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Research Article

Automatic Classification of Hypertension Types Based on Personal Features by Machine Learning Algorithms

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Hypertension (high blood pressure) is an important disease seen among the public, and early detection of hypertension is significant for early treatment. Hypertension is depicted as systolic blood pressure higher than 140 mmHg or diastolic blood pressure higher than 90 mmHg. In this paper, in order to detect the hypertension types based on the personal information and features, four machine learning (ML) methods including C4.5 decision tree classifier (DTC), random forest, linear discriminant analysis (LDA), and linear support vector machine (LSVM) have been used and then compared with each other. In the literature, we have first carried out the classification of hypertension types using classification algorithms based on personal data. To further explain the variability of the classifier type, four different classifier algorithms were selected for solving this problem. In the hypertension dataset, there are eight features including sex, age, height (cm), weight (kg), systolic blood pressure (mmHg), diastolic blood pressure (mmHg), heart rate (bpm), and BMI (kg/m^2) to explain the hypertension status and then there are four classes comprising the normal (healthy), prehypertension, stage-1 hypertension, and stage-2 hypertension. In the classification of the hypertension dataset, the obtained classification accuracies are 99.5%, 99.5%, 96.3%, and 92.7% using the C4.5 decision tree classifier, random forest, LDA, and LSVM. The obtained results have shown that ML methods could be confidently used in the automatic determination of the hypertension types.

1. Introduction

1.1. Background on Hypertension. In this paper, machine learning methods have been used to determine the hypertension types based on personal data. The machine learning is used increasingly in many fields, including medical diagnosis, image processing, signal processing, and finance. Machine learning is a division of artificial intelligence (AI) that uses algorithms and statistical models, using the data to perform a specific task. As the machine learning algorithm, four different classification algorithms have been used to classify the types of hypertension in this paper.

Blood pressure is the force applied by circulating the blood towards the walls of the arteries of the body. Hypertension occurs when blood pressure is high. There are two types of blood pressure: systolic blood pressure (SBP) and diastolic blood pressure (DBP). SBP shows the pressure in the blood vessels when the heart beats. DBP represents the pressure in the vessels between beats. Hypertension is diagnosed when the SBP value is equal to or greater than 140 mmHg for both days and the DBP value is greater than or equal to 90 mmHg for both days when measuring on two different days. Hypertension is defined as a clinical syndrome with an increase in systemic vascular pressure. Table 1 shows the categorization of blood pressure for adults [1, 2].

Prehypertension is not a category of disease. Prehypertension is a preliminary statement used to describe people at high risk for hypertension disease [1]. Hypertension is one of the many cardiovascular diseases which are a group of diseases that affect the heart and blood vessels.

Table 1: Blood pressure values for adults with respect to SBP and DBP [1, 2].

Blood pressure classification	SBP (mmHg)	DBP (mmHg)
Normal	<120	And <80
Prehypertension	120–139	Or 80–89
Stage-1 hypertension	140–159	Or 90–99
Stage-2 hypertension	≥160	Or ≥100

Table 2: SBP and DBP values and definitions of blood pressure according to the hypertension guidelines in Europe [4].

Blood pressure type	SBP	DBP
Classification	mmHg	mmHg
Optimal	<120	<80
Normal	120–129	80–84
High normal	130–139	85–89
Grade 1 hypertension	140–159	90–99
Grade 2 hypertension	160–179	100–109

Cardiovascular diseases include coronary heart disease, cerebrovascular disease, peripheral arterial disease, and rheumatic heart disease [2–4].

The different blood pressure classes are presented in Table 2, according to the hypertension guidelines in Europe [4, 5].

1.2. Related Works. There are several studies in the literature on the detection and classification of hypertension. Among them, Melin et al. used the neural network and fuzzy inference system to classify the hypertension type based on the age, risk factors, and behavior of the blood pressure in a period of 24 h. They obtained the 98% classification performance as the maximum with their method [6]. Singh et al. proposed a new method called rule extraction from the support vector machine to diagnose hypertension in diabetes mellitus patients. And then, they achieved excellent results in the classification of hypertension types in people having diabetes mellitus [7]. In another work [8], Abdullah et al. proposed a fuzzy expert system (FES) to diagnose hypertension in male and female patients of age groups 10, 20, 30, and 40. They modeled the hypertension cases for each age group based on the FES model [8]. Das et al. used different modeling techniques including Levenberg–Marquardt (LM), gradient descent (GD), and bayesian resolution- (BR-) based learning functions to model the hypertension types in people of age groups 20 and 40 [9]. In Shinde's work [10], they proposed two different approaches for the classification of hypertension types. These methods were the information gain-based feature selection and genetic algorithm-based feature selection for the classification of hypertension types, and these methods obtained 97.58% and 99.19%, respectively [10].

Apart from the above papers in the literature, not using any medical signals, based on the personal data, we have performed the automatic finding of the type of hypertension firstly. In general, in the classification of hypertension types, the ECG (electrocardiogram), PPG (photoplethysmo graphy), HRV (heart rate variability), and other medical signals have been used. However, in our study, we have not used any medical signal to classify the hypertension types. The proposed method could be used in the hospital and medical centers.

2. Materials and Methods

2.1. Hypertension Dataset. In this study, PPG-BP (photoplethysmography-blood pressure) database has been used to test the proposed models in the classification of hypertension types [11]. In the dataset, 8 features define the hypertension types: sex, age, height (cm), weight (kg), systolic blood pressure (mmHg), diastolic blood pressure (mmHg), heart rate (bpm), and BMI (kg/m^2). Also, there are four classes: normal (healthy), prehypertension, stage-1 hypertension, and stage-2 hypertension in the dataset. The PPG-BP dataset has been collected from 219 adult subjects aged 21–86 years. Table 3 shows the statistical metrics of each feature in the dataset. Figure 1 denotes the class distribution of the PPG-BP dataset according to three features (age, weight, and SBP). Figure 2 denotes the class distribution of the PPG-BP dataset according to three different features (SBP, DBP, and BMI) concerning the class types. Also, the Pearson correlation coefficients of all the features in the hypertension dataset have been calculated and then tabulated in Table 4. According to Table 4, the most significant feature is the systolic blood pressure having the r correlation coefficient of 0.9342.

In the PPG-BP dataset, the PPG signals have been recorded in the measurement of blood pressure. For each group, including normal (healthy), prehypertension, stage-1 hypertension, and stage-2 hypertension, PPG signals have been given as shown in Figure 3. However, these signals were not used to classify the hypertension types in this study. Only PPG signals were given as the information.

2.2. Method. In this study, we have proposed a machine learning-based method for classification of the hypertension types on the basis of personal data. As the input to the machine learning algorithms, the eight parameters (features) obtained from people were given to the classification algorithm. As the classification algorithms, C4.5 decision tree classifier, random forest, linear discriminant analysis (LDA), and linear support vector machine (LSVM) have been used to determine the type of hypertension. Since the dataset has many classes, we have selected these classification algorithms which are more suitable to these problems. The block diagram of the proposed method is given in Figure 4. The used classifier algorithms have been explained in the following sections.

2.2.1. Random Forest Classifier. Random forests are a combination of tree estimates where each tree depends on the values of a randomly sampled random vector. Random forests are an important modification of the bagging method that makes up a large sum of unbound trees. It was created in 2001 by Breiman. In many classification

Table 3: Statistical metrics of each feature in the PPG-BP dataset.

Name of the feature in the dataset	Minimum value	Maximum value	Average	Variance	Standard deviation
Sex (male: 0; female: 1)	0	1	0.474	0.250	0.5
Age (year)	21	86	57.168	251.994	15.87
Height (cm)	145	196	161.228	67.287	8.202
Weight (kg)	36	103	60.191	141.284	11.886
Systolic blood pressure (mmHg)	80	182	127.945	415.25	20.377
Diastolic blood pressure (mmHg)	42	107	71.849	123.458	11.111
Heart rate (bpm)	52	106	73.639	115.323	10.738
BMI (kg/m^2)	14.69	37.46	23.107	16.034	4.0043

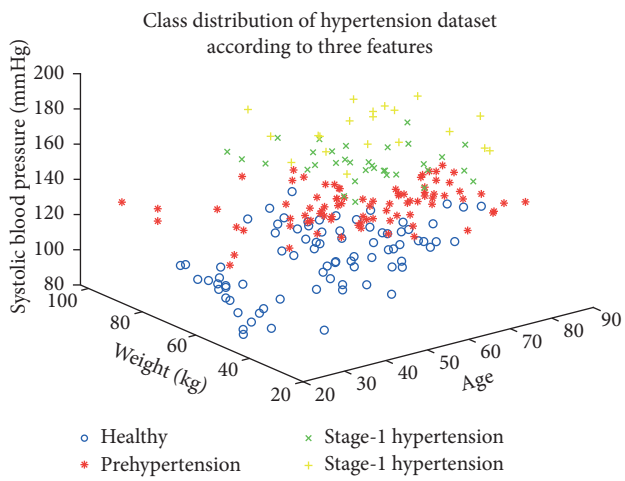

Figure 1: Class distribution of the PPG-BP dataset according to three features (age, weight, and SBP).

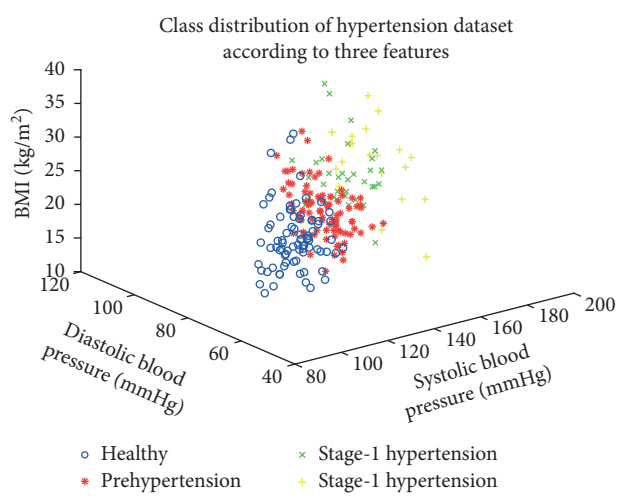

Figure 2: Class distribution of the PPG-BP dataset according to three features (SBP, DBP, and BMI).

problems, the performance of random forests is very close to the boosting method and the random forests algorithm is simpler in training and tuning. Random forests are very popular in ML algorithms and are shown in many packages [12–15]. Figure 5 shows the working of the random forest classifier [16].

2.2.2. C4.5 Decision Tree Classifier. It is an algorithm used to produce a decision tree developed by Ross Quinlan. The C4.5 algorithm is an extended version of Quinlan's ID3 algorithm. The rules produced by C4.5 can be used for classification purposes [17]. The C4.5 algorithm creates a decision tree where each node separates classes on the basis of the

Table 4: Pearson correlation coefficients and p values belonging to the features in the hypertension dataset.

Name of the feature in the dataset	p value between feature and class label (it is significant below 0.05)	r correlation coefficient between feature and class label [−1 and 1]
Sex	0.48775	0.0471
Age (year)	$1.894e-07$	0.343
Height (cm)	0.6522	−0.0306
Weigh t(kg)	0.00810	0.1785
Systolic blood pressure (mmHg)	$3.646e-99$	0.9342
Diastolic blood pressure (mmHg)	$8.7091e-30$	0.669
Heart rate (bpm)	0.1550	0.0964
BMI (kg/m^2)	0.00101	0.2205

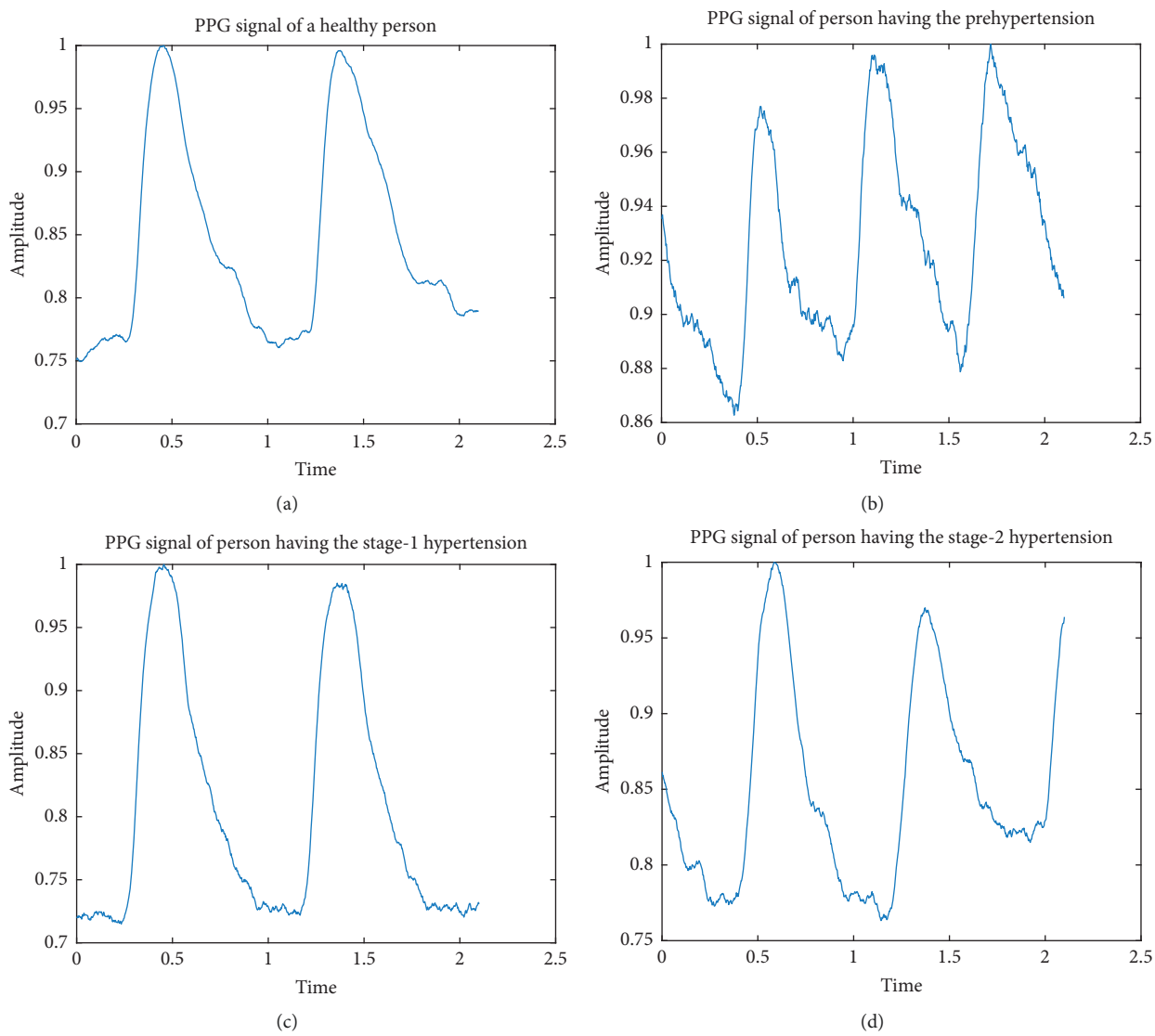

Figure 3: Recorded sample PPG signals for each group including normal (healthy), prehypertension, stage-1 hypertension, and stage-2 hypertension in the PPG-BP dataset.

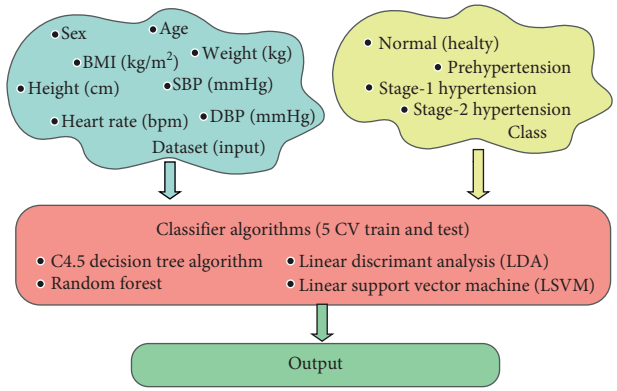

Figure 4: Proposed block diagram of the classification of hypertension types based on machine learning algorithms.

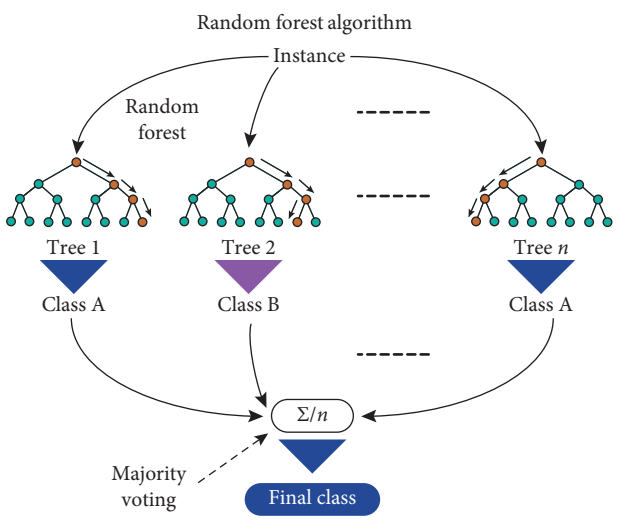

Figure 5: The schematic representation of the random forest classifier [16].

information gain. The pruned tree structure is given below. Pruned tree structure obtained with a C4.5 decision tree for this dataset is as follows:

Systolic blood pressure ≤ 119 : 0 (80.0)

Systolic blood pressure > 119

Systolic blood pressure ≤ 139 : 1 (85.0)
Systolic blood pressure > 139

Systolic blood pressure ≤ 159 : 2 (34.0)
Systolic blood pressure > 159 : 3 (20.0)

Number of leaves: 4

Size of the tree: 7

For more information about the C4.5 decision tree algorithm, refer to [18–21].

2.2.3. Linear Discriminant Analysis (LDA) Classifier. LDA is a classification method developed by R. A. Fischer. Although simple, it is a model that produces good results in complex problems. The LDA is based on looking for a linear combination of variables, which best distinguishes between the good classes. Fisher defines the score function given in equation (1). According to the score function, the problem is to estimate the linear coefficients that maximize the score [22–25]:

$$Z = \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n, \tag{1}$$

$$S(\beta) = \frac{\beta^T \mu_1 + \beta^T \mu_2}{\beta^T C \beta}, \tag{2}$$

$$S(\beta) = \frac{\overline{Z}_1 - \overline{Z}_2}{\text{variance of } Z \text{ within groups}}, \tag{3}$$

$$\beta = C^{-1}(\mu_1 - \mu_2), \tag{4}$$

$$C = \frac{1}{n_1 - n_2}(n_1 C_1 - n_2 C_2), \tag{5}$$

where β defines m the model's parameter, C show the covariance matrixes, and μ_1, μ_2 gives mean the vector.

LDA is also often used in dimensionality reduction processes as a preprocessing step for pattern classification and machine learning applications. Figure 6 shows the graphical representation of the LDA classifier [26]. For more information about the LDA algorithm, refer to [23–25].

2.2.4. Linear SVM Classifier. The foundations of LSVM were laid by Vapnik and Chervonenkis in 1963, and its development was realized in 1995 by Vapnik, Boser, and Guyon. It is a consultative learning method based on statistical learning [27–29]. The starting point is the separation of two classes of data. For this purpose, a separating plane is determined. Linear SVM is a rapidly developing classification algorithm designed to solve multiple classification problems. Figure 7 denotes the schematic representation of the linear SVM model [30]. For more information about the LSVM algorithm, refer to [27–29].

The features of the LSVM are briefly as follows [30, 31]:

(i) Efficiency in dealing with extralarge data sets

(ii) The solution of multiclass classification problems with any number of classes

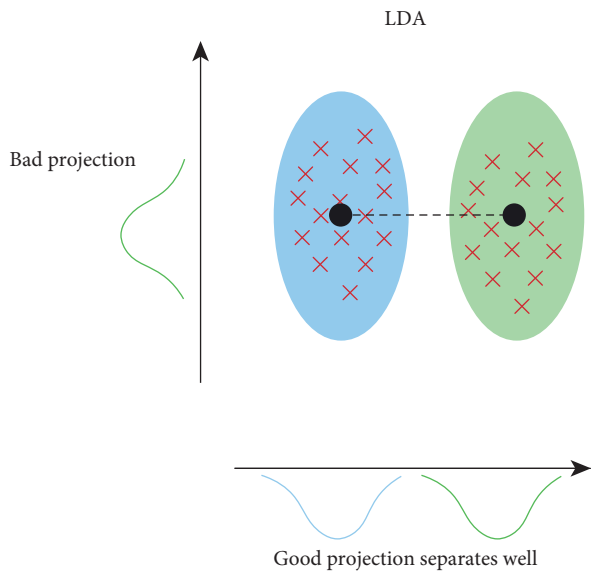

Figure 6: Demonstration of the LDA classifier in a two-dimensional space [26].

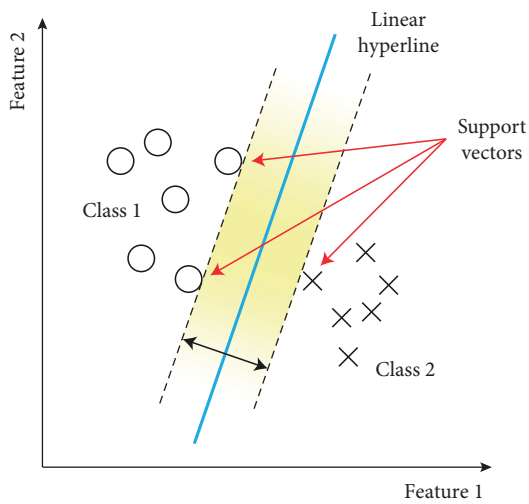

Figure 7: Schematic representation of the linear SVM model.

(iii) No need for expensive computing resources

(iv) Working with high-dimensional data

3. Experimental Results

In this paper, a machine learning approach for the classification of hypertension types based on the personal features comprising sex, age, height (cm), weight (kg), systolic blood pressure (mmHg), diastolic blood pressure (mmHg), heart rate (bpm), and BMI (kg/m^2) has been proposed. There are four types of hypertension as follows: normal, prehypertension, stage-1 hypertension, and stage-2 hypertension.

In the training and testing of the classifier algorithms, the 5-fold cross-validation method was used. The working of the 5-fold CV (cross validation) is explained in Figure 8. All data are divided into 5 equal parts. In each part, the first four parts are used for training and the remaining last part is used for testing in the classifier algorithms. For the next part, the process is repeated for other folds.

As the performance metric, we have used the classification accuracy (%), confusion matrix, and ROC (receiver operating characteristic) curves to evaluate the classifier algorithms in the classification performance of finding the hypertension

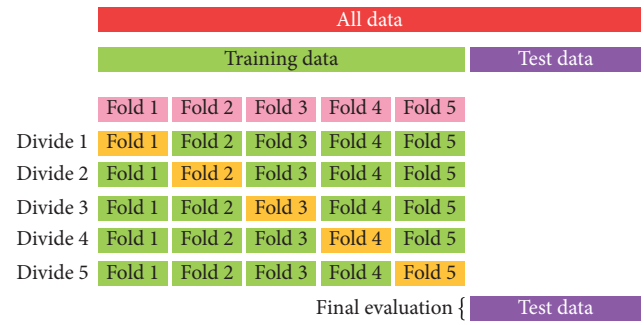

Figure 8: Schematic working representation of the 5-fold cross validation [32].

Table 5: Classification accuracies obtained for C4.5 decision tree classifier, random forest, linear discriminant analysis (LDA), and linear support vector machine (LSVM) in the classification of hypertension types with 5-fold CV.

Classifier algorithm	The obtained classification accuracy (%)
C4.5 decision tree	99.50
Random forest	99.50
LDA	96.30
LSVM	92.70

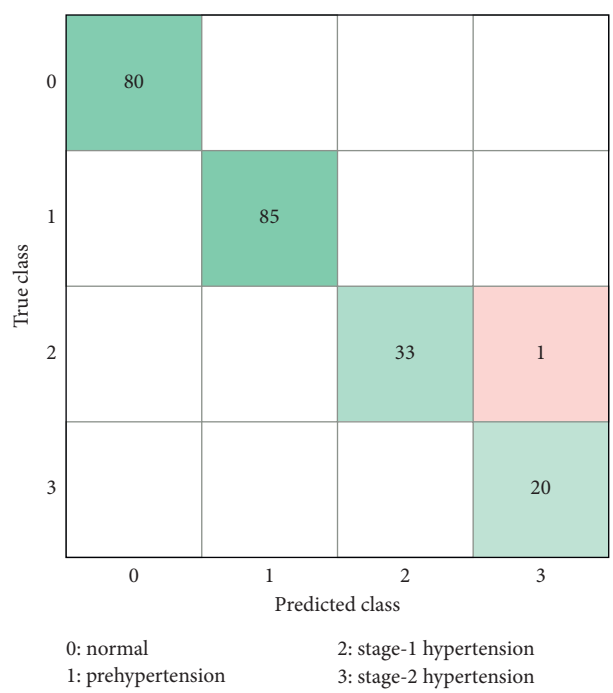

Figure 9: Confusion matrix obtained for random forest classifier and C4.5 decision tree classifier in the classification of hypertension types with 5-fold cross validation.

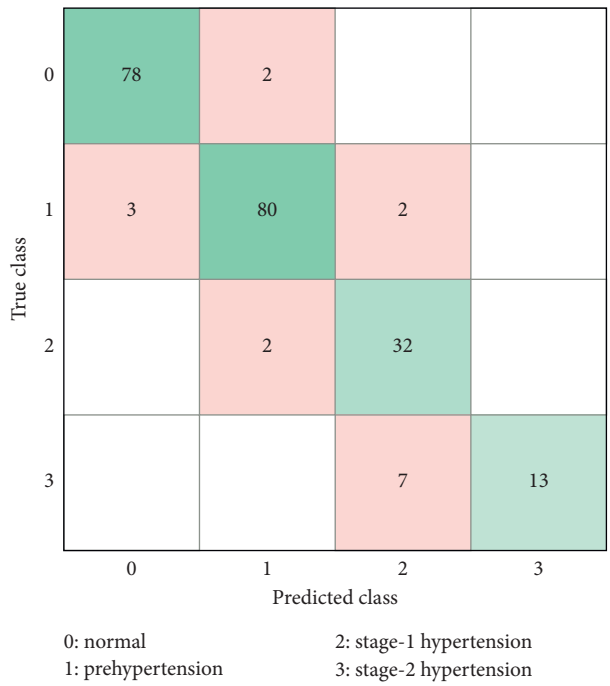

Figure 10: Confusion matrix obtained for linear support vector machine (LSVM) in the classification of hypertension types with 5-fold cross validation.

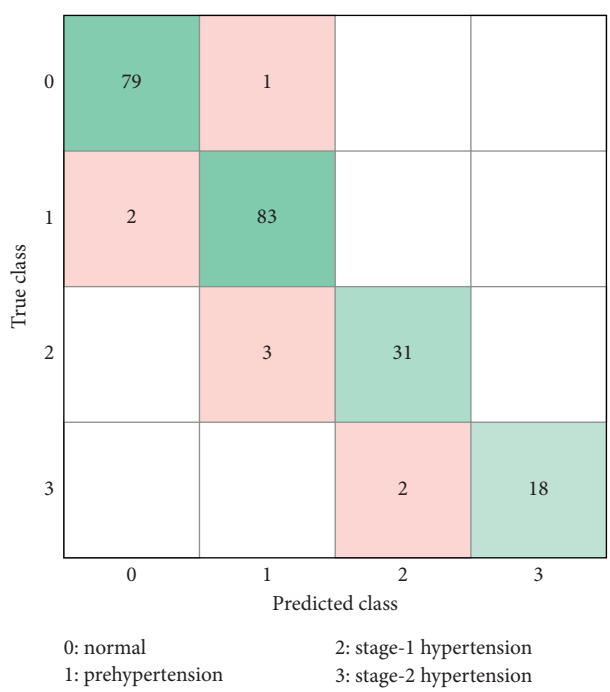

Figure 11: Confusion matrix obtained for LDA in the classification of hypertension types with 5-fold cross validation.

types. Table 5 gives the obtained classification accuracies for four classifiers in the classification of hypertension types.

The obtained confusion matrix has been given for the random forest classifier and C4.5 decision tree classifier in the classification of hypertension types with 5-cross validation in Figure 9. In Figure 10, the confusion matrix has been shown for the linear support vector machine (LSVM). In Figure 11, the confusion matrix has been given for LDA.

The other metric to evaluate the classifier performance is the ROC curve. As the performance metric, the AUC (area under the ROC curve) is used. The higher the AUC value, the higher the classification performance. The AUC is varied within 0 and

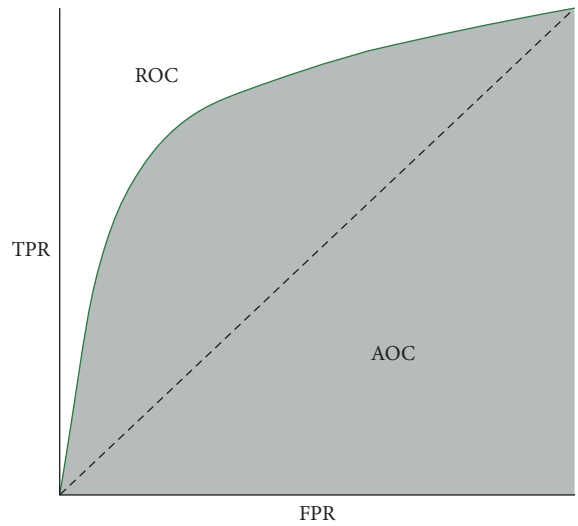

Figure 12: An example of a ROC curve [33].

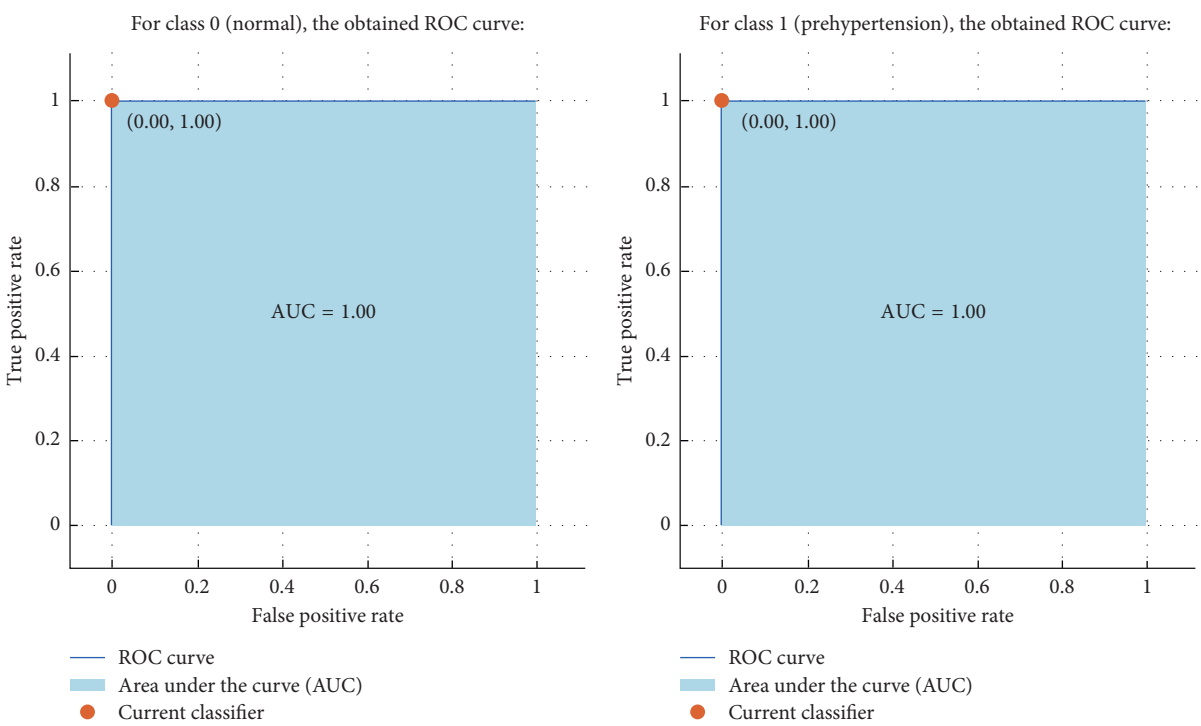

Figure 13: Continued.

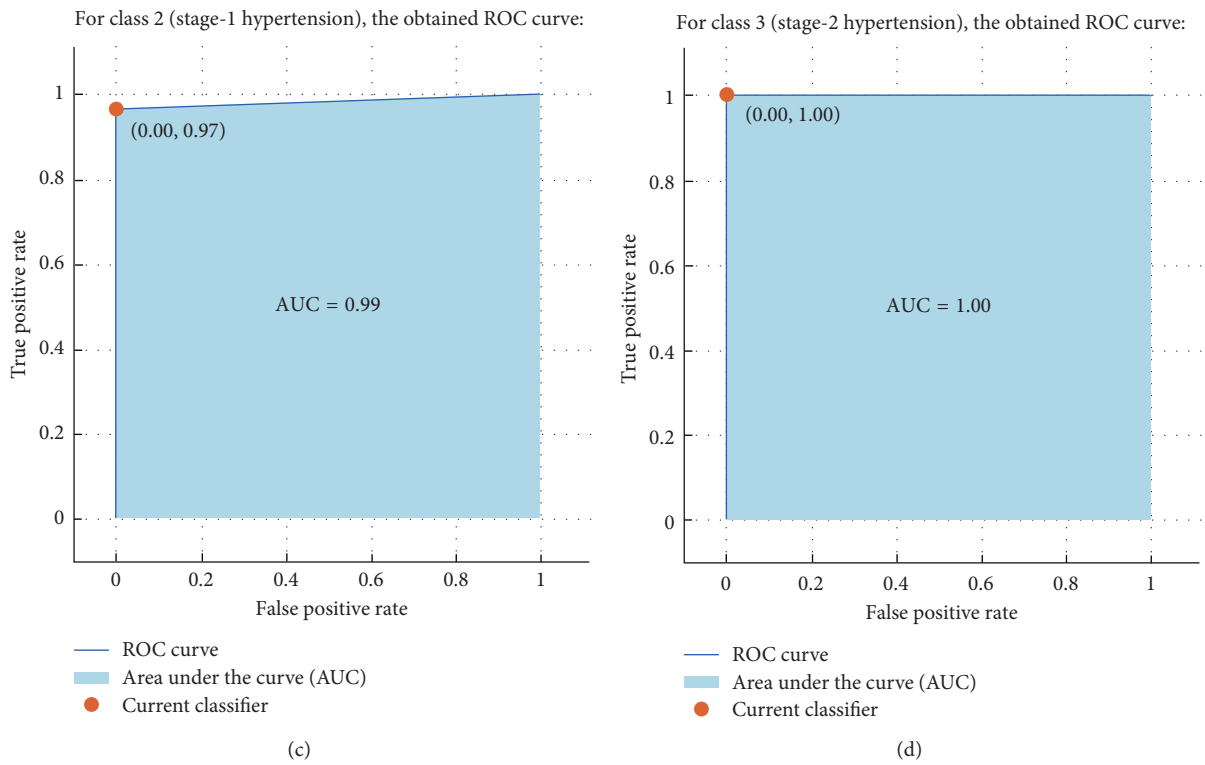

Figure 13: The obtained ROC curves for each class using the random forest classifier and C4.5 decision tree classifier in the classification of hypertension types with personal features.

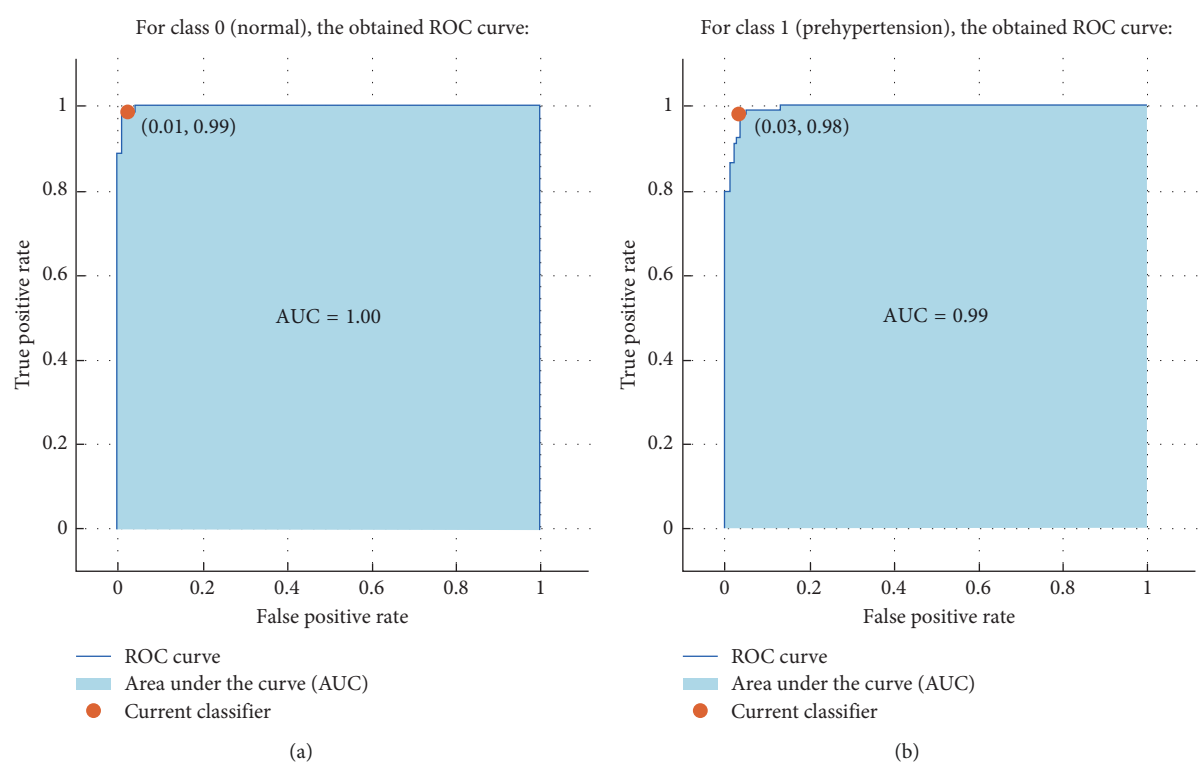

Figure 14: Continued.

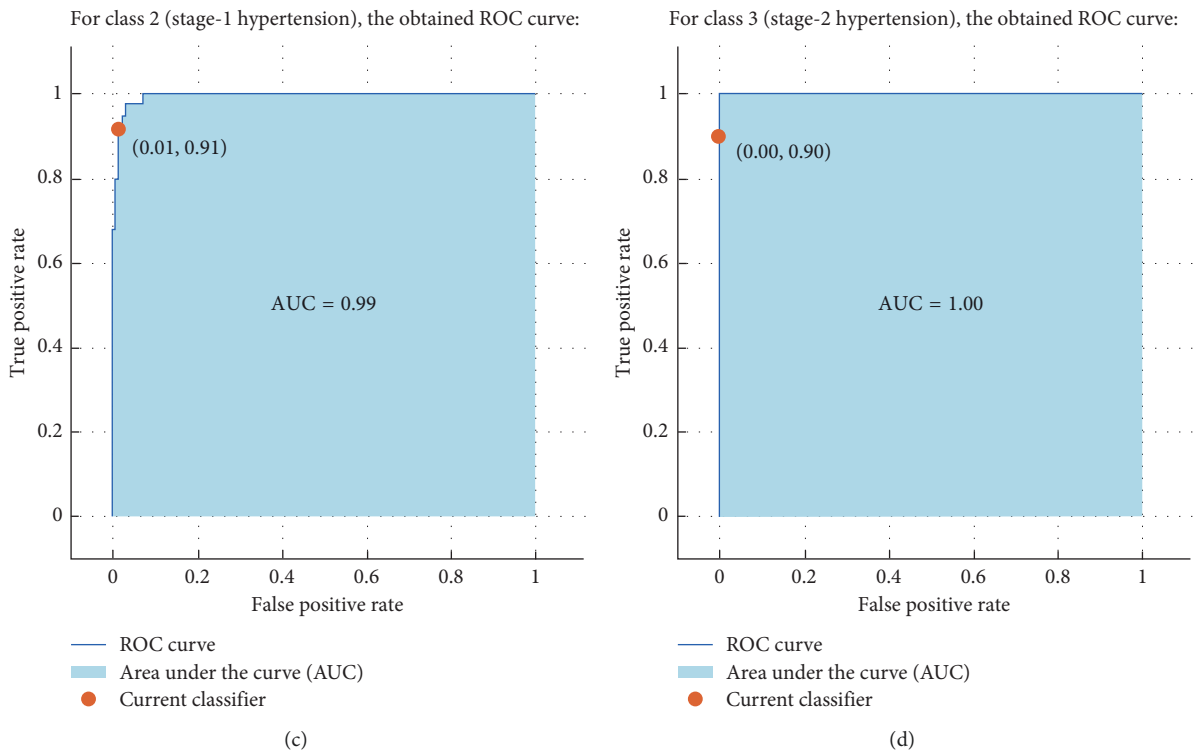

Figure 14: The obtained ROC curves for each class using the LDA classifier in the classification of hypertension types with personal features.

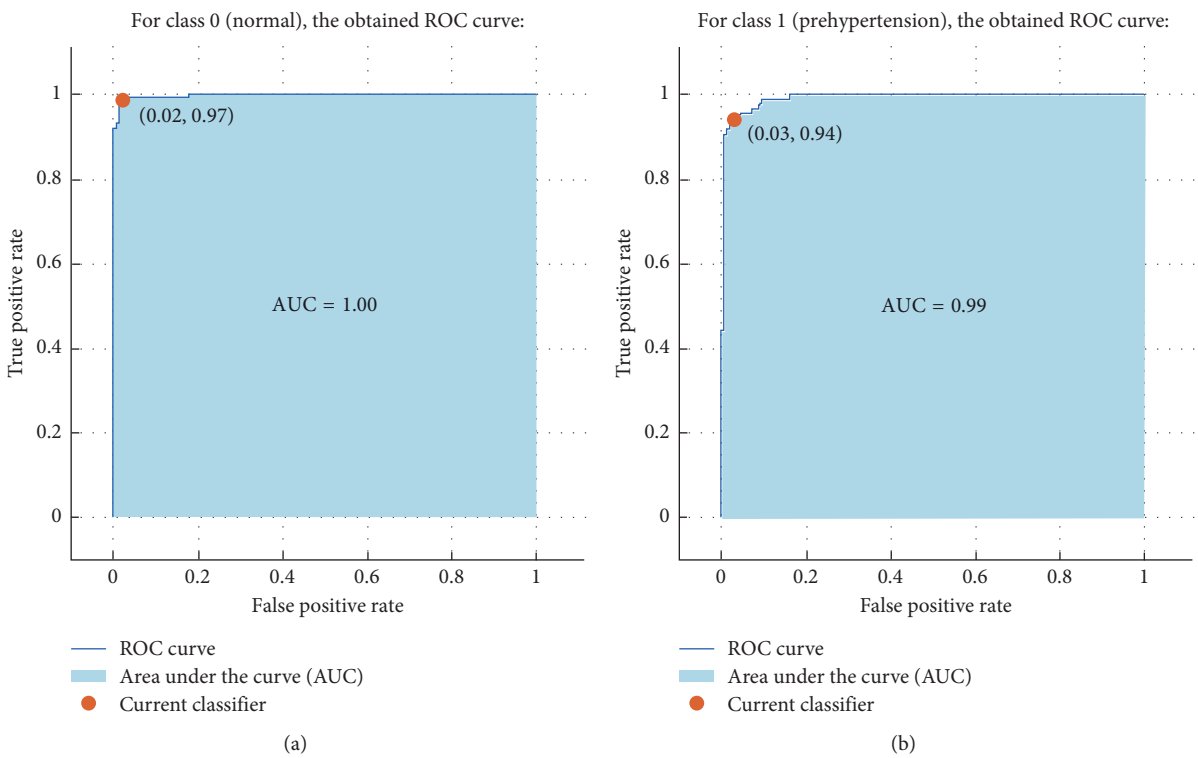

Figure 15: Continued.

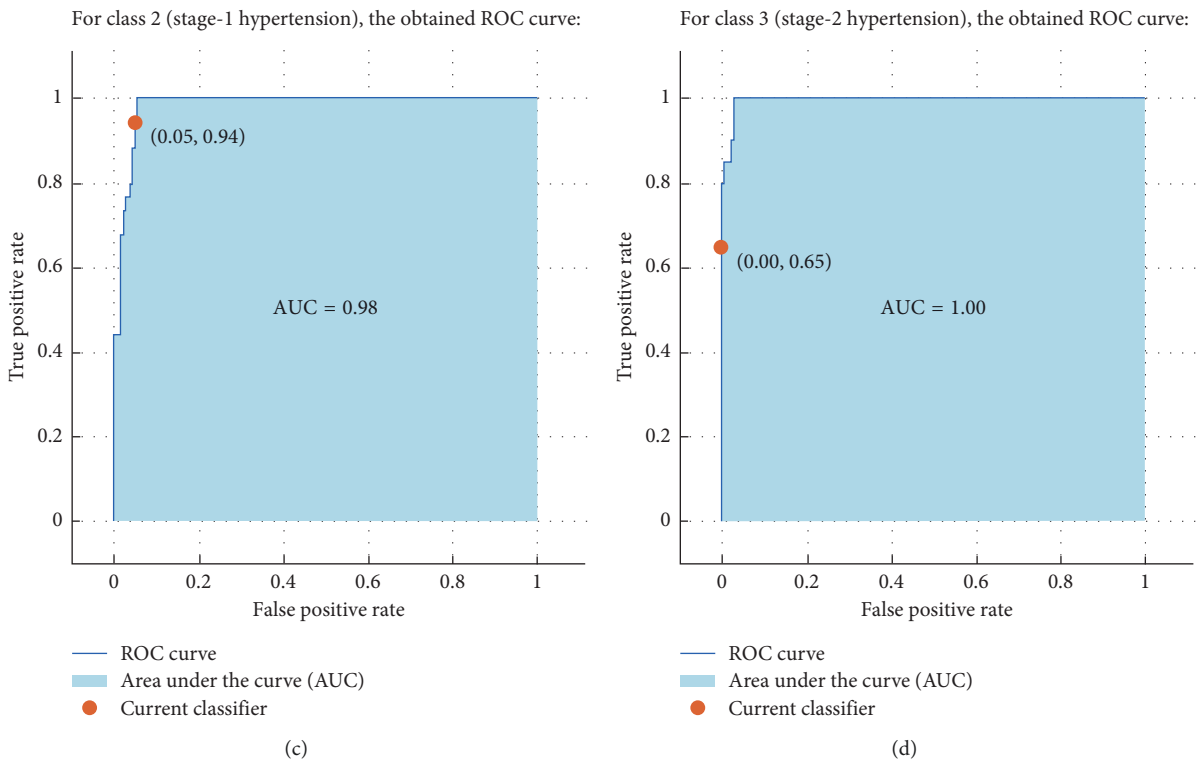

Figure 15: The obtained ROC curves for each class using LSVM classifier in the classification of hypertension types with personal features.

1. An example of the ROC curve is shown in Figure 12. The obtained ROC curves for each class using the random forest classifier and C4.5 decision tree classifier are shown in Figure 13. The obtained ROC curves for each class using the LDA classifier are given in Figure 14. The obtained ROC curves for each class using the LSVM classifier are given in Figure 15.

4. Discussion

The hypertension diagnosis is a long time-consuming process for cardiologists. To decrease this time, we have proposed machine learning-based methods for automatic classification of hypertension types. As seen from the obtained results, the best models in the classification of hypertension types based on the personal features are C4.5 decision tree and random forest classifier among the four classifiers.

Also, this paper is the first study in the classification of hypertension types using machine learning algorithms based on the personal data in the literature. Except for the used classifier algorithms, we have tried some classification algorithms including k-star instance-based learning, weighted k-NN classifier, the k-NN classifier (for $k = 1$), artificial neural network (ANN), naïve Bayes classifier, and AdaBoostM1 classifier on this dataset. The equations of classification accuracy and F-measure values are given in Table 6. The obtained classification accuracies and F-measure values are shown in Table 7.

As can been seen from Table 5, once compared with other classifier algorithms, the C4.5 decision tree and random forest classifier obtained the best accuracy in the classification of hypertension types.

Table 6: Performance measure equations used to denote the performance of the classifier algorithms.

Performance measure	Equation
Accuracy (%)	(TP + TN)/ (TP + TN + FP + FN)
F-measure	(2∗ precision ∗ recall)/ (precision + recall)

Table 7: Comparison with other classifier algorithms in the classification of hypertension types.

The used classifier algorithm	The obtained classification accuracy (%)	F-measure value
k-star instance-based learning	69.40	0.962
Weighted k-NN, (for $k = 1$)	68.90	0.69
k-NN, (for $k = 1$)	71.68	0.719
Artificial neural network (ANN)	93.15	0.931
Naïve Bayes	90.86	0.908
AdaBoostM1	75.34	0.75

5. Conclusions and Future Works

Hypertension is either high blood pressure (systolic) of 140 mmHg (14) or higher or low blood pressure (diastolic) of 90 mmHg (9) or higher. High blood pressure (hypertension) does not cause any symptoms in many people because they are unaware of the presence of high blood pressure which

can damage the heart, the kidneys, and even the brain. Therefore, the diagnosis of hypertension disease is so significant with respect to human health.

In the diagnosis of the hypertension types, four classifier algorithms including C4.5 decision tree classifier, random forest, linear discriminant analysis (LDA), and linear support vector machine (LSVM) have been used and then compared with each other with respect to the classification performance using the classification accuracy, the confusion matrix, and ROC curves. Also, the PPG signals have been recorded for each hypertension type and then extracted some information from these signals to evaluate the disease.

The best methods for classifying the hypertension types were C4.5 decision tree and random forest classifiers according to the obtained results.

In the future, a new device could be developed which uses PPG signals to evaluate the patient automatically. Also, the PPG signals could be combined with ECG signals in the evaluation of hypertension types.

Data Availability

The link of the used dataset in this study is https://ieeedataport.org/documents/bp-data-unsw. (last accessed: December, 2019).

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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