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Classification of Respiration Disorders with its Effectiveness under Different Treatments for Sensor Dataset

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Abstract: Respiratory disease is a medical term that encompasses pathological conditions affecting the organs and tissues that make gas exchange possible in higher organisms, and includes conditions of the upper respiratory tract, trachea, bronchi, bronchioles, alveoli, pleura and pleural cavity, and the nerves and muscles of breathing. Respiratory diseases range from mild and self-limiting, such as the common cold, life-threatening entities like bacterial pneumonia, pulmonary embolism, and lung cancer.In Upcoming days current means of diagnosis are obtrusive and ill-suited for real time applications. The respiration disorder features classification was achieved through various classification techniques. However, Support Vector Machine (SVM) and Decision Tree Bagging (DTB) based classifier does not have better accuracy for respiration disease prediction and also for cloud services to have flexible capacity for both storage and signal processing. Artificial Neural Network (ANN) and K-Nearest Neighbor (KNN) classifiers are having high computational cost. And also the above mentioned classification techniques have high sensitivity, time complexity is high due to long training process, and also it uses only offline data loggers. So we propose effective classification techniques with convenient and low cost automatic diagnosis method that uses wearable MEMS sensor technology. This sensor technology detects different types of respiratory disorders by means of changes in diameter of chest wall during breathing and also their parameters are computed. Then features are extracted and selected by Correlation-based Feature Selection (CFS). These features are classified by using Learning Vector Quantization (LVQ) and Modified-Fuzzy min-max classifier using Compensatory Neurons(M-FMCN) to get more accuracy, to reduce sensitivity, to use online data loggers, to reduce time complexity and to reduce the computational cost compared with SVM, DTB, ANN and KNN. We also propose some effective and drug free Breathing Therapy which helps patients to recover from respiratory problems without medicines. Finally, the experimental results show that the effectiveness of the proposed classification techniques compared with the other classification techniques.

Keywords: Respiratory disease, Support Vector Machine(SVM), Decision Tree Bagging (DTB),Artificial Neural Network (ANN), K-Nearest Neighbor (KNN),Feature Selection, Feature Classification, Learning Vector Quantization (LVQ), Modified-Fuzzy min-max classifier using Compensatory Neurons(M-FMCN).

1. INTRODUCTION

Data mining (sometimes called data or knowledge discovery) is the process of analyzing data from different perspectives and summarizing it into useful information - information that can be used to increase revenue, cuts costs, or both. Data mining software is one of a number of analytical tools for analyzing data. It allows users to analyze data from many different dimensions or angles, categorize it, and summarize the relationships identified. Technically, data mining is the process of finding correlations or patterns among dozens of fields in large relational databases. It allows users to analyze data from many different dimensions or angles, categorize it, and summarize the relationships identified. Technically, data mining is the process of finding correlations or patterns among dozens of fields in large relational databases.

Classification is a data mining function that assigns items in a collection to target categories or classes. The goal of classification is to accurately predict the target class for each case in the data.Respiratory disease is a medical term that encompasses pathological conditions affecting the organs and tissues that make gas exchange possible in higher organisms, and includes conditions of the upper respiratory tract, trachea, bronchi, bronchioles, alveoli, pleura and pleural cavity, and the nerves and muscles of breathing. Respiratory diseases range from mild and self-limiting, such as the common cold, life-threatening entities like bacterial pneumonia, pulmonary embolism, and lung cancer.

In this paper the use of motion MEMS sensors to detect eight types of breathing problems with modeling the small

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movements of the chest wall compartments that occur during expansion and contraction of the lungs in each respiration cycle. Initially sensors are mounted on patient's rib cage and abdomen and this MEMS sensors detects various types of breath disorders such as Bradypnea, Tachypnea, Kussmaul, Cheyn-stokes, Obstructive Sleep Apnea (OSA), Biot's breathing, Sighing and Apneustic. Sensed data streams are dividing into Fixed-size Non-overlapping Window (FNSW) and Fixed-size Overlapping Window (FOSW). Then the features such as Mean, Standard Deviation, Respiration rate and time, Total variability and Number of Peaks are extracted. The features are selected by using filter method called Correlation-based Feature Selection (CFS). The selected Features are classified by using various algorithms including Decision Tree Bagging (DTB), k-Nearest Neighbors (KNN), Support Vector Machines (SVM) and Artificial Neural Networks (ANN). And the features are transferred to cloud through interfaces by using BLE. Then physicians can access the data anytime which are stored in cloud. However Support Vector Machine (SVM) and Decision Tree Bagging (DTB) based classifier does not have better accuracy for respiration disease prediction and also for cloud services to have flexible capacity for both storage and signal processing. Therefore, an effective classification technique is required to improve the classification accuracy.Artificial Neural Network (ANN) and K-Nearest Neighbor (KNN) classifiers have greater computational cost. To overcome these problems we propose effective classification techniques with convenient and low cost automatic diagnosis method that uses wearable MEMS sensor technology.

2. LITERATURE SURVEY

Atena Roshan Fekr et al [1] proposed Respiration Disorders Classification with Informative Features for m-Health Applications. In this paper, they introduced a wearable MEMS sensor technology. In which the changes in anterior-posterior diameter of the chest wall during breathing detects by using motion of sensors as well as extracts respiratory features used for breathing disorders classification. They detect eight types of breathing problem with one and two accelerometer accordingly. The detected data streams are divided into fixed size overlapping and non-overlapping window which are represented as class. The features are extracted by using correlation feature selection filter method. Then features are classified by DTB, SVM, KNN, ANN classification methods. Then accuracy, sensitivity and specificity are computed. The classification methods are not more flexible for cloud services to have high storage and signal processing speed. The effective drug free breathing therapy is not discussed.

F. Mancini et al [2] proposed Classification of Postural Profiles among Mouth-breathing Children by Learning Vector Quantization. In this paper, they proposed LVQ classification method to determine features from postural profiles that are taken by mouth breathing children. LVQ is SOM based model it uses data that are derived by using posture profiles and these are divided into clusters in which the data variables in same clusters are in some correlated. To make slightly changes the neurons weights are increased. Then neighbourhood functions are computed that is used to determine how neurons are strongly connected to each other. Smallest Euclidian distances are computed and then for different rates LVQ classification is performed. This LVQ classification method is used only for postural profile shown by mouth breathing children.

Majid Janidarmian et al [3] proposed Analysis of Motion Patterns for Recognition of Human Activities. In this paper, they discussed about wearable sensor that are used to recognize human activities. Accelerometer sensors are sensed data by mounting it on human body. The features are calculated and segmented as fixed size overlapping and non-overlapping window. The features are extracted from these windows of data. Then the features are classified by NN, SVM, DTB techniques and verified to provide significant results. There is no feature selection process in order to select specific features.

Julien Oster et al [4] proposed Semi-supervised ECG Ventricular Beat Classification with Novelty Detection Based on Switching Kalman Filters. Automatic processing and accurate diagnosis of pathological Electrocardiogram (ECG) signals are remains a challenge. A model-based automate ECG filtering method to ECG data from healthy peoples has been applied to accurate online filtering and analysis. This paper proposed filtering and analysis method for normal and ventricular heartbeats including morphologies. A Switching Kalman Filter technique is used to enable the automatic selection of mostly like heartbeats while simultaneously filtering the signal with prior knowledge. Novelty detection is used for detection of unknown morphologies which is denoted as X-factor. Switching Kalman Filter is more complicated in noisy environments.

Yee Siong Lee et al [5] proposed Monitoring and Analysis of Respiratory Patterns Using Microwave Doppler Radar. In this paper, non-contact detection feature of Doppler radar provides unobtrusive respiration detection and monitoring. This technique avoids the use of physical sensors that are mounted on patient's body. Microwave Doppler radar is used to capture various dynamics of breathing patterns including respiration rate. In addition to that, inhalation and exhalation flow patterns under various breathing disorders are also investigated and also tidal volume is computed for different breathing disorders. Non-contact Doppler radar detection provides less accuracy than contact method detection. Doppler radar may be affected by environmental conditions.

Peter Varady et al [6] proposed a novel method for the detection of Apnea and Hypopnea events in respiration signals. This paper introduces an innovative signal classification method that is capable of online detection of presence or absence of normal breathing. Here four different neural networks are presented to recognize the different patterns in respiration signals. It detects signal without using patient specific information and moderates computational time. Apnea and Hypopnea are identified by using normal breathing signal which is normalized. But heart rate and large signal database are needed.

Mila Kwiatkowska et al [7] proposed analysis of informational and technological requirements for the respiratory therapy workshops in Peru. This paper investigates the use of low cost and low resource methods for at-location and learner-centered medical education and training. This paper helps to us to learn about medical therapy for avoiding respiratory disorders.

Sasan Ahdi Rezaeieh et al [8] proposed microwave system for the early stage detection of congestive heart failure. In this paper, the design and implementation of an automated ultrahigh frequency microwave based system for CHF detection and monitoring is presented. The hardware of the system comprises a controllable scanning stand, a specifically designed unidirectional antenna, a portable custom-made microwave transceiver and a laptop. The software part of the system includes control, signal processing and visualizing algorithms. To detect CHF, the system is designed to vertically scan the rare side of human torso. The collected data from the scanning is then visualized in the time domain using the inverse Fourier transform. These images show the intensity of the reflected signals from different parts of the torso. Using a differential based detection technique a threshold is defined to differentiate between healthy and unhealthy cases.

Ching-Wei Wang et al [9] proposed unconstrained video monitoring of breathing behaviour and application to diagnosis of sleep Apnea. This paper presents a new real-time automated infrared video monitoring technique to detect breathing anomalies. The algorithm uses a novel persistence luminance model that helps to reinforce subtle breathing movements, an activity level to segment the video, and a novel activity template to classify motion events. Human breath activity by adding audio and human sleep behavior are not discussed in this technique.

Yingying Zhenga et al [10] proposed predicting arterial stiffness from radial pulse waveform using support vector machines. In this paper, a new approach is introduced to measure arterial stiffness by radial augmentation index based on implementation of SVM which is used for classification of radial pulse waveform. Here radial pulse signals are decomposed into time-frequency representations using DWT and wavelet scale-energy are calculated. This is used to predict optimum classification method. This features achieved high classification accuracies.

Om Prakash Yadav et al[11]proposed smoothening and segmentation of ECG signals using total variation denoising-minimization-majorization and bottom-up approach. This paper tries to reduce unwanted signals present in ECG signals through majorization-minimization approach to optimize total variation in the signals. The denoised signals are then segmented by using bottom-up approach. In this method accuracy is increased with increase in number of segments.

Laiali Almazaydeh et al [12] proposed Apnea detection based on respiratory signal classification. This paper introduces an automated method to identify the presence of sleep Apnea based on the acoustic signal of respiration. The characterization of breathing sound carried by voice activity detection algorithm which is used to measure energy of acoustic respiratory signal during breathing. But in order to detect sleep Apnea in real time, the proposed algorithm need to be improved and adjusted by adding calibration procedures to run on an FPGA.

Oliver Grundmanna et al [13] proposed mind-body therapies for functional bowel disorders. In this paper, mind-body therapies are discussed for functional bowel disorders. The purpose of this paper is to describe the scientific knowledge based on available mind-body therapies and examine potential benefits of using such therapies. In this paper, the four common mind-body therapies such as yoga, hypnotherapy, cognitive behavioural therapy and biofeedback are proposed.

Lili Erazo et al[14]proposed a benchmark on automatic obtrusive sleep Apnea screening algorithms in children. In this paper, new algorithms are developed which can perform automatic OSA screening in children. Initially the features are extracted and measured from the signals which are taken by using ECG and EEG. Then the features are selected by using selection algorithms such as SVM, NN and Logit model. This paper concluded that OSA screening models in adults are not good enough to be used in children.

Baiying Lei et al[15]proposed content-based classification of breath sound with enhanced features. In this paper, the identification and classification of respiratory disorders based on the enhanced perceptual and cepstral feature set (PerCepD) is proposed. The hybrid PerCepD feature can capture the time-frequency characteristics of breath sound. The classification models based on SVM, ANN are adopted to achieve automatic detection from breath sound data. This method can be improved by using genetic algorithm, optimal selection and parameter optimization techniques.

Trung q. Leet al [16] proposed wireless wearable multi-sensory suite and real-time prediction of Obstructive Sleep Apnea (OSA) episodes. In this paper, Dirichlet process based mixture Gaussian Process (DPMG) is introduced to predict sleep Apnea based on analyzing complex cardiorespiratory signals gathered from a custom-designed wireless wearable multi-sensory suite. For feature classification SVM classifier is used. We can improve OSA prediction method by using various classification methods.

G Dorfman Furman et al [17] proposed Electrocardiogram Derived Respiration during Sleep. This paper is used to measure ECG Derived Respiration (EDR) in order to extend the capabilities of ECG-based sleep analysis. Here R-Wave Amplitude (RWA), R-Wave Duration (RWD) and QRS area are extracted from ECG signal in time series. EDR frequency is correlated with directly measured respiratory frequency. EDR signals are used to characterize Apnea and identify OSA. However, standard deviation calculation is not computed in this method.

Argyro Kampouraki et al[18]proposed Heartbeat Time Series Classification with Support Vector Machines. In this paper, heartbeat time series are classified using support vector machines (SVMs). Statistical methods and signal analysis techniques are used to extract features from the signals. The SVM classifier is favourably compared to other neural network based classification approaches by performing leave-one-out cross validation. Feature selection is major problem in this method.

Vinh Phuc Trana et al [19] proposed non-contact dual pulse Doppler system based real-time relative demodulation and respiratory & heart rates estimations for Chronic Heart Failure (CHF) patients. This paper presents novel real-time demodulation technique and estimations algorithms for the non-contact physiological vital signs assessments for CHF patients based on a patented novel non-contact bio-motion sensor. The propose algorithms analyse the non-contact bio-motion signals and estimate the patient's respiratory and heart rates. This method has good accuracy for twenty CHF patients in the complexity of sleep environment.

Dolly Gupta et al[20]proposed detection of Gallbladder stone using Learning Vector Quantization Neural Network (LVQNN). In this paper, a biomedical study based on LVQNN has been proposed in order to classify gallbladder stone. There is also detail description of patient's symptoms. Clustering is used to separate all patients into affected and not affected. Then classification is done to categorize the patients having disease and normal patients. This is technique is improved by classification to classify patients having particular disease from different diseased patients during clustering.

Martin s. Holmeset al[21]proposed Acoustic Analysis of Inhaler Sounds from Community-Dwelling Asthmatic Patients for Automatic Assessment of Adherence. This paper presents a method of automatically evaluating inhaler adherence through acoustic analysis of inhaler sounds. An acoustic monitoring device was employed to record the sounds patients produce while using a Diskus dry powder inhaler, in addition to the time and date patients use the inhaler. An algorithm was designed and developed to automatically detect inhaler events from the audio signals and provide feedback regarding patient adherence. This method provides real-time personalized medical care for chronic respiratory illness.

Roger Dzwonczyk et al [22] proposed a method of powering a Nebulizer manually using parts locally available in Honduras. The design consists of bicycle pump, two pump needles, plastic medical tubing, a soccer ball, air filter and a nebulizer/mask, all connected in series. A common motorcycle fuel filter serves as the air filter in the system. Pumping the foot operated bicycle pump generates airpressure/flow in the system. The soccer ball acts as a low-pass mechanical compliance filter to smooth the time-varying pressure/flow pattern. In this paper, patient's breathing performance also evaluated and improved.

Mohammad Hasan Imam et al[23]proposed analyzing Systolic-Diastolic Interval Interaction Characteristics in Diabetic Cardiac Autonomic Neuropathy (CAN) Progression. This paper is used to analyse the changes in mechanical function of ventricles in terms of Systolic-Diastolic Interval interaction (SDI) from a surface ECG to assess the severity of CAN progression. The severity of CAN was determined by Ewing's cardiovascular autonomic reflex tests. It helps the physician to determine an efficient treatment plan for the patient if diagnosed at an early stage of CAN.

Keegan Kosasih et al[24]proposed Wavelet Augmented Cough analysis for Rapid Childhood Pneumonia Diagnosis. This paper proposed a novel cough feature extracted by wavelet-based crackle detection in lung sound analysis. Then these features are then combined with other features such as Mel Cepstral coefficients and non-Gaussianity index to develop classification method. It increases the performance such as sensitivity and specificity.

Danielle F. Pace et al [25] proposed a Locally Adaptive Regularization based on Anisotropic Diffusion for Deformable Image Registration of Sliding Organs. In this paper, they apply the method for respiratory motion estimation in longitudinal thoracic and abdominal computed tomography scans. This algorithm uses locally adaptive diffusion to determine the direction and magnitude of expected sliding boundary. Potential clinical applications of this method include longitudinal change detection and radiotherapy for lung or abdominal tumours, especially those near the chest or abdominal wall. This algorithm modelled sliding around lungs and liver but not along entire abdominal wall.

3. PROPOSED METHODOLOGY

In the proposed technique, sensors are used to detect eight types of breathing problems with modelling the small movements of the chest wall compartments that occur during expansion and contraction of the lungs in each respiration cycle. Initially sensors are mounted on patient's rib cage and abdomen and this sensors detects various types of breath disorders such as Bradypnea, Tachypnea, Kussmaul, Cheyn-stokes, Obstructive Sleep Apnea (OSA), Biot's breathing, Sighing and Apneustic. Sensed data streams are dividing into Fixed-size Non-overlapping Window (FNSW) and Fixed-size Overlapping Window (FOSW). Then the features such as Mean, Standard Deviation, Respiration rate and time, Total variability, Number of peaks are extracted. The features are selected by using filter method called Correlation-based Feature Selection (CFS). The selected features are classified by using various algorithms including Decision Tree Bagging (DTB), k-Nearest Neighbors (KNN), Support Vector Machines (SVM) and Artificial Neural Networks (ANN). In this proposed system we include two more classification algorithms namely Learning vector Quantization (LVQ) and Modified Fuzzy Min-Max Classifier using compensatory Neurons (M-FMCN).And

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the features are transferred to cloud through interfaces by using BLE. Then physicians can access the data anytime which are stored in cloud. Drug free breathing therapy is considered which an effective and drug-free treatment and also cost of diagnosis and medical care are less.

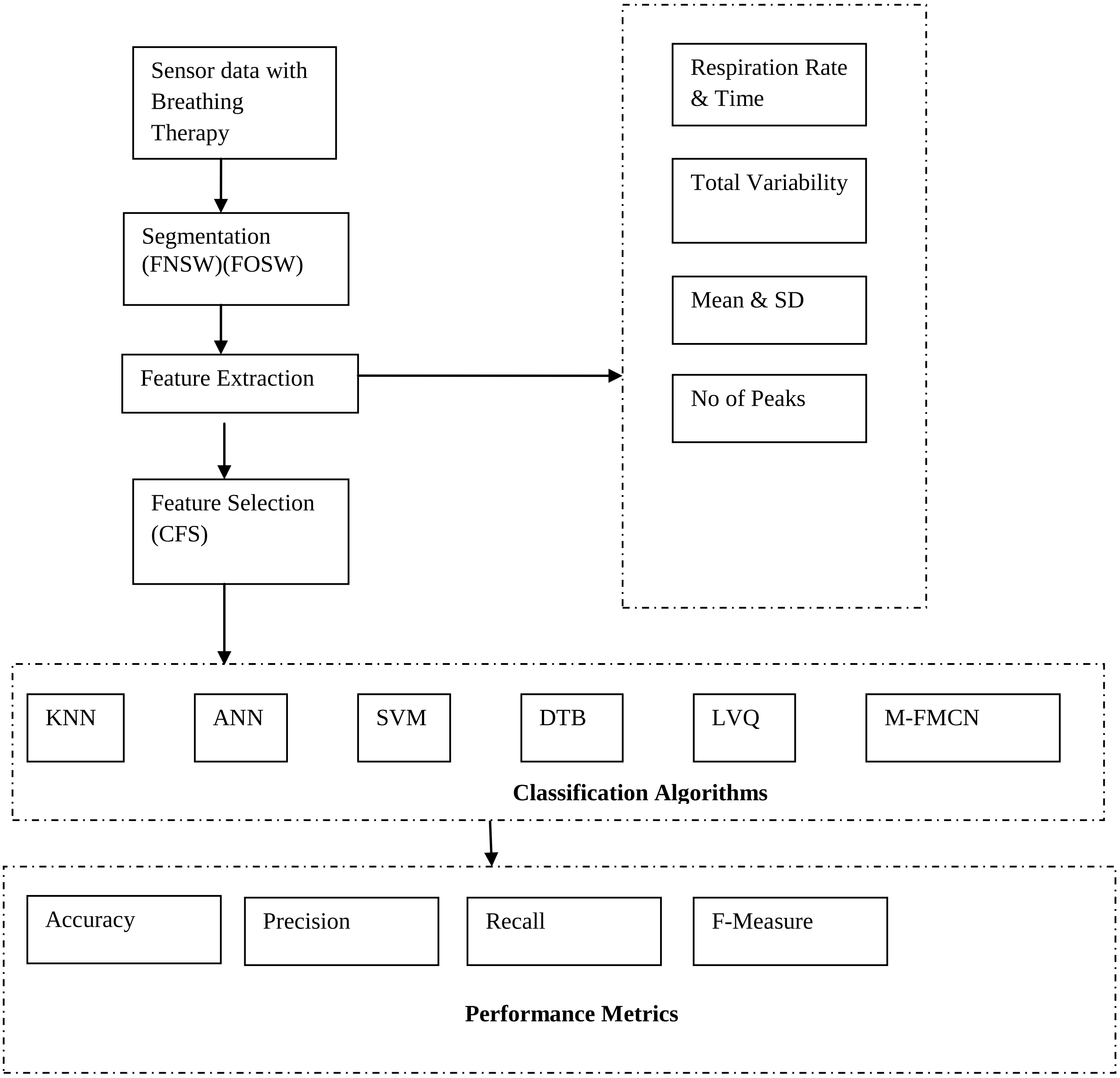

Fig 1:Overall Process Flow Diagram

3.1 Learning vector quantization

In this classification, initially assign weight vectors to the first m training vectors, where m is the number of different categories and set a(0). For each training input vector find the new vector J in which Euclidean distance is a minimum and updates their weights as follows:

Input vector, $F = (f_1, f_2, f_3, \dots, f_n)$(1)

Weight vector for j^{th} vector is,

$$w_j = (w_{1j}, w_{2j}, \dots, w_{nj}) \qquad (2)$$

Euclidean distance between the input vector and weight vector is denoted as:

$$D(j) = \sqrt{\sum_{i=1}^{n} (P_i - w_{ij})^2} (3)$$

The correct category for input F is T and Category represented by j^{th} vector is C_j. If $T = C_j$ then update the weights of J vector as:

$$w_j(new) = w_j(old) + a\left(F - w_j(old)\right)(4)$$

The above equation defined as move the weight vector toward the input vector F. If $T \neq C_j$ then update weights of J vector as:

$$w_j(new) = w_j(old) - a\left(F - w_j(old)\right)(5)$$

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The above equation defined as move w away from F. Then reduce the learning rate a. The classification may be a fixed number of iterations or the learning rate reaching a sufficiently small value.

3.2 Modified fuzzy min-max classifier using compensatory neurons

In this classification, the feature vector extracted from the input is considered as input vector to the neural network. This input vector is applied to the input layer for the neural network and number of nodes in the input layer is equal to the dimension of applied input vector A_h . Where the $A_{h1}, A_{h2}, \dots, A_{hn}$ are the input sample belongs to the pattern area I^n. And $A_1, A_2, \dots, A_n$ are the corresponding input nodes. The second layer neuron called hyper-box nodes $B_1, B_2, \dots, B_j$ are created at the training time, which represents the Min-Max points of the hyper-box and are stored into the *(V, W)* matrix. The activation function B_j is given as:

$$B_j = \{A_h, V_j, W_j f(A_h, V_j, W_j)\} \quad where\ A_h \in I^n \quad (6)$$

- Min point of j^{th} Hyper-box is, $V_j = (V_{j1}, V_{j2}, \dots, V_{jn})$
- Max point of j^{th} Hyper-box is, $W_j = (W_{j1}, W_{j2}, \dots, W_{jn})$
- Input vector of j^{th} Hyper-box is, $A_h = (A_{h1}, A_{h2}, \dots, A_{hn})$
- Number of dimension is *n*

The membership function for the j^{th} Hyper-box is, $0 \le B_j(A_h, V_j, W_j) \le 1$

In this classifier, we assume that the degree of membership of input vector A_h for the hyper-box is B_j one if A_h is in or within the hyper-box B_j and the degree of membership decreases as A_h moves away from the hyper-box B_j .Thus, the new activation function is given as:

$$b_j = (A_h V_j W_j) = \min(\min\left[\left(1 - f(a_{hi} - w_{ji}, \gamma)\right), \left(\left(1 - f v ji - hi, \gamma \right.\right.\right. \quad (7)$$

$$for\ i = 1, \dots, n\ f(x, \gamma) = \begin{cases} 1, if\ x\gamma > 1 \\ x\gamma, if\ 0 \le x\gamma \le 1 \\ 0, if\ x\gamma < 0 \end{cases}$$

Where $\gamma = (\gamma_1, \gamma_2, \dots, \gamma_n)$ are sensitivity parameters regulating how fast the membership values decrease. This activation function is assigned if a input sample is within the hyper-box. Otherwise its membership function calculation is based on the distances between Min-Max points of the pattern A. Hyper-box nodes in Main Section are created if training sample belongs to a class. This has not been encountered that the existing hyper-boxes of that class cannot be expanded further to accommodate it. The connections between hyper-box node and class node in main section are represented by matrix *U* and hence the learning process is improved. The OCN takes over the control from the overlapped hyper-boxes and assigns membership to the test sample depending upon its distance from the min-max points.

The hyper-box nodes in middle layer OCN section are created whenever the network faces problem of overlap or containment. The OCN section takes care of the overlap problem. The connections between hyper-box and class nodes in OCN section are represented by matrix *Y*. The connection weight from neuron d_p is representing the overlap between i^{th} and j^{th} class hyperbox. A connection between hyper-box nodes to a class node is adjusted by the following equation.

$$u_{ij} = \begin{cases} 1\ if\{b_j \in c_i\} \\ 0\ if\{b_j \notin c_i\} \end{cases} (8)$$

OCN Produces two outputs, one each for the two overlapping classes. OCN is active only when a test sample belongs to the overlap region. The activation function is given as:

$$d_{jp} = U\left(b_j(A_h V_j W_j) - 1\right) \times \left(-1 + \frac{1}{n}\sum_{i=1}^{n} max\left(\frac{a_{hi}}{w_{pi}}, \frac{v_{pi}}{a_{hi}}\right)\right) (9)$$

The Activation function of this neuron is such that it protects the class of the min and max point of overlapped hyper-boxes. The class node in OCN section is given by,

$$y_{ip}\ and\ y_{jp} = \begin{cases} 1, if\{d_p \in c_i \cap c_j, i \ne j\} \\ 0, otherwise \end{cases} (10)$$

4. RESULT AND DISCUSSIONS

5.

This section presents the experimental results that are performed to prove the proposed fuzzy min-max classification technique achieves high accuracy and less time. The performance of the proposed feature classification is evaluated in terms of precision, recall, accuracy, f-measure and time with existing classification techniques such as KNN, ANN, SVM and DTB classifiers.

Precision

Precision value is evaluated according to the feature classification at true positive prediction; false positive.It is expressed as follows:

$$Precision = \frac{True\ positive}{True\ positive + False\ positive} (11)$$

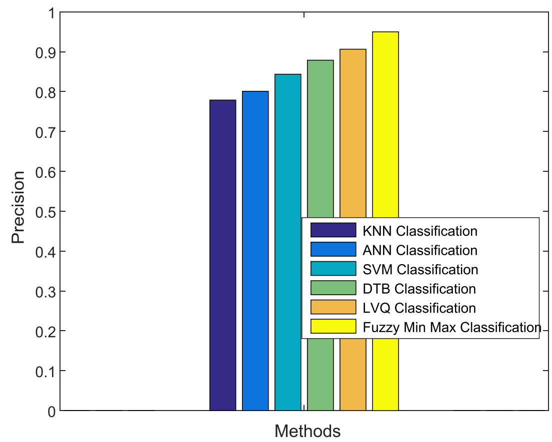

Fig 2: Precision comparison

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Recall

Recall value is evaluated according to the feature classification at true positive prediction, false negative. It is given as,

$$Recall = \frac{Truepositive}{(Truepositive + Falsenegative)} \quad (12)$$

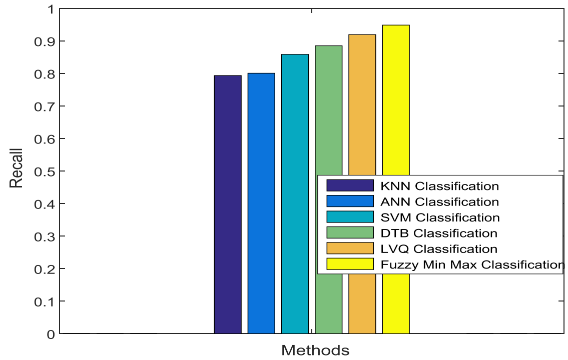

Fig 3: Recall comparison

F-Measure

F-measure is calculated from the precision and recall value. It is calculated as:

$$f - measure = 2 \times \left(\frac{precision \times recall}{precision + recall}\right) \quad (13)$$

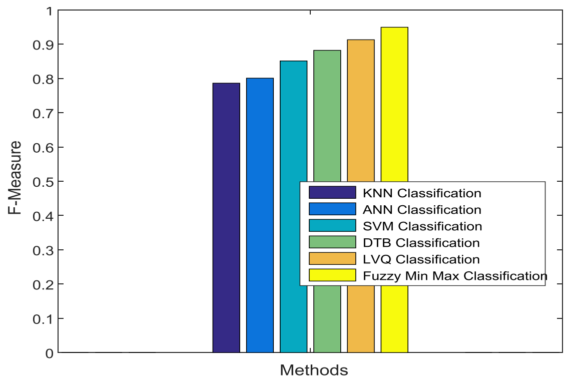

Fig 4: F-Measure comparison

Accuracy

The accuracy is the proportion of true results (both true positives and true negatives) among the total number of cases examined.

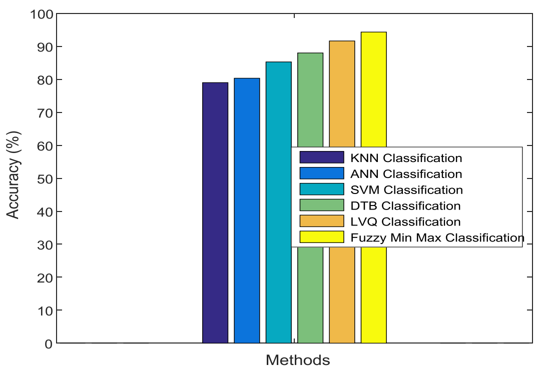

Fig 5: Accuracy comparison

$$Accuracy = \frac{True\ positive\ + True\ negative}{True\ positive\ + True\ negative\ + False\ positive\ + False\ negative} \quad (14)$$

Time

Time is calculated based on the run time of the methods in sec.

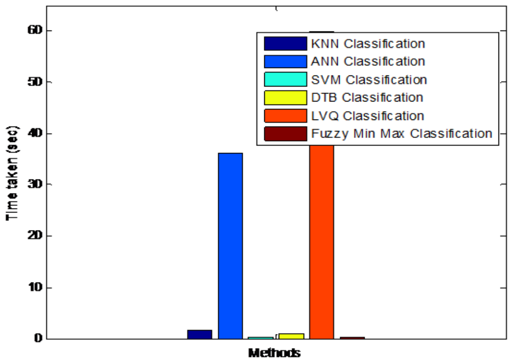

Fig 6: Time comparison

Table 1: Comparison of performance metrics with existing and proposed methods

Performance metrics	KNN	ANN	SVM	DTB	LVQ	M-FMCN
Precision	0.7815	0.8022	0.8527	0.8726	0.9169	0.9459
Recall	0.7918	0.7909	0.8608	0.8817	0.9056	0.9496
F-Measure	0.7866	0.7965	0.8567	0.8771	0.9112	0.9477
Accuracy	79.2642	80.6667	85	88	91.3333	95
Time	0.6595	24.9210	0.6229	0.6251	58.0805	0.3077

6. CONCLUSION

This paper presented an efficient classification method for classifying the different types of respiration disorder patterns. The features are classified based on two different classification techniques such as LVQ and Fuzzy min-max technique to improve the classification accuracy, sensitivity, to reduce the time and to reduce the computational cost. The experimental results are demonstrated that the fuzzy min-max classifier has better accuracy, sensitivity, computational cost and time than other classification techniques. Comparison results illustrates that our proposed system outperforms than the existing system. The drug-free breathing therapy such as breathing methods helps patients to recover from their respiratory disorders without any effect. The future extensions of this research are to transmit the sensory data securely by introducing security mechanisms. Also, Internet of Things (IoT) will be added for effective real time applications. Moreover, this technique will be extended towards big data analytics to analyse the large set of respiration patterns.

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