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A Novel Cuff-less Measurement Method for Noninvasive Blood Pressure Prediction using Body Vital Signals

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Abstract

Hypertension or the abnormal increase of blood pressure is a chronic disease which can damage the other parts of the body such as the kidneys, heart, and vessels. The high cost of treating the injuries caused by hypertension is undeniable. Various techniques exist for measuring the blood pressure. In recent years, machine learning models became more popular due to being non-invasive and their continuous supervision, remote use, and low cost. Several analyses were performed by the audio signals of cardiac palpitations, electrocardiograms, on photo plethysmogramy on software and hardware platforms. Researchers used machine learning techniques to present the alternative methods for aggressive and costly methods. Among the presented methods, regression algorithms, support vector machine (SVM), and neural network (NN) are highly popular. This study presented a method for analyzing ECG and PPG signals for diagnosing hypertension. The proposed method can improve the classification accuracy regardless of the classification algorithm by providing the combined features. In the conducted evaluation, the neural network algorithm was proposed for the data with continuous label while the C4.5 tree was proposed for the data with discrete label. In addition, the proposed generalized method was provided by calculating the cosine distance and optimizing the genetic algorithm for low data and noise conditions.

Keywords : *Noninvasive blood pressure prediction, ECG, PPG, and ABP signals, vital signal classification, neural network, C4.5*

1. Introduction

The reliance of health care on data is increasing. Medical researchers, physicians, and health care providers are encountered with the problem of the effective use of stored data when more clinical information systems are used with larger databases. Clinical information system databases include various data such as patient records, physician diagnosis, and information supervision where data are useful in many clinical decision support systems to save the patients' lives [1]. Clinical decision support systems help the decision-making process in the medical field such as clinical decision-making support systems, medical imaging, and bioinformatics techniques. Some services of these systems include the reduction of the medical errors and costs, by the early diagnosis of diseases, and the realization of preventive medicine. The advantages of using computer clinical decision support systems (CDSS) include the decision support systems which can manage bulk data and extract the knowledge through them [2]. The use of KDD approach leads to incensement of the medical information and researchers use it in different areas such as statistics, machine learning, intelligent database, data visualization, pattern recognition, and high performance computing [3]. Detecting the relationships between risk factors and their effect as considered the results in the medical area is even problematic for experienced medical researchers or healthcare manager. Data mining assistances physicians to improve their health services by helping them with diagnostic rules, procedures, and unexpected data events [4]. Hence, using data mining tools with advanced algorithms is popular for pattern discovery in biological data and problems include protein interactions, sequence and analysis of gene data, drug discovery, the discovery of homologous structures or sequences, the production of phylogenetic trees, gene discovery and mapping, and sequence alignment [5]. However, machine learning was not completely accepted in the medical community because physicians believe that their work was more complicated than using such tools, because of different specific explanations for specific model methods in some cases [6]. The possibility of numerical regression can be provided using the regression algorithms. Then, the possibility of blood pressure prediction based on a specific class is provided through the discretization of values. In addition, the bandwidth for transmission is increased as there is less information for transmission [7]. However, the population with hypertension suffers from higher blood pressure exponentially with increasing age. Several studies estimated the increasing incidence of hypertension in the long term [8]. High blood pressure and hypertension cause cardiovascular disease, end stage of renal disease, unrecognizable atherosclerosis, and all causes of death [9, 10]. Several methods for measuring blood pressure in order to collect the initial information of dataset have been discussed in the literature [7-9]. In general, there are two main methods of invasive and direct as well as noninvasive and indirect for measuring BP [11]. Measuring blood pressure is relatively easy in the clinic albeit, there are common mistakes and can provide incorrect values from the individual's blood pressure. Various methods exist for measuring blood pressure in the clinic [12].

The rest of the paper contains: in 2nd part, a research method on machine learning is raised including several operational phases being described step-by-step. Then, then discussion of results are presented to indicate the accuracy of the proposed method is deliberated in 3rd part. Finally, a conclusion is made of the results and a roadmap is presented for future works.

2. Reviewed Methodology

In this section, some case studies and recent studies are reviewed and analyzed. It worth to mention, this reviewing has a major role in relating the present study and previous studies. Various systems discussed in the area of analyzing medical signals and the accuracy of their diagnosis based on difference techniques like pulse estimate time, and BP estimate based method through PTT approach, telemedicine based method using ECG and EEG tools, WSN based method have been presented in studies [13,14]. Albeit, non-invasive methods are not required to penetrate the skin, but require a technology based on upper-arm cuff. Although there were recent advances in measurement systems without upper-arm cuffs in a body sensor network, they are not available for commercial purposes [13]. In addition, indirect measurements rely on technique or a brief amount of blood pressure. While, they provide an alternate waveform similar to invasive measurement criteria [14]. Excessive or irrelevant features often cause some interventions for predictions. Instead, the non-principled elimination of features leads to the increase of errors in the prediction. Thus, this process should be carried out by an appropriate logic [15]. In [16], some estimates from the pulse estimate time and BP estimate, using different models with the aim if discovering the best model or set of models for non-invasive BP estimation through the PTT approach were proposed. In [17], each patient has a personal WSN including a set of small / light sensor nodes and a gate. A WSN enables the continuous health supervision both in the hospital and the house. In [18], a cuff-less blood pressure prediction device was presented using photo plethysmography (PPG) and electrocardiography (ECG) as the input. A content-based method was presented in [19], to retrieve a big medical image in a cloud computing environment. Some attempts were made to classify the patients with cardiovascular disease using the k-nearest neighbors, Naive Bayes (NB), fuzzy logic systems, neural networks (NN) and decision trees (DT) in [20]. Mean absolute error was calculated in [21] for three factors of systolic blood pressure, diastolic blood pressure, and mean arterial pressure represented by regression modules. A method could produce appropriate results in noisy environments by analyzing ECG and Korotkoff signals and an ensemble-based machine learning model is discussed in [22]. As a result, the classification process was conducted by regression models in an ensemble [22]. A portable PPG-BP device was presented by [23] for the continuous cuff-less blood pressure measurement. The change in blood volume was continuously measured based on PPG to measure the blood pressure. Invasive blood pressure is a boring technique for the continuous supervision of patients and requires an appropriate alternative in the long term [24]. As mentioned, predicting the invasive blood pressure from other vital signals is possible. In a nutshell, all proposed techniques, attempt to predict blood pressure effectively in order to eliminate venipuncture operations to obtain the invasive blood pressure.

3. THE PROPOSED METHOD

The proposed method in the paper, indicates the predictive operations can be conducted using the algorithms based on regression and tree techniques. This method aims to approach the results of invasive blood pressure because the initial results obtained from data mining techniques are not applicable [6]. Medical predictions refer to a more accurate task of producing a model creating a numerical expression about a patient based on the data obtained from that patient. Models can become more complicated using statistical techniques and machine learning. Such a complexity often offers a better accuracy. Blood pressure measurement by cuff is appropriate when the continuous supervision over the short periods of time is not desired. Therefore, using it in continuous supervision methods will be highly problematic. On the other hand, intra-arterial techniques are considered as invasive and can lead to the patient discomfort. In this section, a method based on machine learning is presented. The method can detect the patient's blood pressure class and identify the numerical value of the patient's blood pressure with the lowest error rate.

The dataset of vital signals was derived from the UCI base including ECG, PPG, and ABP features. The final objective of the proposed method is to disconnect the ABP signal and perform the ABP prediction operations after a period of time from transmitting these 3 vital signals to decrease the transmitted signals. Based on the available data of the patient's ECG and PPG, the distance of transmitted samples from each other can be detected by clustering operations. The samples which are unexpected are regarded as an anomaly and are reported for further supervision. Here, the clustering operation is conducted by the K-means cluster [25]. This algorithm measures the distance between each sample from the cluster center by considering the Euclidean distance of the samples and determines the samples having an abnormal distance [25]. Such abnormal points can be within the allowed range. Classification algorithms are used for predicting the ABP signal. 1st, some classification algorithms are compared based on the efficiency obtained from the ROC figure. The selected classification algorithm has more space below the curve to detect the positive class. The main idea of the proposed method is shown in figure 1. In the 1st phase, the outlier and possibly incorrect data are detected from input signals through clustering. After eliminating the outlier in the 2nd phase, the correct datamining of blood pressure is detected by classification algorithms. Then, the selected algorithm is selected by comparing the ROC figure, the classification algorithms (DT, NN, SVM, NB, and Linear Regression) and training on the available dataset. Prediction is generally conducted as discrete and continuous. In the continuous method, the neural network algorithm performs prediction based on regression with minimum squared error compared to other algorithms and delivers the results to discrete classification steps. The C4.5 tree algorithm improves the accuracy of blood pressure detection with a tree approach based on the maximum information gain in each group of features. The production of combined features was one of the most important common parts in continuous and discrete predictions improving the classification results regardless of the algorithm used in the validation process. It worth to mention, the proposed scheme works under different conditions when the training samples have noise probability.

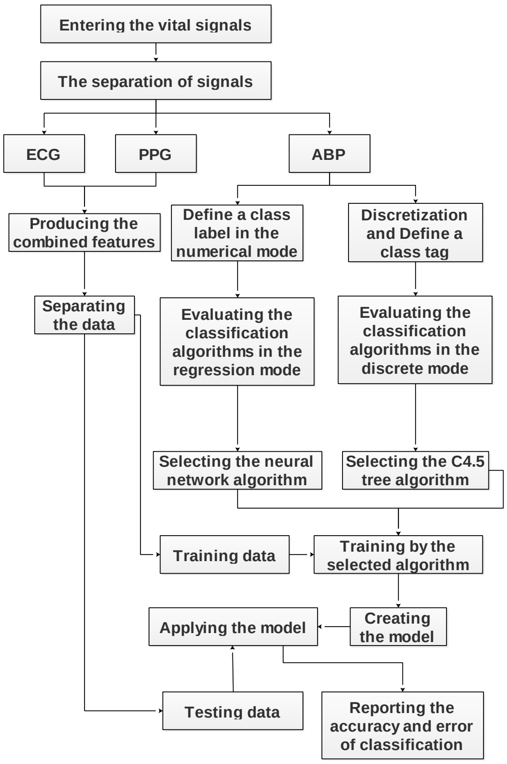

Fig. 1. The operations of the proposed scheme for ABP estimation

As indicated in Figure 2, the data entered this section after the production of combined features and are examined in term of having the outlier sample or not. The procedure begins by adjusting the genetic algorithm parameters and then the cosine distance measurement is performed by determining the number of neighboring samples and the number of outlier samples. After the temporary elimination of the detected abnormal samples, the classification is performed by decision tree. Then, this cycle of updating the parameters continues by the genetic algorithm. The genetic algorithm generates the best compounds for the next generation by producing a random population of parameters in the 1st generation, measuring the cosine distance, and then classifying. Each generation produces new generations. Finally, if it reaches the last generation, the best chromosome will be selected or the same chromosome of the stopped generation will be reported in the absence of improvement in several generations. The outlier samples are removed and the conditions are provided for validation by re-measuring of cosine distance with new parameters. Combined features involve new values obtained from other features. The main advantage of combined features is revealing the possibility of a hidden relationship between the samples of one feature of the relationship between the features. In the proposed scheme, 6 combined features were employed. Before presenting the mathematical relationship of each feature, each combined variable can be obtained as the following pseudo-code.

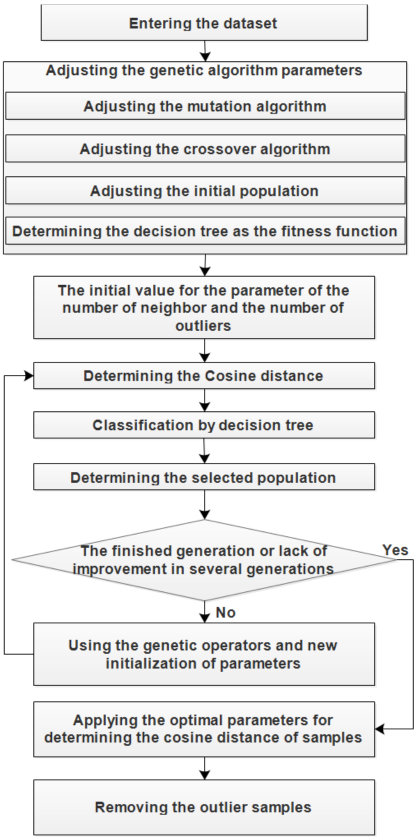

Fig. 2. Outlier detection module for the generalized proposal scheme

The following block indicates the pseudo code for producing statistical features of the proposed scheme. The features F1 to F6 are initialized based on the comparison of the threshold values which are obtained from the mean, mode, and median. The first feature is obtained from Equation 1.

$$\mathrm{Avg_E} = \frac{\sum_{i=1}^{n} F_{Ei}}{n} \qquad (1)$$

In Equation 1, F_E represents the ECG feature, F_{Ei} represents the i-th feature of ECG, Avg indicates the mean samples of ECG, and n indicates the number of data records. The first combined feature is obtained based on the comparison presented in the above pseudo-code. The mean of PPGs is obtained from Equation 2 having a performance similar to Equation 1 and is applied only to PPG data. Equation 2 is used for extracting the second combined feature.

$$\mathrm{Avg_P} = \frac{\sum_{i=1}^{n} F_{Pi}}{n} \qquad (2)$$

In Equation 2, F_P represents the PPG feature, F_{Pi} represents the i-th sample of PPG, and represents the number of data records. The combined feature of Equations 3 and 4 uses the mode rule for defining a new feature. Thus, we will have:

$$\mathrm{Mod_E} = \left(L + \frac{f_{F_E} - f_{F_E-1}}{(f_{F_E} - f_{F_E-1}) + (f_{F_E} - f_{F_E+1})} * n\right) \qquad (3)$$

$$\mathrm{Mod_P} = \left(L + \frac{f_{F_P} - f_{F_P-1}}{(f_{F_P} - f_{F_P-1}) + (f_{F_P} - f_{F_P+1})} * n\right) \qquad (4)$$

In Equations 3 and 4, F_E, represents the ECG feature, F_P implies the PPG feature, $F_P + 1$ implies the sample of PPG feature to the current PPG, f_{F_E} indicates the number of sample repetition from ECG feature, f_{F_P} refers to number of sample repetition from PPG feature, L represents the smallest sample size for each feature of ECG and PPG, and n is the number of data records. The third and fourth combined features respectively use these equations. Equations 5 and 6 use the median rule for defining a new feature. Thus, we will have:

$$\mathrm{Mid_E} = (\mathrm{L} + \frac{\frac{\mathrm{n}}{2} - \mathrm{cf_b}}{\mathrm{f_{F_E}}} * \mathrm{n}) \quad (5)$$

$$\mathrm{Mid_P} = (\mathrm{L} + \frac{\frac{\mathrm{n}}{2} - \mathrm{cf_b}}{\mathrm{f_{F_P}}} * \mathrm{n}) \quad (6)$$

In Equations 5 and 6, F_E represents the ECG feature, F_P represents the PPG feature, $\mathrm{cf_b}$ refers to the cumulative amount of the frequency before the i-th sample for each feature of ECG and PPG, $\mathrm{f_{F_E}}$ implies the number of sample repetition from ECG feature, $\mathrm{f_{F_P}}$ implies the number of sample repetition from PPG feature, L represents the smallest sample size for each feature of ECG and PPG, and n is the number of data records. The 5th and 6th combined features are obtained from the results of these two equations. After the approximate prediction of the ABP label, the difference between the prediction label and the obtained approximate value should be determined with a simple difference. This feature is obtained for each test sample. By implementing different algorithms, the cumulative amount of prediction e will be used as a comparison criterion. Thus, the selected algorithm can be selected based on to criterion and the runtime of the algorithm. In this section, a model was proposed based on machine learning algorithms (Fig.3).

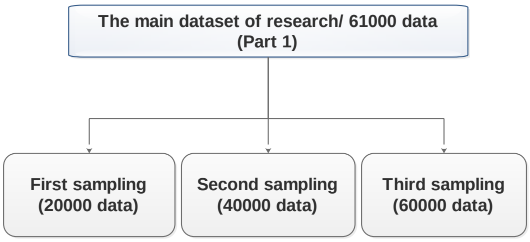

Fig. 3. Dividing the main dataset into several subsets for analysis

4. ANALYSIS AND RESULTS

In this section, the proposed solution of machine learning for estimating the ABP signal with ECG and PPG signals is evaluated. The present study aimed to identify the risk patterns related to the prevalence of hypertension through data mining methods in a group of individuals. The data are available on the University of California website. The simplest method for estimating the invasive blood pressure signal is to select a base regression algorithm. Therefore, a form of estimating the proposed scheme is proposed using regression and its efficiency is discussed here. K-fold cross validation (KCV) is used based on the type and nature of the work which results in the balanced accuracy throughout the set. The studies [26] and [27] being related to the research background discussed about this dataset and were presented in other studies such as [28] using this dataset. The validity of this dataset was justified by research [26]. In the evaluation section, Equations 1 to 6 are executed on the input sample sets and the combined features are extracted after the necessary comparisons. Finally, the dataset is validated by new features. Despite the second limitation, three samplings were conducted from the main dataset. Figure 3 indicates that the main dataset is divided into three sub-sets and the number of each sampling is specified. As discussed in the previous section about the production of statistical features. Three features were presented for each ECG and PPG signal. Finally, 6 features were proposed for producing a new data set on each sampling. Figure 4 indicates that linear regression classification without added features has the maximum squared error.

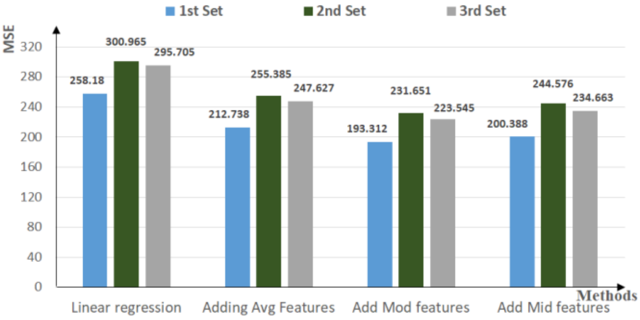

Fig. 4. Comparing the squared error after adding any statistical characteristic with linear regression classification

The created features of median and mean, respectively after the mode feature, result in a reduction in the error rate. Then, 6 features are placed in a design and tested on three samples sets. Figure 5 indicates that 42% in the first set, 36% in the second set, and 39% in the third set improvement was obtained in the squared error reduction. Due to the presence of noise in different sets, the 1st set has the highest accuracy like the comparison with the previous designs. After determining the combined features and improving the results, various algorithms can be measured to select the optimal algorithm for the proposed scheme.

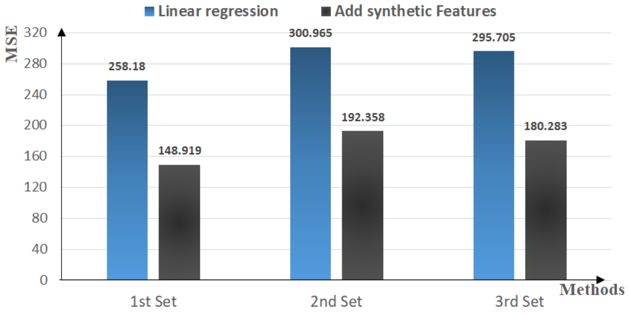

Fig. 5. Comparing the squared error after adding all combined features by linear regression classification

In this study, the 3rd sample set was selected due to the data integrity. Table 1 demonstrates that the linear regression models, neural network and generalized linear model, which is a kind of regression, have a proper runtime. Neural network algorithms and deep learning [29], which are a type of neural network, have low error rates. Due to the estimate of run-time and squared error rates, the neural network is considered as an appropriate algorithm for regression classification. The neural network was implemented in MATLAB software and the obtained results indicate the better classification of this algorithm.

Table I Comparing the machine learning algorithms after adding the combined features in the third sample set

Classification algorithm	Squared error	Runtime (second)
Linear regression	180.283	7
Neural network	69.02	11
K-nearest neighbor	214.802	84
Generalized linear model	180.410	4
Local poly-nominal regression	444	93
Deep learning	142.265	49

Table 2 indicates the classification results by the neural network algorithm. Different results are obtained in 3 sets of the 1st to 3rd samples. The 1st sample set, with less noise, indicates less error in 3 sets of training, validation, and test. The results indicate that the cause of stopping the generation is the failed improvement and reduced error of the generation 125. In the 2nd sample set, 64 repetitions were conducted but no improvement was obtained from the generation 58.

Table II The results of training with neural network algorithm after adding combined features

	Squared error in training set	Squared error in validations et	Squared error in the test set	Training/testing/validation
1st set	69.26	75.63	69.02	18000/1000/1000
2nd set	122.4	115.16	119.94	36000/2000/2000
3rd set	111.02	109.85	113.36	54000/3000/3000

Based on the evaluation conducted on the input data of the third sample set, the C4.5 tree algorithm has more favorable conditions in prediction with the nominal class. Thus, the C4.5 decision tree is selected as the classifier of the proposed scheme in the class mode. In Table 3, the selection priority is based on the tree models having a good efficiency in discrete classification. On the other hand, based on the appropriate implementation time of all algorithms, the C4.5 tree algorithm was selected due to higher classification accuracy.

Table III Comparing the machine learning algorithms with discrete labels in the third sample set

Classification algorithm	**Classification accuracy**	**Cohen's kappa**	**Runtime (second)**
Normal decision tree	79.58	0.647	1
C4.5 tree	81.59	0.685	55
Random forest	79.97	0.652	5
Naïve Bayes	74.56	0.578	1

In the last step, the generated regression values obtained by the neural network are used to classify the C4.5 tree algorithm effectively. The third sample set includes the first and second sample sets and a part is related to the samples of this set. The final results of accuracy are reported according to this set. Figure 6 indicates the result of the classification of three sample sets for hypotension, normal, and hypertension as well as the overall accuracy. All steps were conducted using C4.5 tree training algorithm and KCV validator. Then, the proposed method suggests an additional phase for hypertension mode being raised as the generalized proposed scheme. In this mode, the calculations are increase because non-supervised operations merge into the supervised operations and can be implemented only when it has few samples for training and noise is highly effective on the data.

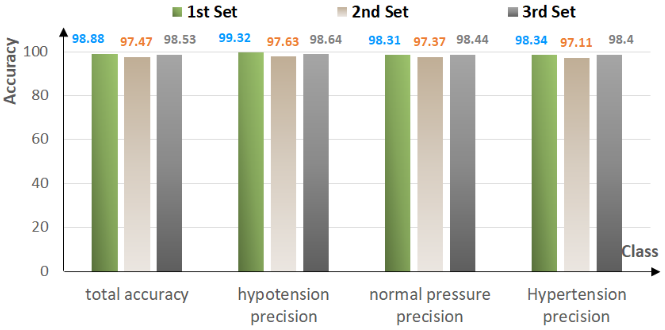

Fig. 6. Calculating the accuracy of the classes obtained by the proposed scheme

In this mode, a sub-process is added to the proposed scheme to adjust the optimal value of the parameters for the outlier detection module by the genetic algorithm. The added module from the cosine distance with a number of samples in a 2 dimensional space, like the K-Means clustering [25], calculates the sample distance and removes the outlier according to the determination of the optimal amount of the genetic algorithm. In this study, the number of genetic algorithm generations was selected as 100, the population size was 20, and crossover was 90%. The remaining 10% was adjusted to select the mutation and the initial population selection. This test was conducted on 200 data. A number of 80 samples were removed based the optimal amount determined by the genetic algorithm and the outlier module was removed and then reached to the accuracy of 97.50% with 120 data while the accuracy of the proposed scheme in the non-generalized mode for 200 data was 92%. The parameters of the number of samples were selected by the genetic algorithm to measure the cosine distance as 43 and the number of outliers as 80. The validation result by the C4.5 training algorithm equals to 97.50%. The proposed design has been implemented with three classes of low pressure, high pressure and normal with C4.5 and neural network classifiers on three datasets. Classification was done by regression and discrete methods. Each type of classification has its own applications. The response time limitation has been one of the main objectives of the evaluation in addition to the classification accuracy for the determination of algorithms.

5. CONCLUSION

Todays, technology plays a critical role in the quality of human life. Supervising the human health by health devices and biosensors develops every day. Blood pressure measurement is widely used in clinical environments. In this study, the blood pressure estimation was regarded using ECG and PPG signals. In this study, an evaluation of several data samples was performed by different machine learning algorithms. After applying the preprocessing and increasing the effective features, the elimination of noisy samples was performed by clustering measurement of classification operations. Since the response time limitation as well as the classification accuracy for determining the algorithms was one of the main objectives of the evaluation, it was indicated that the algorithm of the neural network with the optimization of parameters is an ideal algorithm for regression labels and the C4.5 tree algorithm has appropriate classification accuracy in the discrete mode. The proposed scheme is applicable by high-efficiency software optimizations while the generalized proposed scheme is suitable for bulk data computation requires hardware support. Determining the cosine distance and the C4.5 tree in the generalized proposal scheme is one of the available and expandable resources of the GPU application for the parallel implementation of genetic algorithms to improve the sub-process of outliers and classification module detection.

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