Machine (SVM) and Probabilistic Neural Network (PNN) Classifiers in Diabetes Retinopathy Detection. Also, in this paper a Mobile based Diabetes Retinopathy Detection System was developed to make it available for the masses for early detection of the disease.

Keywords: Support Vector Machine, Decision Tree, Classifier, Diabetic Retinopathy (DR), Fundus, Diabetes Retinopathy Detector, Exudates, Retinal Images.

1. INTRODUCTION

The fast progression of diabetes is one of the main challenges of current health care. The number of people afflicted with the disease continues to grow at an alarming rate. The World Health Organization expects the number of people with diabetics to increase from 130 million to 350 million over the next 25 years (World Diabetes, 1998). So far, the most effective treatment for DR can be administered only in the first stages of the disease. Therefore, early detection through regular screening is of paramount importance. To lower the cost of such screenings, digital image capturing technology must be used, because this technology enables us to employ state-of-the art image processing techniques which automate the detection of abnormalities in retinal images.. Currently, several highly accurate programs exist for automated detection of specific DR related lesions (Giancardo et.al.,2011; Antal et.al., 2011; Fleming, et. al., 2006). These programs require different pre and post processing steps of retinal images depending on the lesion of interest as well as corrections for resolution and colour normalization to account for images with different fields of view and ethnicity (Cree, Gamble and Cornforth, 2005).

Many classification techniques have been employed in literature such as ANN, SVM Decision Tree, Hidden Markov Model, Bayesian statistical classifier e.t.c for classification of Diabetes Retinopathy but little effort has been directed towards their performance evaluation. Hence in this paper, evaluation of performance of Decision Tree, Support Vector Machine and Probabilistic Neural Network (PNN) is carried out to test classification capabilities of the three selected classifiers. However, a cost effective and easily accessible Mobile Based Diabetes Retinopathy Detection System was developed to make it available for the masses for early detection of the disease that can assist the Ophthalmologist in handling growing number of people afflicted with Diabetes Retinopathy.

2. RELATED WORKS

Pires, et.al (2012), proposed a method based on points of interest and visual dictionary for retinal pathology images for the detection of DR using support vector machine(SVM) as the classifier. They extracted the visual features from the images using SIFT.

Osareh, et al. (2003) proposed a system on Automatic Recognition of Exudative Maculopathy using Fuzzy C-Means Clustering and Neural Networks. Diabetic retinal exudates in digital color images were identified automatically by segmenting using fuzzy C-means clustering method following some key preprocessing steps. In his system, in order to classify the segmented regions into exudates and non-exudates, an artificial neural network classifier was investigated. This system could achieve a diagnostic accuracy of 95.0% sensitivity and 88.9% specificity for the identifying the images containing any evidence of DR.

Kullayamma,(2013),made a system on Retinal Image Analysis for Exudates Detection in which classification of a glaucomatous image was done using texture features within images and was effectively classified based on feature ranking and neural network. Efficient detection of exudates for retinal vasculature disorder analysis was performed. The segmented region was post processed by morphological processing technique for smoothening.

Hunter et. al (2000) have studied neural network based exudates detection. They introduced a hierarchical feature selection algorithm, based on sensitivity analysis to distinguish the most relevant features. The final architecture achieved 91% lesion-based performance using a relatively small number of images.

A new approach to automatically extract the main features in colour fundus images was proposed by Li et..al (2000). Optic disk was localized by the principal component analysis (PCA) and its shape was detected by a modified active shape model (ASM). Exudates were extracted by the combined region growing and edge detection. Their results show 99%, 94%, and 100% for disk localization, disk boundary detection, and fovea localization respectively. The sensitivity and specificity for exudate detection were 100% and 71%.

Colour features were used by Wang et.al (2000) on Bayesian statistical classifier to classify each pixel into lesion or non-lesion classes. They have achieved 100% accuracy in identifying all the retinal images with exudates, and 70% accuracy in classifying normal retinal images as normal.

Local contrast enhancement fuzzy C-means and support vector machine was used by Zhang (2004) to detect and classify bright lesions. Their classification results are as follows: Classification between bright lesions and bright non-lesion: sensitivity = 97%, specificity = 96%. and Classification between exudates and cotton wool spots: sensitivity = 88%, specificity = 84%.

3. METHODOLOGY

An automated approach for classification of an eye defect Diabetes retinopathy using fundus images acquired is adopted. In order to diagnose diabetic retinopathy, a number of features such as area, mean and standard deviation of the pre-processed images are extracted to characterize the image content. Object oriented approach of software development was used to build a mobile application, which provides an interface to communicate with the user. Microsoft visual studio

IDE is used to develop the application and SQL Server database was used to manage the data involved within the program. The Decision Tree Classifier (DTC) classifier is first trained using the histograms of the images and then they are employed to classify whether a retinal image is normal or not using a well-known database RetIDB and Messidor, which contains number of clearly labeled sample images for each anomaly.

The block diagram for the proposed Mobile Based Diabetics Retinopathy Detector is as shown in figure 1 below:

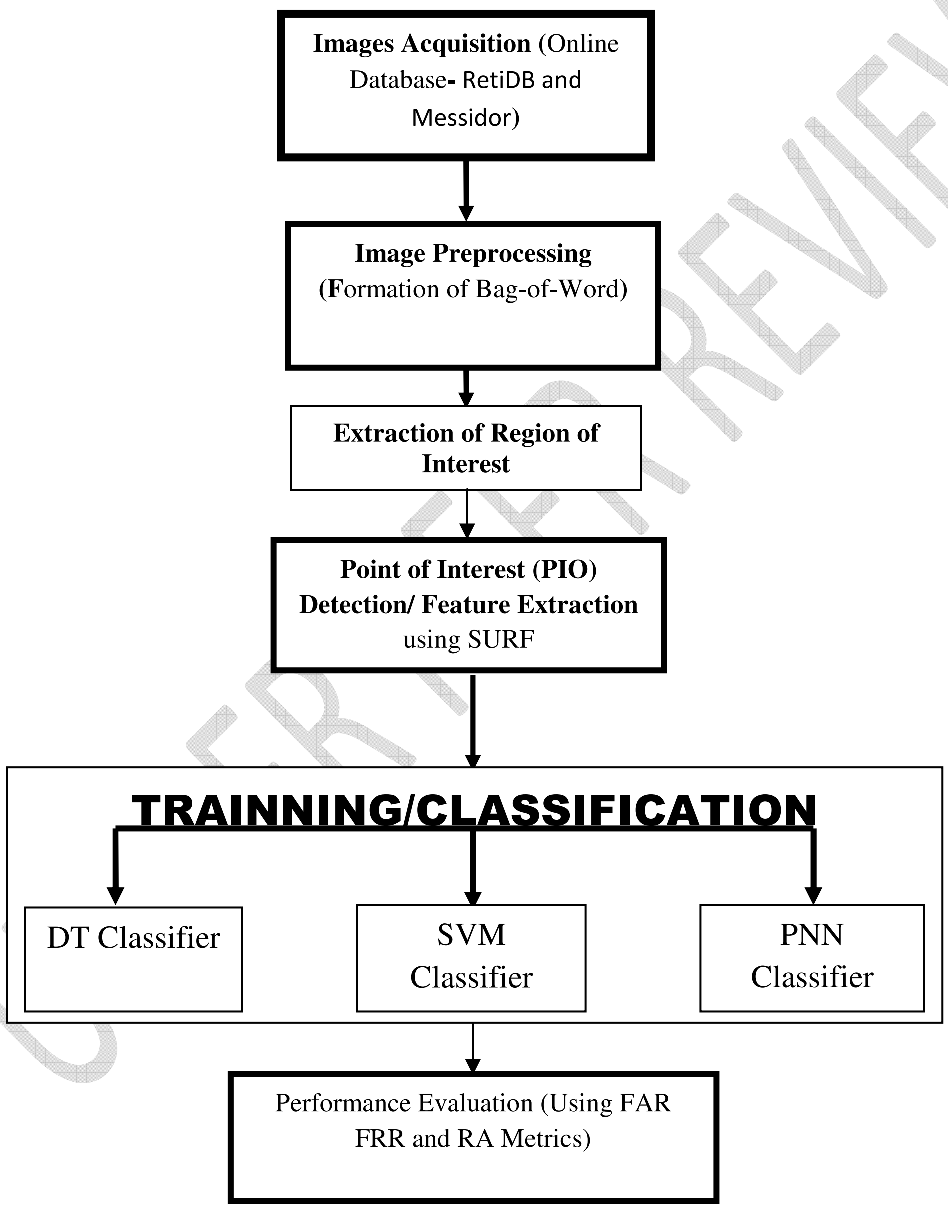

Figure 1: The Block Diagram of the Proposed System

The stages of the system development are as discussed in section 3.1 to 3.6

3.1 Data Acquisition

Online database is used which contains the images affected by Diabetes Retinopathy and the ones that are not affected. In this work, two well-known databases: RetiDB and Messidor(Xu, 2012)were adopted. Messidor database was chosen for training because it contains large number of clearly labelled sample images for each anomaly. It contains a total of 1200 images. The database RetiDB that we used for testing contains a total of 130 images with 22 normal images and 108 abnormal images (containing 1 or more anomalies).

3.2 Pre-processing of Images

The pre-processing of image involve formation of Bag-of-Word, Bag-of-Word is basically an adaptation of document retrieval method for image retrieval application.

3.3 Extraction of Region of Interest

To detect bright or red lesions, the specialists marked ROIs within the retinal images are considered as good representatives of bright or red lesions. For normal/control images, the entire retinal region represented in the image can be considered a ROI. The images with Diabetes Retinopathy-related lesion are marked by the specialists.

3.4 Point of Interest (PIO) Detection/Feature Extraction

The POI algorithm makes use of the concept of repeatability. We adopted “Speeded-Up Robust Features (SURF)” algorithm proposed in the year 2006 by Bay et, al. as POI detector. Features are extracted from the images using the result of point of interest (POI) acquired and they are then quantized and was later used to generate histogram.

3.4.1 Vector Quantization

Vector quantization creates visual dictionaries from the extracted features (POI). It first splits the high dimensional descriptors into regions using a clustering algorithm to determine the groups or regions of most important points. Each cluster is considered as a visual word of a dictionary. K-means algorithm is chosen as the clustering algorithm for this work.

3.4.2 Histogram Generation/Image Segmentation

After the creation of the “dictionary”, the POIs of each image are assigned to the nearest visual word. The POIs are assigned by calculating the distance between each POI and each visual word. Once the POI obtained the distances to all available visual words, it will be assigned to the visual word with the smallest distance. By determining how much POI are assigned to each of the “visual words”, we could create a histogram for each image by plotting the number of occurrences of POIs in each visual word.

3.5 Image Classification

The classification system consists mainly of two parts: formation of visual word histogram and classification. In this paper, we compare the performance of three different classifiers based on “exudates” anomaly. The retinal pathology images that have been represented with histograms are then classified into two groups, normal or abnormal (containing signs of Diabetic Retinopathy) using DT, SVM and PNN classifiers.

3.5.1 Decision Tree Classifier

According to Rasoul and David (1991) Decision Tree Classifier is one of the possible approaches to multistage decision making. It decomposes a multiclass problem into a series of binary class problems. The decision tree is constructed by applying a recursive procedure where each node representing one of the features is selected using a performance measure. Class labels are assigned based on a weighted vote.

3.5.2 Support Vector Machine Classifier

SVM classifier makes use of supervised training concept and associated learning algorithm is available. It predicts the appropriate output class corresponding to the given input data sets. After training SVM has the ability to classify an unknown input into the correct class. By applying SVM, a hyper-plane between two classes is constructed with maximum distance between the support vectors (Buddhiraju and Rizvi, 2010). SVM first transforms the binary data into a higher dimension feature space before separating the data into binary classes using a hyperplane.

3.5.1 A Probabilistic Neural Network (PNN)

PNN is a feed forward neural network, which was derived from the Bayesian Network and a statistical algorithm called Kernel Fisher discriminant analysis. The choice of PNN is determined by the fact that it is faster and more accurate than multilayer perceptron networks. A Probabilistic Neural Network is a multilayered feed forward network with four layers; Input layer, Hidden layer, Summation layer and Output layer. The first layer is used to compute the distance from the input vector to the training input vectors when there is an input. This produces a vector where its elements indicate how close the input is to the training input. The second layer sums the contribution for each class of inputs and produces its net output as a vector of probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 (positive identification) for that class and a 0 (negative identification) for non-targeted classes. In this paper, we apply PNN adopted by Radha and Bijee (2013) for training and classification of the network and this extract the exudates determining whether the retina is normal or abnormal.

3.6 Software Requirement Specification

When the user of the system (Ophthalmologist) gets to the system, he or she provides the username and the password, if successfully logs in, the user will be able to perform the following set of operations:

- Do eye test
- Set medication for the patient
- Set appointment for the patient
- View medication history of a patient
- Make subscription

The Sequence Diagram and the Architecture Diagram of the proposed system are as shown in figure 2 and 3 below.

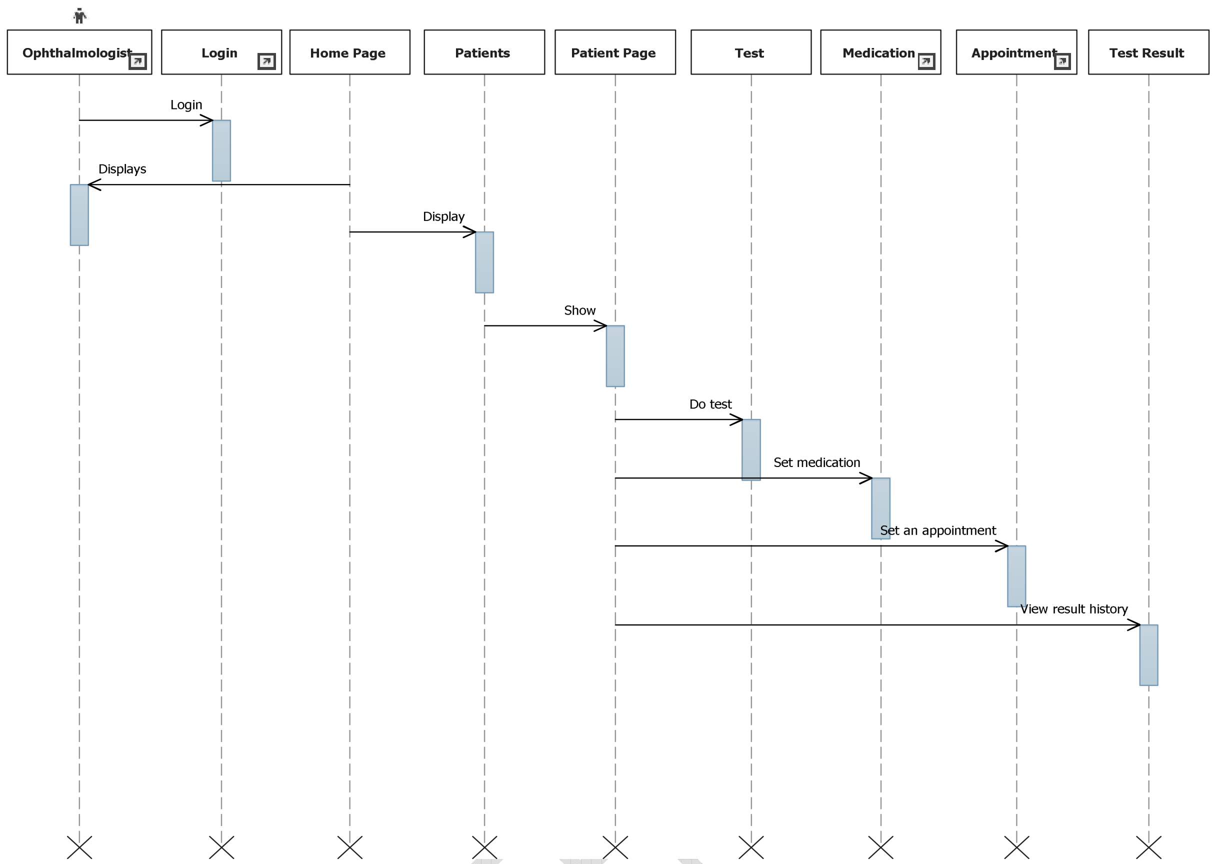

Fig. 2 Sequence diagram

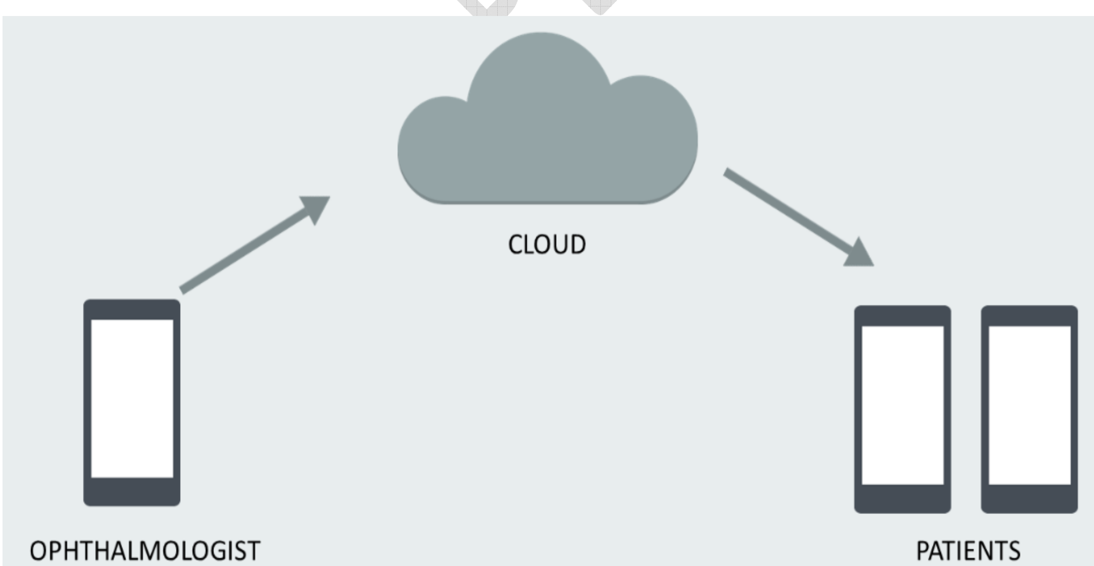

Figure: 3 Architecture Diagram of the Proposed System

4. RESULTS AND DISCUSSION

4.1 Overview of Results and Discussion

The program is written in MATLAB on machine specifications: Intel i7 3630QM 2.4GHz, 8GB RAM, GeForce GT650M 4GB graphics card.

4.1.1 Classification Results

We tested all 3 selected classifiers; DT, SVM and PNN for the exudates anomaly and used table 1 below to compare the results of the classifiers. Performance Metrics adopted are: False Acceptance Rate (FAR). False Rejection Rate (FRR) and Recognition Accuracy. The results are as indicated in table 1 below:

(i) False Acceptance Rate (FAR): This is the percentage of invalid face incorrectly accepted by the system and calculated as: FAR = (no of invalid inputs incorrectly accepted / all invalid inputs) * 100 i.e.

$FAR = (FP / (FP + TN)) * 100$

where FP indicates the number images that incorrectly accepted by the system.
TN indicates the number of images that are correctly rejected by the system

(ii) False Rejection Rate (FRR): This is the percentage of valid face incorrectly rejected by the system and calculated as:

FRR = (no of valid inputs incorrectly rejected / all valid inputs) * 100 i.e.

$FRR = (FN / (FN + TP)) * 100$

where FN indicates the number images that are valid but incorrectly rejected by the system.
TP indicates the number of images that are valid and are accepted by the system.

(iii) Recognition Accuracy (RA): This represents the number of images that are correctly recognized in percentage and calculated as:

$RA = 100 – (FAR + FRR)$

Table 1: Performance Evaluation Results of the Developed System

Classifiers	FAR	FRR	RA
DT	11.10	13.21	89.20
SVM	7.21	8.50	98.50
PNN	9.30	10.10	97.60

4.1.2 Mobile Application Results

Having tested the algorithm, the solution is deployed on web service to be used on mobile devices. When the image is been captured on the phone, it is sent to the cloud for the processing, the image is then analyzed on the cloud and the result is sent back to the user of the application. On the user’s phone, the result of previous test could be seen as a test history. The results of the developed system are as shown in figures 4.1 to 4.4 which include; the Image Preview page; Ophthalmologist Home page; Medication page and Results History page of the developed mobile application respectively.

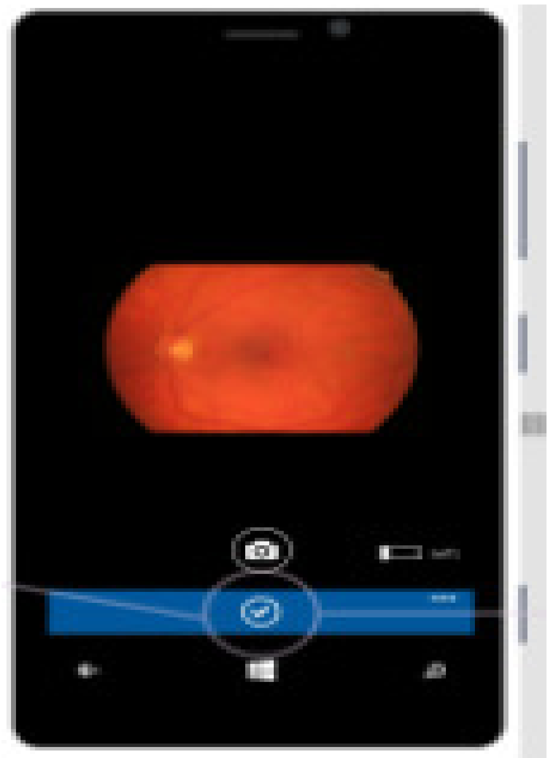

Figure 4.1: Image preview page

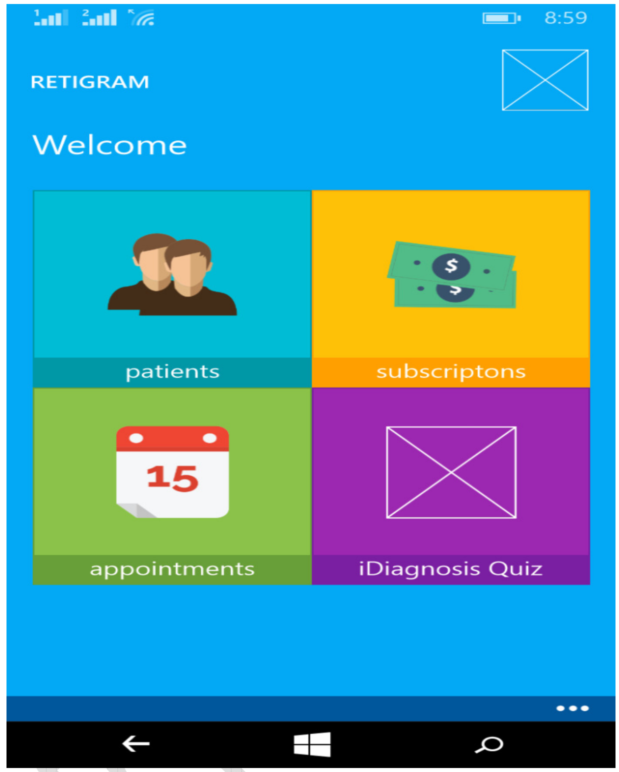

Fig. 4.2 Ophthalmologist Home page

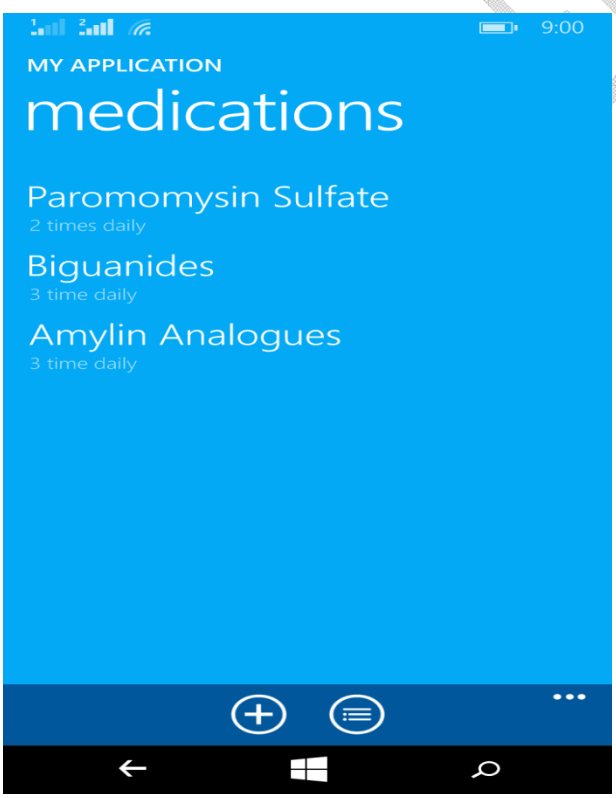

Figure 4.3: Medication Page

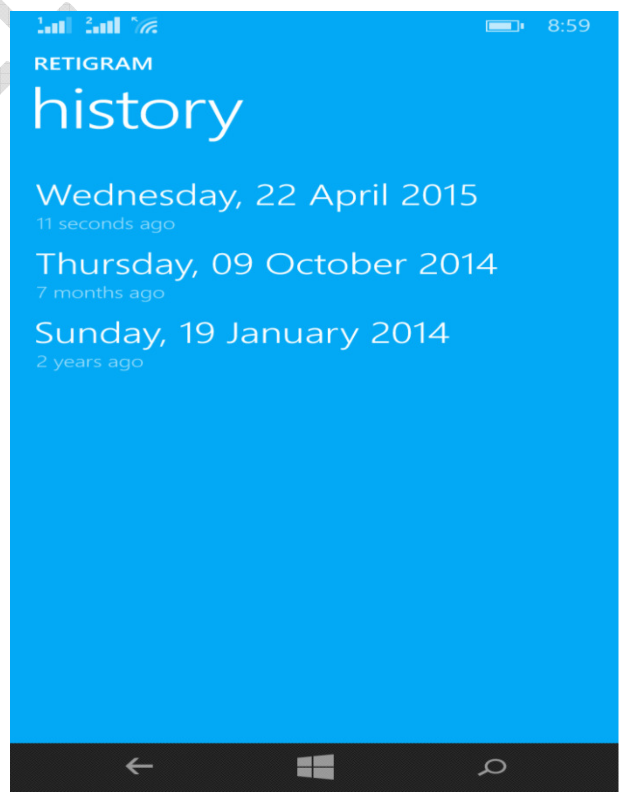

Figure: 4.4 Result History Page

5. CONCLUSION, RECOMMENDATION AND FUTURE WORK

In this paper an evaluation of performance of Decision Tree (DT), Support Vector Machine (SVM) and Probabilistic Neural Network (PNN) Classifiers in Diabetes Retinopathy Detection was carried out. From the experimental results, it is discovered that among the three classifiers, the SVM Classifier performs the best. However, a mobile phone application was developed using object oriented programming methodology; the application provides the interface needed for an ophthalmologist to implement the algorithm adopted in detecting Diabetes Retinopathy. The mobile phone based detection of Diabetes Retinopathy will however make the carrying out of the Diabetes Retinopathy test available to the masses, most especially in the developing countries. This work is recommended to the Health Care centres, Pharmaceutical shops, Driver Licensing centers, local community and individual families. Future work will be targeted towards using the developed system to classify other Diabetes related diseases.

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