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PREDICTIVE PATIENT MONITORING AND ANALYSIS FROM CLINICAL DATA USING OPTIMIZATION TECHNIQUES

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ABSTRACT — Support Vector Machine (SVM) is an emerging data classification technique that is valuable in healthcare applications. In the SVM, the classification is generated from the training stage using the vital sign data. The SVM optimization method accurately identifies abnormality of physiological data, arising due to patient deterioration and achieves the highest accuracy than other classification methods. But, Support Vector Machine without feature selection lowers the performance of SVM. Thus, the proposed system implements an intelligent optimization method for feature selection called Particle Swarm Optimization (PSO). To perform feature selection along with classification model which concurrently resolves the parameter values while discovering the feature subset that increases the classification accuracy and their performance in terms of accuracy, sensitivity and specificity is measured in Receiver Operating Characteristics (ROC) Plots. Thus, the above system can developed in MATLAB Tool.

KEYWORDS- Predictive monitoring, SVM Classifier, Particle swarm optimization (PSO).

I. INTRODUCTION

The majority of patients in the hospital are to be monitored using wearable sensors for the purposes of predictive care.

Prediction is an approach that is widely used in healthcare field which helps to identify the events that not occurred so far. The healthcare providers in the medical domain are getting more prevalent since it helps to prevent further chronic disease such as stroke, heart disease, diabetes, obesity and arthritis . The aim of the predictive in data mining is considering wearable sensors acquired from vital signs in human bodies. This classification approach is also known as supervised learning models where it includes feature extraction along with training and testing steps while performing the prediction of the data behavior. The vital sign parameters are: Oxygen Saturation (SpO2), Heart Rate (HR), Blood Pressure (BP) and Respiratory Rate (RR) can be seen continuously to build a predictive model in healthcare. Now-a-days wireless pulse oximeter is used for continuous measurement in real world by secure transmission of signals [11-13]. Prediction of the abnormality in its early stage followed by treatment can reduce the chronic disease. So classification of physiological data is most important, in order to classify what type of disease really the patients suffered from. The patients having their physiological conditions acquired continuously using low-power wearable sensor which explores the principle machine learning approach to provide early warnings of physiological determination so that the high degree of predictive care can be provided. A two-class classification is an approach used for identifying the patient deterioration using the result to train the classifier which separates the normal data from the abnormal data. Here the number of misclassification i s lower in 2-D dataset than 4-D dataset [1-3].

A system has been applied to jet engine vibration analysis and audio signal segmentation where the computational performance and accuracy has been demonstrated [5-6].A device named visensia has been developed in real time for prediction of the early detection of the patient deterioration [7].

The chronic disease generally cannot be prevented by vaccines or cures by medication and the disease might progress steadily or remain stable such as cardiovascular disease (CVD), cancer, kidney disease, diabetes etc., The proposed system should posses an optimization method for feature selection called Particle Swarm Optimization (PSO) which determines the parameter values while discovering the feature subset that increases the classification accuracy of +2 to 3% in -terms of predictive care for aged peoples.

II. OVERVIEW OF THE ARCHITECTURE

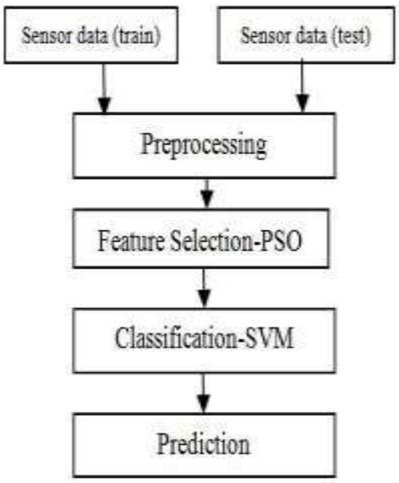

Fig 1. Steps involved in Predictive diagnosis

In the figure 1, the raw sensor data is collected and the sensor data is provided for both training data and testing data in order to learn the system and to make a model of features for the real-world usage model and make the prediction result. The main steps consist of pre-processing, feature selection and modeling the data from the input features to perform the prediction task.

III. ARCHITECTURE

The overall architecture of the proposed system shown in the figure 2.

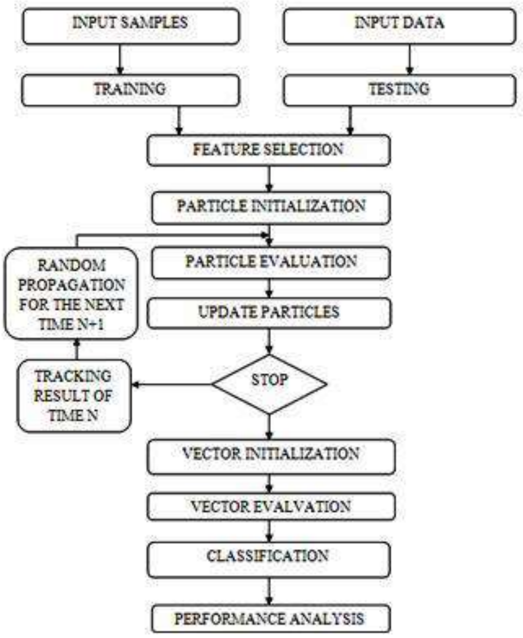

Fig 2. The flow chart of the parameters selection of SVM with PSO algorithm

In the figure 2, the input samples/Input data has been taken for Training/Testing process and then Feature selection (Particle Swarm Optimization) has been performed to be optimized. The optimization methods are implied, which simultaneously determines the parameter values while discovering a subset of features to increase SVM classification accuracy. The optimization methods with SVM are used to choose appropriate subset features and SVM parameters [4]. Vector initialization and vector evaluation has to be performed then classification of the physiological data will be useful to find out the chronic disease such as diabetes and the

Performance analysis is performed using Receiver Operating Characteristics (ROC Curve).

IV. FEATURE SELECTION METHOD

Feature selection is done for optimizing the features of collected data and it can be done through particle swarm optimization (PSO) and it is one of the population- based optimization technique which is shown in the figure 3.

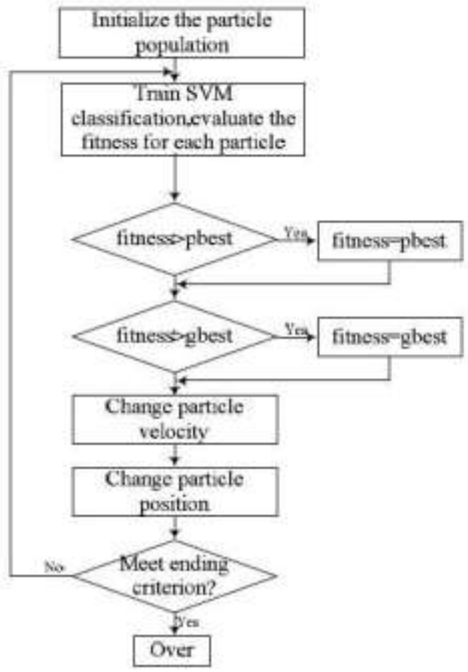

Fig 3.System Architecture of Particle Swarm Optimization

The initialization of the particles is to randomly generate initial part icles and then the support vector machine (SVM) will classify the selected particles similarly; it evaluates the fitness which measures the fitness of each particle in the population.

When fitness> pbest it checks for fitness = pbest else goes to next step and then it checks for fitness > gbest and it checks for fitness=gbest.

Update is done continuously by computing the velocity of each particle. Construction is done for each particle, so that it moves to the next position. Termination stops the algorithm if termination criterion is satisfied then it will return to Step 2 otherwise the iteration will be terminated if the number of iteration reaches the predetermined maximum number of iteration.

V. CLASSIFICATION USING SVM

Generally, Machine Learning takes a known set of input data and known responses to the data which seeks to build a predictor model that will generate reasonable predictions for the response to new data acquired. The support Vector Machine (SVM) maps features non-linearly into n dimensional feature space when provided with a feature set and then a kernel is introduced in the SVM algorithm, the inputs in the form of scalar products [10]. A dot product of input data mapped into the higher dimensional the feature space by transformation Φ is represented by a kernel function which is defined as $k(xi, xj) = \Phi(xi) \cdot \Phi(xj)$. The Radial Basis function is basic kernel function and it is given as follows:

$k(xi, xj) = \exp(-\, xi - xj / 2\sigma),\ i = j = 1, 2, \ldots, n$

where σ is the width parameter associated with the Gaussian kernel.

Proper parameter setting in the kernels increases SVM classification accuracy. By tuning C and gamma (γ) parameters in SVM model with RBF kernel, PSO will search for the optimized combination for the better performance [8].

A set of features is in the form of a vector and the features vectors define the hyper plane and the optimal hyper plane is constructed by the SVM with the aim to separating vector clusters with a class of attributes (positive) on one side of the plane and with different attributes on the other (negative).The margin in the SVM represents the distance between hyperplane and support vectors. The SVM analysis tries to positions the margin in where the space between it and support vectors are maximized.

VI. PERFORMANCE ANALYSIS

The prediction task includes the subtask of raising alarms,and diagnosis where a decision making process categorizes the data into different groups that depends on the diseases. The performance of the method is constructed with the sensitivity,specificity, and accuracy of the results. The ROC (Receiver Operating Characteristics) plots [9] can be defined in four quadrants as true-positive (TP), true-negative (TN), falsepositive (FP), and false-negative (FN).

VII. RESULTS

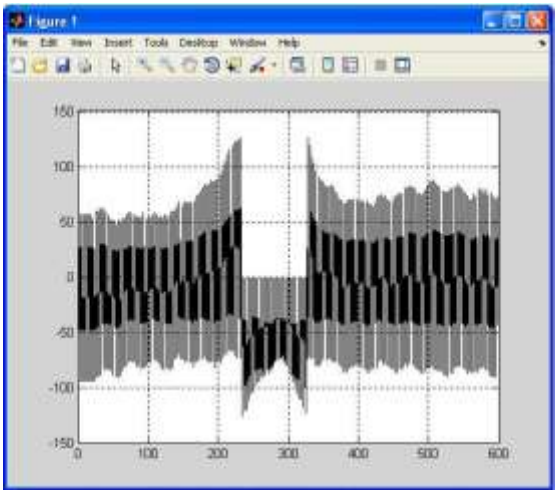

Fig 4. Output of training and test data

The figure 4 shows the ECG Signal [14] from Test (New data) and Train folder(Normal data) Patient.

Fig 5. Patient's data

The figure 5 shows the number of analyzed patient'sdata will be displayed in MATLAB.

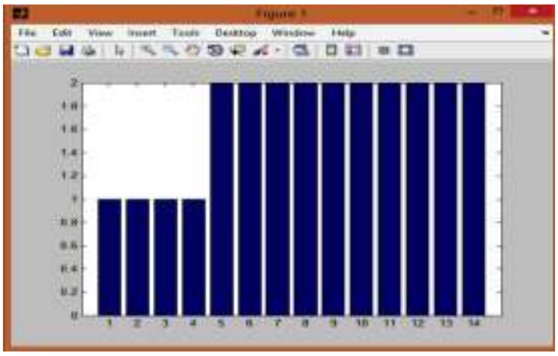

Fig 6. TARGET GRAPH

The figure 6 shows the graph with normal and abnormal data.

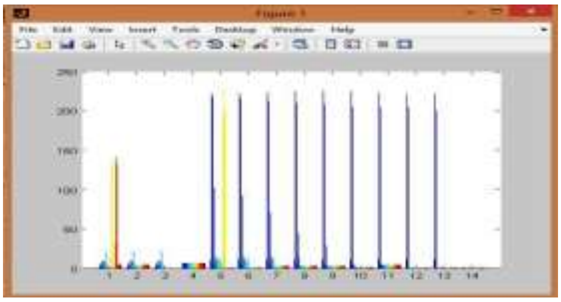

Fig 7. FEATURE VECTOR

The figure 7 shows the feature vector of normal and abnormal data of the patients.

A. Classifier Performance

In Table I, the overall results after 50 experiments, at "optima l" threshold for each experiment .Here, we have included the results for conventional SVM parameter optimization referred to as SVM-0 in the table, for comparison with results obtained using the proposed parameter optimization technique exploiting partial AUC. The SVM using the proposed optimization method achieves the highest accuracy and partial AUC in comparison to the other methods. Therefore, the SVM is higher than that for comparator methods.

Table I Novelty detection performance, one standard deviation

Classifier	Accuracy	Partial AUC	Sensitivity	Specificity
GMM	0.90 ± 0.02	0.24 ± 0.02	0.97 ± 0.02	0.84 ± 0.05
Kernel	0.91 ± 0.02	0.26 ± 0.01	0.94 ± 0.04	0.87 ± 0.04
GP	0.90 ± 0.02	0.26 ± 0.01	0.91 ± 0.05	0.89 ± 0.04
SVM-0	0.90 ± 0.01	0.26 ± 0.02	0.92 ± 0.03	0.87 ± 0.04
SVM	0.94 ± 0.01	0.28 ± 0.03	0.96 ± 0.02	0.93 ± 0.02

The patient vital sign data has been acquired continuously for observation and the alert is heard at the fifth set of observation in the conventional early warning system (EWS) but the abnormality falls between second or third observation (i.e., abnormally high HR peaking at 130 beats/min) which is not been noted. However, this serious deterioration is clearly shown in support vector machine (SVM) and in Gaussian mixture model (GMM). And therefore the patient is immediately admitted to the ICU ward under the emergency condition.

Fig 8. Comparative results of novelty detection approaches

The figure 8 depicts the performance of generative and discriminative approaches for predictive monitoring has been demonstrated from abnormal patients who were ending with ICU, death etc., Therefore, the goal is to identify the patient deterioration as early as possible, so that the preventative action for the patient will be provided which is the advance of emergency condition.

VIII. CONCLUSION

This project aims an automated method to detect the abnormality of physiological data by applying machine learning concepts in the field of medical diagnosis. This work is carried out in selection and exploration of a feature extraction technique and the ECG signal for various patients with the help of database of physiological signals [16] containing both normal and abnormal signals and viewed in the MATLAB 2013a Software. Work consists of training data, test data, feature extract ion such as PSO, which is feed as the input to the classifier for the predict ion of abnormality so that the chronic diseases can be identified by the experts.

IX. FUTURE WORK

The next phase of work is to perform the feature selection technique and the heart rate(HR) signal, Respiratory Rate(RR) Signal, Systolic Blood Pressure (SysBP) signal and Pulse oximeter (SpO2) signal is taken from the Clinical database and those signals are taken as a feature vector representation of the data. With this data feature extraction using particle swarm optimization and classification using support vector machine will be implemented to achieve high accuracy which is applied to the chronic disease.

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