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An Accurate Diagnosis of Asthma Disease by Learning Patients Information Using Ensemble Classification Approach

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Abstract : Asthma is a chronic lung disease that inflames and narrows the airways in the lungs. These airways, or bronchial tubes, permit air to breath in and out of the lungs. The causes of asthma symptoms can vary from person to person. This makes airways resistance increases and the work of breathing more difficult, causing shortness of breath, cough, and wheezing. In the real world, the asthma participated a most dangerous role in the environment. In this work, a new mechanism is introduced to analyze the accurate asthma related factors, and this information is collected from the asthma patients. This work is done by using the collection of classification approach and it combines the classifiers to be exact SVM, Adaboost, and Random forest. This method is used to analyze the breathing characteristics and this work is done by applying the classification approach to the asthma dataset. The asthma dataset is containing the pulmonary function attributes. After this process, to analyze the asthma disease by using the pulmonary function attributes. and these attributes are tidal volume(Vt), breathing period (Ttot), aspiratory time(Ti), duty cycle (Ti/Ttot), Spirometry, exhaled nitric oxide(NO), Carbon monoxide (CO), peak expiratory flow (PEF), and oxygen (O2) etc., this attributes are gathered by using the airway opening volume tracking approach. This information is used to the training data and this data would be utilized to analyzing the asthma for the test data. The relevancy filtering technique is used to eliminate unwanted information in the dataset to improve the computational process. By using this filtering technique the size of the data set will be reduced, so that the time complexity also reduced in the ensemble classification approach. The proposed research methodology is used to analyze the accurate asthma disease based on the pulmonary function attributes. The experimental assessment was conducted in the mat lab simulation which tends to proves that the future research tends to provide accurate classification and prediction rate than the before research methodologies.

Keywords : Asthma diagnosis, pulmonary function attributes, ensemble classification, filtering.

1. INTRODUCTION

Asthma is a general breathing problem of the airways of lungs. Asthma symptoms vary from person to person depending upon the age factors. The symptoms are occurred only at certain times like few times a day or per week. The symptoms are shortness of breath, chest tightness or pain, trouble sleeping caused by shortness of breath, coughing or wheezing and so on. These symptoms may become worse at night or early in the morning depending upon the person. The most common reason of asthma disease is genetic and environmental factors like whether condition, dust allergies. Other possible reasons are medication like aspirin and beta blockers. The analysis of asthma disease is varies depends on the symptom patterns, effect of therapy over time and spirometry. And it is also classified depending on the frequency of symptoms, forced expiratory volume in one second (FEVI), and peak expiratory flow rate. It is also used to classify an atopic or non-atopic which refers to the predilection in the direction of increasing a type 1 hypersensitivity reaction [1].

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There is no proper test is available in the asthma disease. Doctors make the decision to analyze the asthma disease by using signs of the persons. The symptoms of asthma are varying from person's age and sometimes the breathing condition flows are very bed in the airways of lungs. The airflow is also varying the healthy people too like who have cold in their lungs may not work as well as usual. There is a major difference available in the strong peoples based on how their lungs work at their superlative and at their most terrible. The spirometer function is used to analysis lungs function. The people blow the air forcefully in the spirometer tubes in a few seconds. After that the spirometer analyze the amount of air pushed through the tube, and the lung capacity and other measurements too. This method is not used for below six years child and some adults who have some medical condition.

The spirometer tube test is done by physically by the doctors. And it does not produce a accurate results in the asthma disease. It gives a wrong direction to lead the wrong treatment to the human. This wrong treatment causes a human loss. The many scientist research a asthma disease by conducting various ways and procedures. This work is mainly focused to get the exact and improved analysis report of the asthma disease based on the pulmonary function attributes based on how the lung functioning can be well monitored. This process is done by ensemble classification approach with significance based filtering approach. In this work the filtering method is used to remove the unnecessary data's and the ensemble classification approach is used to get the exact classification rate.

The overall association of the research work is given as follows: different research methodologies that are conducted to analyze the asthma disease in many ways are discussed in section 2. The functioning procedures and the suitable diagrams and examples are discussed in section 3. In section 4, tentative and performance assessment of the proposed research methodology and its comparison analysis with previous methods were given. Finally in section 5, overall research of the proposed research methodology is concluded.

2. RELATED WORKS

The correlation detection techniques and regression models are used to bring to a close a positive and negative correlation between asthma attacks and individual threat factors in the medical science. The asthma attacks with impurity exposures is studies [2], [3] and [4]. The influence of weather instability and risk of asthma are studied in [5] and [6]. On the other hand, the results are in the form of correlation coefficients and p-values. This result is not enough to assessing the strong or weak positive/negative correlations and positively not sufficient for designing complex predictive models.

Bae et al. [7], establish a structure it can be used to check and examine the person disclosure to environmental triggers of asthma attack. This method is used to find the correlation between the patients health condition and the negative collision of environmental strategies by using patient's locations, environmental pollution, temperature, and humidity. Even though, in this research work there is no detailed experimental results to see how well an application built on this framework works in reality at the hypothetical level.

An auto-regressive model is used to apply the weather data coming from physical sensors and these data's is used to predict the asthma attacks [8]. Researchers describe three policies to replicate the susceptibility of asthma patients to the vacillation of meteorological factors. This research does not be familiar with any rules from weather or air pollution.

To build a classification model for asthma disease by applying the decision tree and association rule mining techniques Lee et al. [9]. In this method, by using the combining patient's physical data and environmental factor to create a integrated patient dataset. In the each individual patients record the environmental data's are repeated and it may cause some serious flaws. Also, scientist uses a discretization method to allocate signs to statistical environmental values. In this method conversely, to consider the data analyzing report as disparate to raw data and allot significant proceedings to states and state transitions in leaning data. Recognizing the lagging of time difference between proceedings is one of the most imperative donations of this approach. In the healthcare applications there is no studied report of correlation between the different risk available.

Bener et al [10] attempted to examine the household and environmental risk factors connected with asthma surrounded by school children in United Arab Emirates. They have composed the data from survey among erratically chosen families in the countryside areas. In this work the X2-test and logistic regression method was used. Finally, they concluded, that parental (genetic) asthma, vegetation, scent, dust tempest, wetness, and pets were most important risk factors in determining the proneness of the respondent to asthma.

Gorman et al [11] investigated threat factors connected with asthma to find the significance of family related (genetic, parental) and social threat factors (home environment, social status and demographic characteristics) in formative asthmatic outcomes between adults in the United States. They applied logistic regression modeling to a dataset from National Asthma Survey (2003-2004) with samples for over 6000 adults. Logistic regression model was elected to analyze the data. They originate those public factors, as well as the individuality of family atmosphere (subsistence of smoker in the family) has important collision in the threat of the adult being diagnosed with asthma.

3. ASTHMA DIAGNOSIS SYSTEM

Asthma is a ordinary provocative unceasing disorder of the lungs in which airways are level to restrict. Asthma has some symptoms such as out of breath, and coughing especially at nights or in the early hours12]. 7-10 percent of children and 7-9 percent of adults endure from this disease. On the other hand, the transience frequently happens in the countries with least amount of public health authorities [13]. The genetically and environmental factors are mainly caused by the asthma [14]. Its analysis is generally based on patient's medical history and spirometry. There is no proper tests are found to diagnose asthma disease in terms of respiratory dynamics and the response to medical treatments [15]. Breathing is a cyclic process which has convoluted patterns that depend on patient's personal factors such as age, sexuality, etc.

Pulmonary function tests are used to measure how well the lungs seize in and blow out air and how resourcefully they move oxygen into the blood. Spirometry is used to measures how well the lungs breathe out. This kind of data are collected during this test is useful in analyzing certain types of lung disorders, but is most useful when assessing for disruptive lung diseases (particularly asthma and chronic obstructive pulmonary disease, COPD). Lung volume measurement detects restraining lung diseases. In this kind of asthma diseases, a human being cannot breathe in a usual amount of air. Restrictive lung diseases may be caused by irritation or scarring of the lung tissue (interstitial lung disease) or by abnormalities of the muscles or skeleton of the chest wall. Testing the dissemination ability (also called the DLCO) permits an approximation of how resourcefully the lungs move oxygen from the air into the bloodstream.

The proficient asthma analysis can be done with the assist of pulmonary function tests attributes based on which classification can be done professionally. In the proposed work, asthma disease analysis is performed for the timely treatment of patients, so that causes can be avoided. This method is done by a new method that is Weighted based ensemble classification with relevancy filtering (WEC-RF). This can be used in the data set which is gathered from the asthma patients with different ages and symptoms. The steps implicated in the proposed asthma analysis scheme are scheduled as follows:

1. Asthma patient's physical condition data collection.
2. Filtering of data based on asthma relevancy.
3. Ensemble based classification of filtered asthma patient data.

This dispensation of proposed asthma diagnosis system is illustrated in the figure 1.

The above diagram illustrated the overall processing flow of the proposed asthma diagnosis system. The complete clarification of this working procedure is given in the following sub sections.

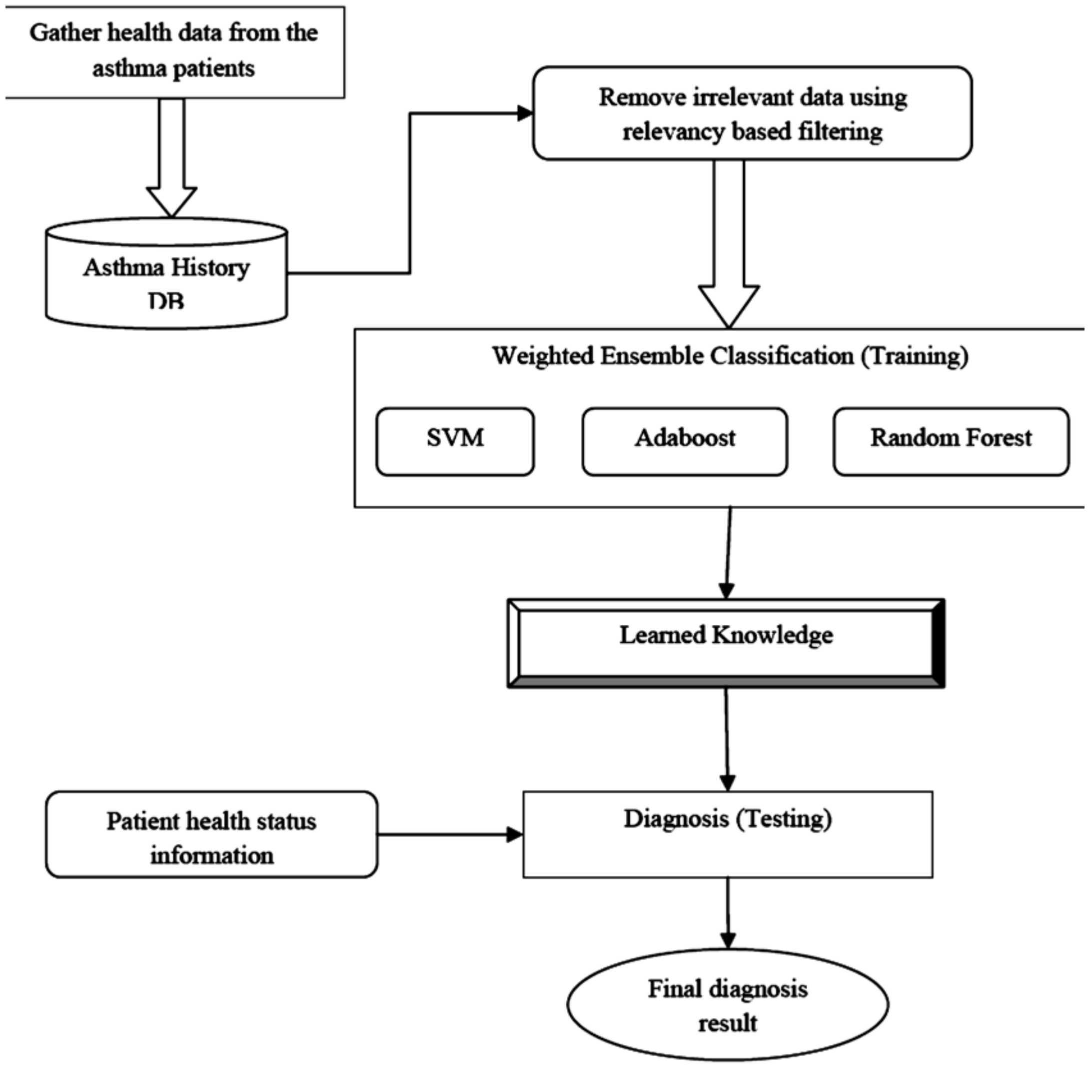

Figure 1: Overall processing of Proposed Asthma Diagnosis System

A. Asthma Patient’s Health Data Collection

At first the information are collected from the asthma patients depending on ages and asthma symptoms to dorm a data set. The past information of those patients and their symptoms are collected and stored in the repository. The Pulmonary function tests was conducted by each asthma patients to find their lung breathing level. After this test, the values of pulmonary function tests attribute are collected and stored in the particular patient information. By using this information, varying possibilities of signs of asthma disease can be identified based on which exact analysis can be performed. This information’s are collected from the different more number of patients from many hospitals, so that the risk factors in many forms can be analyzed and identified.

B. Filtering of Data Based on Asthma Relevancy

The dataset consists of health related attributes and as well as patients personal information. These information are collected from the different human being. Some of the information are not useful to the analysis of asthma disease which is used in the analysis process would guide to more computational overhead. Thus the filtering of that unwanted data’s are used to get the resourceful and precise analysis of the asthma disease with reduced computational overhead. While classifications the unwanted information is avoided by using the relevancy based filtering approach. The term relevancy distinct as how well the exacting instance or attribute matches with the asthma disease condition. Every instance and attributes in the data needs to be analyzed to find its relevancy, so that the exact classification can be done in the well-organized manner. In this work, kalman filtering is used for eliminating the unrelated data's that are present in the asthma dataset collected.

Another name of Kalman filtering is linear quadratic estimation (LQE), is an algorithm that uses a continuous measurements found in particular period of time, including statistical noise and other inaccuracies, and guessing of unidentified variables that be liable to be more accurate than the unique measurement alone, by using Bayesian inference and estimating a combined possibility allocation over the variables for each timeframe.

This algorithm can be done by two-step process. At first the prediction step, in this step the Kalman filter generated guessing values of the present state variables, along with their suspicions. Once the result of the next measurement (inevitably despoiled with some amount of error, as well as random noise) is observed, these estimates are simplified using a weighted average, with more weight being given to estimates with higher assurance. The algorithm is recursive. It can be used to real time environment, using only the current input measurements and the before designed state and its improbability matrix; no extra past information is required.

The Kalman filter does not necessitate the any supposition that the errors are Gaussian. On the other hand, the filter yields the correct provisional possibility estimate in the special case that all errors are Gaussian-distributed. Extensions and generalizations to the method have also been residential, such as the extensive Kalman filter and the neutral Kalman filter which work on nonlinear systems. The fundamental model is a Bayesian model similar to a secreted Markov model but where the state space of the hidden variables is incessant and where all hidden and observed variables have Gaussian distributions.

The Kalman filter to used to estimate the internal state of a process given only a series of noisy clarification, one must model the process in accord with the structure of the Kalman filter. This means specifying the following matrices: the state-transition model (F_k); the observation model (H_k); the covariance of the process noise (Q_k); the covariance of the observation noise (R_k); and the control-input model (B_k) , for each time-step, k, as explained below. The Kalman filter model fixes the accurate and final condition at time k is derived from the state at $(k - 1)$ according to

$$X_k = F_k x_{k-1} + B_k u_k + w_k \tag{1}$$

where

1. F_k is the state transition model which is applied to the previous state x_{k-1};
2. B_k is the control-input model which is applied to the control vector u_k;
3. w_k is the process noise which is assumed to be drawn from a zero mean multivariate normal distribution with covariance Q_k. $W_k \sim N(0, Q_k)$

At time k an observation (or measurement) z_k of the true state x_k is made according to

$$Z_k = H_k X_k + v_k$$

where H_k is the observation model where true state space is mapped into the observed space and v_k is the observation noise which is initalized zero mean Gaussian white noise with covariance R_k.

$$v_k \sim N(0, R_k)$$

The initial state, and the noise vectors in every iteration $x_0, w_1, \ldots, w_k, v_1 \ldots v_k\}$ are all initialized as mutually independent. Most of real world application cannot be adapt with this model. Generally these models would reduce the performance of filters under unknown stochastic signal which is given as input. This is due to dynamic variation of the estimated input values based on network environment whereas this divergence wont occur in case of presence of white signals.

C. Ensemble Based Classification of Filtered Asthma Patient Data

Ensemble learning are the most popular technique in the machine learning based application where the learning is done based on multiple classifier results. It is based on only finite set of classification models, thus the better prediction can be made in terms of retrieved alternatives. In this research work, this ensemble classification procedure is adapted to obtain the better prediction accuracy in terms of accurate diagnosis of asthma disease. This is achieved by introducing the weighted based ensemble procedure which attempts to combine the results of the different classifiers with their weight based on which accurate diagnosis would be done.

In this research novel weight based voting classification approach is introduced which make use of two weighting vectors namely a weight vector of classifiers and a weight vector of instances. The typical hard data's to classify are assigned with the higher weight values using instance weight factor. The classifiers that are hard to classify data's are assigned with high weight values using weight vector of classifiers. This would run in the iterative manner to produce the better prediction result. This iteration would lead to better converged solution with the help of learned result from multiple classifiers. Finally the prediction is generated using weigh based voting classification procedure. The classifiers that are considered in this work for ensembling are, "SVM, Random forest, Adaboost".

D. Support Vector Machine Classification

Support Vector Machine Classification algorithms are used to analyze the information and identifying the patterns in the regression analysis technique. Below are the few training examples, there are two categories in SVM training algorithm and it is used to assign the values in one category to other category

Formula

The following formula for reduce the error minimization

$$(w) = \frac{1}{2}||w||^2 \quad (2)$$

Estimating function

$$F(x) = \sum_{j=1}^{nsv}(x_i, y_i) \quad (3)$$

Algorithm

Given dataset X = (x1, y1),……,(xn, yn), C // x and y –labeled sequence and C-class

Initialize vector v = 0, b = 0; class // v-vector and b-bias

Train an initial SVM

For each $x_i \in X$ do // x_i is a vector containing features describing example i

Classify x_i using $f(x_i)$

If $y_i f(x_i) < 1$ // prediction class label

Find w', b' for known data // w', b' for new data

Add x_i to known data

If the prediction is wrong then retrain

Repeat

End

The equation (1) is used to minimize the error values.

The equation (2) is used to classify results.

Adaptive Boost Classification

The Adaptive Boosting (AdaBoost) is a first and famous ensemble algorithm by Freund and Schapire (1996), and it is used to increase the boosting algorithm through iterative process. The major role in this algorithm is to provide additional focus to the patterns, they were difficult to categorize. The sum of quantity of focus is quantified by a mass that is assigned to all patterns in the training set. Firstly, the similar mass is assigned to every pattern. In all iteration process, the mass of all misclassified instances are improved while the mass of the accurate classified instances are decreased. As a result, the beginner is forced to focus on the complicated instances of the training set by performing extra iterations and create extra classifiers. In addition to that mass is assigned to each individual classifier. This mass determines the whole accurate values of the classifier and this process of the total mass classified patterns in the correct manner. Therefore, higher mass are gives an additional accurate classifiers. And it is also used to classify the novel patterns too. This iterative algorithm gives a sequence of classifiers that balance with one another. In exactly, AdaBoost algorithm shows that the approximately a huge margin classifier like SVM.

Algorithm

Require : I (a weak inducer), T(the number of iterations), S (training set)

Ensure : M_t, α_t; $t = 1,\ldots,T$

1. $t \leftarrow 1$
2. $D_1(i) \leftarrow 1/m$; $i = 1,..,m$
3. Repeat
4. Build classifier M_t using I and distribution D_t
5. $E_t \leftarrow \sum_{i\,:\,Mt\,(xi) \neq yi} D_t(i)$
6. If > 0.5 then
7. $T \leftarrow t - 1$
8. Exit loop
9. End if
10. $\alpha_t \leftarrow \frac{1}{2} \ln \left(\frac{1 - \varepsilon_t}{\varepsilon_t} \right)$
11. $D_{t+1}(i) = D_t(i).\ e^{-atytMt(xi)}$
12. Normalize Dt + 1 to be a proper distribution
13. T++
14. Until $t > T$

(*a*) Random Forest Classification

A Random Forest ensemble classification algorithm is also known as random subspace. And it is used to the more number of individual and in the decision trees. This algorithm is mainly used to build individual trees. The number of input parameter is represented in N and these parameters are used to classify the decision at a node of the tree.

Algorithm

Necessitate: a decision tree inducer (IDT), the number of iterations (T), the training set (S), the subsample size (μ), number of attributes used in each node (N)

Ensure : Mt; $t = 1,..,T$

1. $t \leftarrow 1$
2. repeat
3. St ← sample μ instances from S with replacement
4. Build classifier Mt using IDT(N) on St
5. t ++
6. Until $t > T$

(*b*) Weighted voting classification ensemble

In this proposed work the ensemble classification approach is used to assign a individual voting of 43 mass in every classifiers. Particularly, by using an iterative process, a 44 mass vectors for the classifiers and the other vectors for the instances will be 45 gathered in the learning phase model. At last, to get the 47 mass is very difficult to classify, afterward, to get the 48 mass instances are become larger mass. The final calculation of the ensemble classification approach is obtained by the voting using the weight vectors of classifiers.

There are two classifiers are used in this approach. In simple greater part voting, all classifiers have the same mass. At the present the first one tends to categorize extra instances are hard-to-classify in the correct manner. While the second classifier was difficult to classify the instances in the correct manner. These two types of classifiers are to build different calculations on an unusual instance, it also reasonable to give more mass to the first classifier which classifies more difficult instances correctly.

(*c*) Iterative weight adjust algorithm:

1. Set an primary instance mass vector

$$Q_0 = \frac{(J_{nk} - X)(J_{kk} - I_k)1_k}{1_n'(J_{nk} - X)(J_{kk} - I_k)1_k}$$

   Q_0 takes upper instance mass for the rows of X with fewer 1's. The denominator is a normalizing factor for unit norm.

2. For $m = 1, 2\ldots$ Repeat (*a*) and (*b*).

   (*a*) Compute a classifier mass vector

$$P_m = \frac{X'Q_{m-1}}{1_k'X'Q_{m-1}}$$

   The above formula P_m gives a exact classifiers by assigning higher weights (*i.e.*, columns of X with more 1's) after the instance mass Q_{m-1} included. The denominator is a unit norm factor.

   (*b*) Update the instance mass vector

$$Q_m = \frac{(J_{nk} - X)(J_{kk} - I_k)P_m}{1_n'(J_{nk} - X)(J_{kk} - I_k)P_m}$$

   The above formula is used to assigns higher mass on hard-to-classify instances after including the classifier weight vector P_m.

3. When the weight vectors P_m and Q_m are become stable at that stage the step 2 process will be stooped. Denote P* and Q* be the last mass vectors.

(*d*) Asthma diagnosis

The asthma analysis process is done by using the ensemble classification approach. The health information's are collected from the patients, and in this data's the pulmonary function attributes also one of them. And these information are used to compare the repository which is based on the calculations would be made. These testing process of asthma analysis report guide to the exact stages of asthma disease of patients, so the patients can be treated on time. In this proposed work the classification approach can distinguish the asthma disease stage of dissimilar peoples with changeable ages and signs.

4. EXPERIMENTAL RESULTS

In this section, the performance evaluation of asthma diagnosis system is done with the concern of the varying age groups and asthma symptoms. The prediction accuracy of the proposed system is compared with the varying existing classification algorithms in terms of their prediction values. The performance measures that are considered in this work for evaluation are true positive rate, false positive rate, accuracy and f measure.

(*a*) True Positive Rate (TPR)

The true positive rate is defined as the percentage of actual positive which are spam subjects class correctly classified. It is representation of acceptably classified percentage of spam and non spammer detection .The TPR is defined as below:

$$\text{True Positive Rate (TPR)} = \frac{T_p}{(T_p + F_n)}$$

(*b*) False Positive Rate (TPR)

False positive ratio is the ratio of wrongly eliminating the null hypothesis for a particular test.

$$\text{False Positive Rate (FPR)} = \frac{F_p}{(F_p + T_n)}$$

(*c*) Accuracy

Accuracy is defined as the overall correctness of the model and is calculated as the sum of actual classification parameters (separated by the total number of classification parameters ($T_p + T_n$) separated by the total number of classification parameters ($T_p + T_n + F_p + F_n$)

$$\text{Accuracy} = \frac{T_p\, T_n}{T_p + T_n + F_p + F_n}$$

(*d*) F-measure

F-measure combines precision P and recall R by,

$$F = 2.\frac{PR}{P + R}$$

For evaluating the classification algorithms, focus on the F-measure as it is a standard measure of summarizing both precision P and recall R.

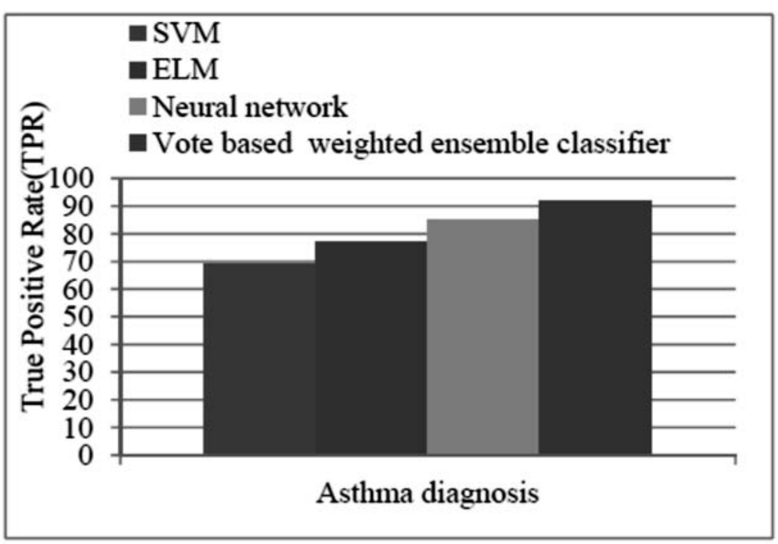

Figure 2: True Positive Rate for Features

Performed an extensive TPR evaluation for different features with the classifiers presented above that are implemented to asthma health data collected from patients in Figure 2. Results demonstrated that vote based weighted ensemble classifier has improved TPR for asthma diagnosis.

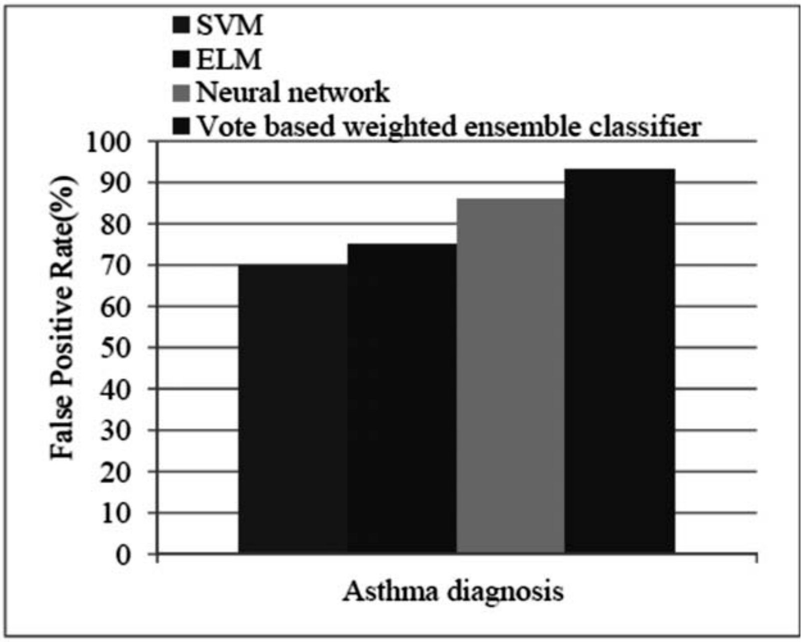

Figure 3: False Positive Rate for Features

Performed an extensive FPR evaluation for different features with the classifiers presented above that are implemented to asthma health data collected from patients in Figure 3 Results demonstrated that vote based weighted ensemble classifier has improved FPR for asthma diagnosis.

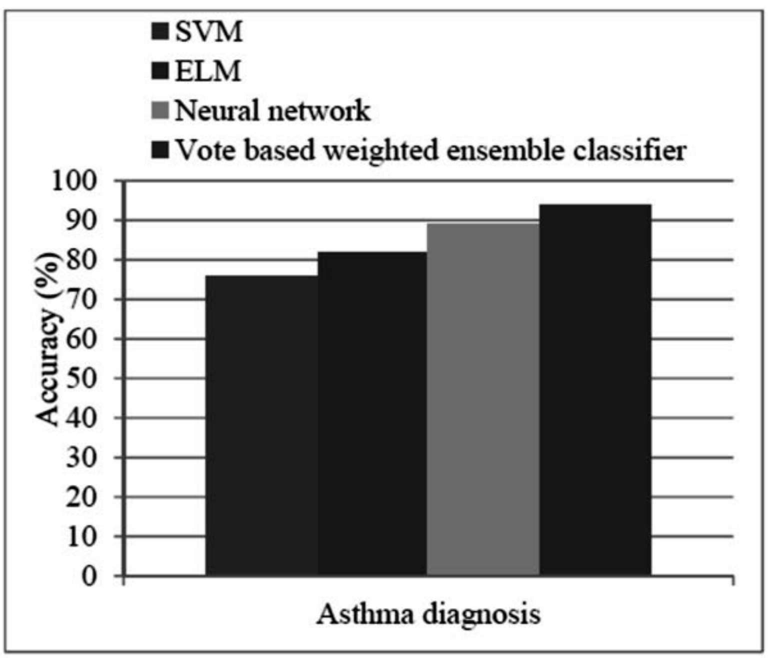

Figure 4: Classification Accuracy for Features

Performed an entire experimentation results for different features with classifiers such as SVM and ELM, neural network and Vote based weighted ensemble classifier in Figure 4. Results demonstrated that vote based weighted ensemble classifier has improved accuracy for asthma diagnosis.

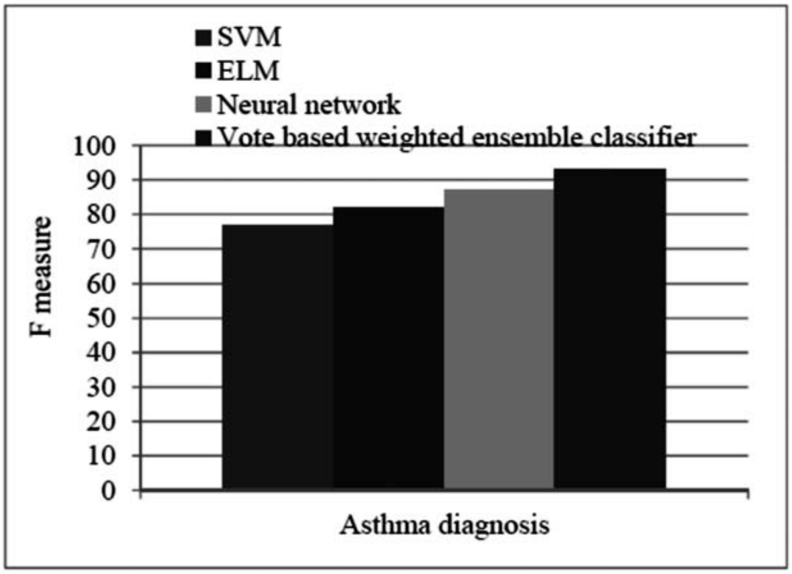

Figure 5: F-Measure Accuracy for Features.

Performed an entire experimentation results for different features with classifiers such as SVM and ELM, neural network and Vote based weighted ensemble classifier in Figure 5 for standard measure of summarizing both precision P and recall R. Results demonstrated that vote based weighted ensemble classifier has improved f-measure for asthma diagnosis.

5. CONCLUSION

Asthma diagnosis plays a most vital role in the bio medical field which needs to be diagnosed well for the on time treatment. The asthma symptoms would be varying for different peoples based on their ages and environmental condition. In this research work, novel asthma diagnosis system is introduced for accurate prediction of the asthma disease based on varying risk factors. In this system, initially data set would be preprocessing by using kalmann filtering approach which would eliminate the irrelevant data's from the asthma patients health data so that prediction can be done accurately. After filtering vote based weighted ensembling classification is done to perform the better and accurate learning which would lead to successful prediction of the asthma disease. The experimental tests conducted were proves that the proposed research methodology tends to provide the accurate diagnosis result.

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