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A Brief Review on Classification of Patients with High Blood Pressure Using Machine Learning Algorithms

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Abstract

Blood pressure is the force and pressure that the blood exerts on the walls of the vessels when it flows through the vessels, and it is not a problem on its own. One of the important diseases is high blood pressure, which is caused by various factors. Many patients with high blood pressure (or hypertension) do not control their disease. As a person ages, blood pressure naturally increases. Blood pressure is proportional to dietary and behavioral habits, excitement, and stress, and even changes during the hours of the day and night. Today, the use of machine learning algorithms is widely increasing to classify patients with high blood pressure. This paper conducts a succinct investigation into the application of machine learning algorithms for the classification of individuals with high blood pressure, drawing on a comprehensive analysis of existing research in the field. The machine learning algorithms considered are categorized into three distinct groups: unsupervised learning, supervised learning, and reinforcement learning. While the majority of studies have traditionally concentrated on the analysis of at least one performance criterion, a limited number have ventured into the exploration of multiple criteria. Various patient data are analyzed by machine learning algorithms to predict and classify the likelihood and severity of high blood pressure. This study can help the application of machine learning algorithms to improve medical services for patients with high blood pressure, and to provide a model for effective health management.

Keywords: classification model, high blood pressure, hypertension detection, machine learning algorithms
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1. Introduction

In recent years, artificial intelligence has become a part of many technologies used by humans. Artificial intelligence is a broad field of building machines that have the ability to mimic human intelligence, but machine learning is a subset of artificial intelligence that focuses on enabling machines to learn from data without explicit programming. Intelligent methods, characterized by their adaptive and data-driven nature, have become ubiquitous in numerous domains, including but not limited to engineering, medicine, management, and economic. The pervasive adoption of these smart methodologies underscores their transformative impact on various facets of contemporary society. A comprehensive body of research has been dedicated to harnessing the potential of intelligent methods for system enhancement and quality improvement [1-19].

This evolving field has witnessed a multitude of studies exploring novel applications and methodologies, contributing to a deeper understanding of how intelligent techniques can be effectively employed to optimize the performance and elevate the quality standards of diverse systems. This ongoing research trajectory reflects a collective effort to unlock the full potential of smart methods across a spectrum of applications [21-27].

High blood pressure (hypertension) is a silent disease and causes disturbances in the normal functioning of the body. The diagnosis of this disease may take a long time until the symptoms of high blood pressure appear in humans [28-31]. High blood pressure can cause tissue damage [32], and in the long term it can cause heart diseases [33,34], kidney failure [35], arteriosclerosis [36] and stroke [37,38]. Therefore, early detection of high blood pressure is important and necessary for health and a better life [39,40]. High blood pressure is common among people over the age of 45, with a higher proportion of men than women [41,42]. More than half of people with high blood pressure are not aware of their disease, and most patients find out about their high blood pressure by accident [43,44].

The causes of high blood pressure can be environmental, genetic and biological, but the exact cause is not known [45]. High blood pressure is placed in one of the two groups of primary hypertension or secondary hypertension, most of the cases are primary hypertension, and in other words, there is no specific medical reason for it [46,47]. Blood pressure is established through two key measures: systolic and diastolic [48]. These measures correspond to the contraction and relaxation phases of the heart muscle between beats, respectively. Systolic blood pressure (SBP) (maximum blood pressure indicating the pressure of the arteries during heartbeat and blood pumping) and diastolic blood pressure (DBP) (minimum blood pressure indicating the amount of arterial pressure between heartbeats) [49,50]. It should be noted that SBP has more prognostic significance than DBP.

In the state of ablution, the customary systolic blood pressure hovers around 120 millimetres of mercury, while the typical diastolic blood pressure is approximately 80 millimetres of mercury. Consequently, maintaining blood pressure below 120/80 is considered ideal for a healthy condition. It is worth noting that blood pressure changes are a complex phenomenon that can fluctuate throughout the day due to various factors such as activity levels and emotional behaviors [51,52].

The categorization of individuals' blood pressure, based on systolic blood pressure and diastolic blood pressure, is illustrated in Figs. 1 and 2, respectively [53-55]. Fig. 3 shows the blood flow in the heart for two blood pr3essure measurements [56,57].

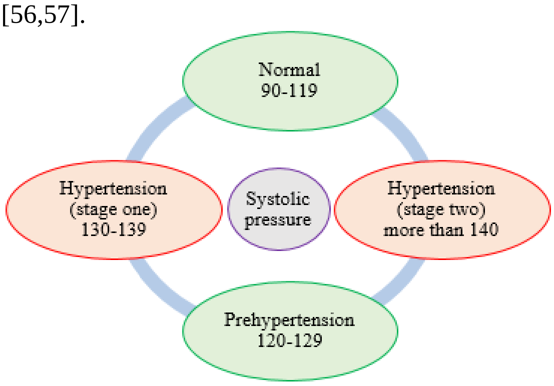


Fig. 1. Classification of systolic pressure

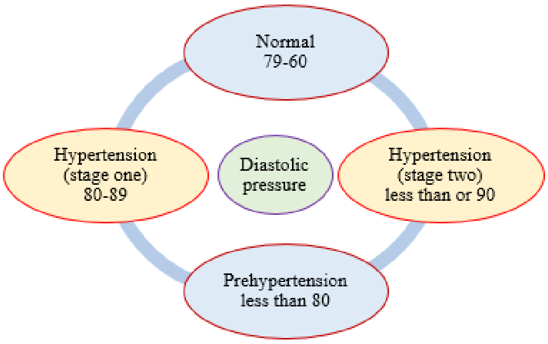


Fig. 2. Classification of diastolic pressure

Many modifiable and non-modifiable risk factors are associated with high blood pressure [58,59]. For this reason, various studies have been conducted in different fields for blood pressure such as blood pressure measuring [60,61], blood pressure estimation [62,63], record blood pressure at home [64], evaluation of the blood pressure device [65], prediction of blood pressure without cuff [66], predicting individual responses to antihypertensive treatments [67] and blood pressure control [68].

Table (1) presents a compilation of review studies within the realm of blood pressure.

Machine learning algorithms have also been used in the improvement and diagnosis of other diseases, and various studies have been conducted in this field, such as improving cancer diagnosis and prevention mechanisms [69], diagnosis and classification of breast cancer [70], diagnosis of chronic kidney disease [71,72], early diagnosis of Parkinson's disease and prevention [73], diagnosis and treatment of neurological diseases [74].

Table (2) lists a number of review articles in other fields of application of machine learning algorithms to show the importance of the use of these algorithms.

High blood pressure is a chronic disease and is caused by various causes. Hence, as a consequence of unregulated blood pressure, there is an elevated likelihood of acquiring health complications that impact various organs within the body.

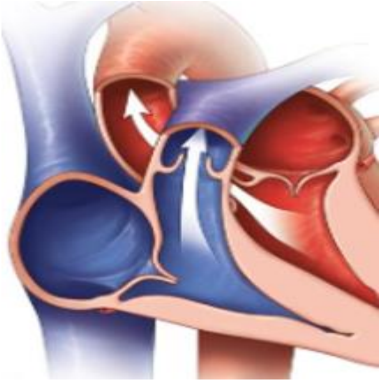
Machine learning is one of the important branches of artificial intelligence that has been the focus of researchers in various fields in recent years. There are different methods of machine learning algorithms, which are used to identify and predict blood pressure. Three categories of machine learning algorithms include unsupervised learning, supervised learning, and reinforcement learning. In this paper, various methods of supervised learning have been studied in blood pressure classification. More than 150 researches have been reviewed. In the studies conducted, various criteria have been examined, and the advantages of each method compared to other methods have been pointed out.

Table.1.
A summary of a number of review studies in the field of blood pressure

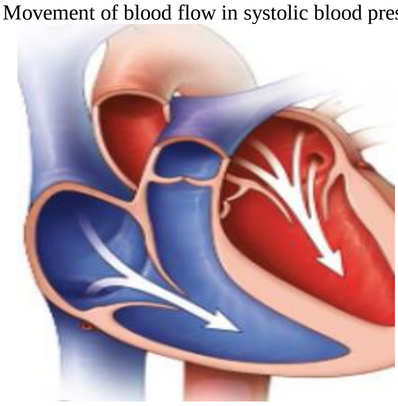
Ref.	***Subject***	***Contributions***
[75]	Lowering blood pressure with interval training	An evaluation has been carried out to scrutinize the influence of high-intensity interval training on blood pressure in older individuals. The effectiveness of high-intensity interval training has been juxtaposed with that of continuous moderate-intensity exercise. While both forms of physical activity contribute to the reduction of blood pressure, high-intensity exercise demonstrates greater efficacy in lowering blood pressure among older individuals.
[76]	uric acid levels as potential indicators for adverse maternal outcomes	A comprehensive assessment was undertaken to evaluate the reliability of uric acid as a predictor of adverse outcomes for both mothers and babies in pregnant women with hypertension. The results suggest that the measurement of uric acid does not offer substantial evidence to substantiate its utility in forecasting adverse maternal and neonatal outcomes.
[77]	Blood pressure measurement	A literature review on home blood pressure measurement has been conducted, leading to the formulation of recommendations. In the case of systolic blood pressure, the variance between office blood pressure measurement and home blood pressure measurement is observed to escalate with age and office blood pressure elevation. Notably, a home blood pressure monitor demonstrates a high level of accuracy in detecting normal blood pressure.
[78]	Hypertension machine learning	The utilization of machine learning in hypertension research is reviewed, along with an assessment of the quality of reporting, and the identification of potential barriers to machine learning to change hypertension care. Conclusions indicate that recent machine learning research on blood pressure is limited to exploratory research, and has significant shortcomings in reporting quality, model validity, and algorithmic bias.
[79]	Using biosensors to estimate blood pressure	The diverse advantages have led to the proliferation of physiological sensors paired with artificial intelligence in various areas of the healthcare industry. An analysis and comparison of advanced methods for machine learning-based blood pressure estimation using photo-plethysmography biological signals is presented. Machine learning is divided into two groups: shallow learning and deep learning based on a survey of research work.
[80]	Non-invasive cuff-less blood pressure measurement	Signal processing techniques including machine learning and artificial intelligence have improved photo-plethysmography-based continuous and cuff-less blood pressure monitoring methods. A review of non-invasive cuff-less blood pressure estimation using the photo-plethysmography approach is presented.

Table.2.
Application of machine learning algorithms in the improvement and diagnosis of diseases other than high blood pressure

Ref.	***Subject***	***Contributions***
[81]	Heart disease	Proper heart function is essential for maintaining good health, and has a significant impact on other organs in the body. The heart circulates blood throughout the body. The prediction and diagnosis of heart disease is recently being done by machine learning algorithms, which help in early diagnosis and treatment by analyzing clinical data.
[82]	Sleep disorders	Sleep disorders play an important role in human health and have a significant impact on improving human quality of life. Deep learning algorithms for sleep disorder classification are compared. An optimal method for sleep disorder classification is proposed, and the model is evaluated using public sleep health and lifestyle data.
[83]	Alzheimer's disease	Alzheimer's disease worsens over time, leading to cognitive decline and memory loss. A review of machine learning algorithms for implementing early Alzheimer's classification is presented.
[84]	Cancer detection	Personalized and data-driven care in cancer treatment remains a challenge to improve one of the leading causes of death worldwide. The use of artificial intelligence for prediction and automation of many cancers has expanded. The use of artificial intelligence and machine learning algorithms in cancer prediction is reviewed, along with current applications, limitations, and future prospects.
[85]	Neurological disease	Prediction of neurological disorders using machine learning models is reviewed, and a comparison between biomarkers used in the field of machine learning and non-machine learning-based biomarkers is presented. The reviews show that deep learning techniques, especially convolutional neural networks, are useful for disease prediction.
[86]	Kidney disease	Chronic kidney disease is a progressive disease that is a major cause of mortality and morbidity. Nuclear medicine imaging offers noninvasive assessment of renal function, but its clinical use is hampered by complexity and interpretative variability. An overview of the applications of machine learning in the diagnosis and monitoring of chronic kidney disease using renal scans is presented.
[87]	Stress	Supervised learning and soft computing techniques for stress detection are reviewed, and the effects of social, behavioral, and biological stressors are outlined. Factors such as real-time data collection and multidimensional data along with data privacy pose challenges in designing accurate AI-based stress detection systems.



(a) Movement of blood flow in systolic blood pressure



(b) Movement of blood flow in diastolic blood pressure

Fig. 3. Movement of blood flow in two values of blood pressure

Table.3.
Parameters used for statistical analysis of classification learning algorithms

Parameters	*Symbol*	*Description*
True positives	TP	The count of test samples accurately classified within the positive class
True negative	TN	The count of test samples accurately categorized within the negative class
False positive	FP	The number of false positives among the test samples belonging to the negative class
False negative	FN	The count of test samples that pertain to the positive class but are incorrectly labelled as negative

2. Performance Evaluation Criteria of Models

Generally, diverse evaluation metrics can be employed to gauge the effectiveness of a learning model [88,89]. Sensitivity and specificity measure the proportion of positive and negative labels that are correctly identified, respectively [90-93]. Accuracy shows the ratio of predictions made by the model. The positive predictive value (PPV) and negative predictive value (NPV) signify the probability that positive results from a screening test accurately correspond to true positives, and negative results from a screening test are accurate representations of true negatives, respectively [94,95].

Evaluation criteria for machine learning classification algorithms are [96-98]:

$$AC = Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$SE = Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

$$SP = Specificity = \frac{TN}{TP+FN} \quad (3)$$

$$RC = Re\,c\,all = \frac{TP}{TN+FP} \quad (4)$$

$$PPV = Positive\ predictive\ value = \frac{TP}{TP+FP} \quad (5)$$

$$NPP = Negative\ predictive\ value = \frac{TN}{TN+FN} \quad (6)$$

$$FPR = Falsepositiverate = \frac{FP}{FP+TN} \quad (7)$$

In the above relationships, TP, TN, FP and FN parameters are defined according to Table (3) [99,100]. The false positive rate represents the frequency of negative samples that are incorrectly classified as positive, highlighting the specificity of the model. The F-score is defined as follows [101]:

$$F - Measure = 2 \times \frac{PPV \times RC}{PPV+RC} = \frac{2 \times TP}{2 \times TP+FN+FP} \quad (8)$$

The highest score for F is 1, which indicates perfect precision and recall. If X_P and X represent the predicted data and the actual data, respectively, the mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE) are defined as follows, where n is the number of samples or recordings:

$$MAE = \frac{1}{n}\sum_n |X_P - X| \quad (9)$$

$$MSE = \frac{1}{n}\sum |X_p - X|^2 \quad (10)$$

$$RMSE = \sqrt{\frac{\sum |X_p - X|^2}{n}} \quad (11)$$

The standard deviation of the prediction error, or residuals, is a measure of the dispersion of the residuals, so the smaller the dispersion, the better the model will be [102,103]. The optimum value is 0 for MSE, RMSE and MAE.

In general, machine learning algorithms are compared based on their suitability for a particular study and criteria. Key aspects of the comparison between learning algorithms are shown in Fig. 4.

3. Machine Learning Algorithms for Blood Pressure

Artificial intelligence and machine learning are closely related but distinct concepts. Machine learning, situated within the broader scope of artificial intelligence, is a practical technology designed to develop computer programs capable of accessing and learning from data. The fundamental goal is to enable these programs to make predictions or judgments without relying on explicit programming [104]. Machine learning algorithms leverage sample or training data to construct mathematical models, facilitating autonomous decision-making [105]. Machine learning algorithms analyze the characteristics of input signals, thereby creating metrics for studies such as prediction, classification, and clustering.

In Fig. 5, various categories of machine learning are depicted. This section specifically explores the application of diverse machine learning methods in the classification of blood pressure [106].

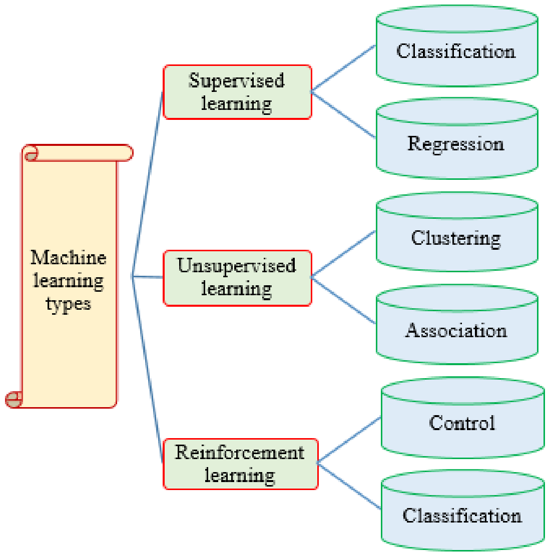


Fig. 4. Types of machine learning

A) Decision Tree Learning

Decision tree learning is a versatile learning method that operates without relying on predefined assumptions about the underlying data distribution. This methodology is applied to tackle a range of problems, with classification being one of its common applications. Decision trees are composed of internal nodes, branches, and leaf nodes. Internal nodes are responsible for decision-making, while the results of algorithms are represented by the leaf nodes. This approach finds utility in both classification and regression learning models. In classification models, leaf nodes exclusively consider a finite set of values, whereas in regression models, they have the capability to encompass continuous values [107,108].

Decision trees are divided into two groups based on the type of output variable: categorical variable decision tree and continuous variable decision tree. The advantages of this algorithm include modeling problems with multiple outputs and requiring less data for preprocessing. Disadvantages include not being suitable for big data, the effect of noise in the data, not handling high complexity, and the possibility of disproportionately valuing features [109,110]. According to the algorithm specifications, a sample decision tree is shown in Fig. 6.

A calibration-free method for blood pressure estimation by training blood pressure and photo-plethysmography data signals on a machine learning regression model is presented in [111]. The outcomes indicate that the standard deviation of error for systolic pressure is 5.3 mmHg, and for diastolic pressure, it is 6.4 mmHg. Additionally, the mean absolute error is approximately 4.2 mmHg for systolic pressure and 4.5 mmHg for diastolic pressure.

In [112], a large number of samples have been conducted, and the application of decision trees to investigate predictors related to hypertension is presented, which is considered a representative sample of the Iranian population. The results show that the prevalence of hypertension in the sampled population is about 32%.

B) Support Vector Machine

Support vector machine (SVM) is a supervised machine learning algorithm that identifies data points by mapping the data into a feature space with a high number of dimensions. The algorithm creates a hyperplane (or a line), which separates the data into different classes. In this algorithm, the basis of the classifier's work is the linear classification of the data, and in the linear division of the data, a hyperplane is usually chosen, which will have a higher confidence margin. SVMs are divided into two types: linear (simple) and non-linear (kernel). This algorithm is a linear model for classification and regression problems. In SVM classifiers, a subset of training points is used when making decisions, and therefore requires less memory [113-119]. The advantages of support vector machines include nonlinearity, high-dimensional performance, resilience to outliers, and memory efficiency. The disadvantages of support vector machines include slow training, difficulty in parameter tuning, and sensitivity to noise. Fig. 7 shows a sample operational flowchart for the support vector machine algorithm, which outlines how the algorithm works, including training, classification, regression, and prediction.

Fig. 8 shows the common steps in developing a machine learning model such as Support vector machine to solve a classification or regression problem [120-123].

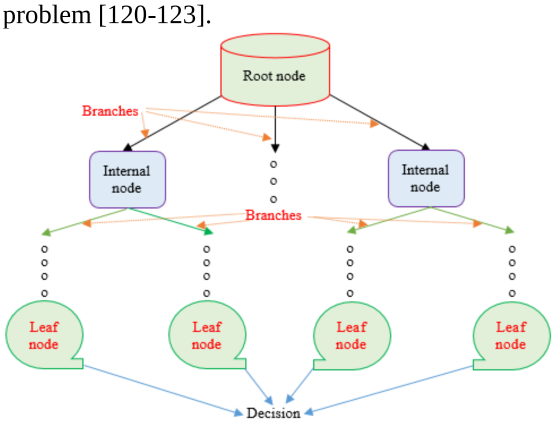


Fig. 5. An example decision tree

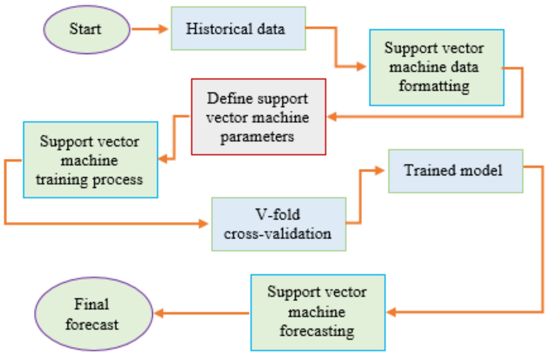


Fig. 6. Operation flow chart for the support vector machine algorithm

To create predictive models of blood pressure disorders, three types of risk factors and SVM were used in [124], which were applied to pregnant women in different weeks. The outcomes suggest that with the progression of pregnancy, the model's average accuracy has consistently improved, eventually surpassing 92% by the end of the pregnancy period.

Single finger photo-plethysmograph (PPG) signals and support vector regression (SVR) method have been used to predict blood pressure in [125]. The results show that the SVR model can accurately and consistently predict blood pressure for both training data and new data.

Machine learning methods are used in the early assessment of stroke risk and also for the early prevention of identifying patients at risk. Early screening of stroke risk in patients with hypertension using a support vector machine as the base model has been investigated in [126], where a two-stage adaptive particle swarm optimization algorithm has been used to optimize parameters to increase the classification accuracy and computational efficiency of the model.

A strategy for diagnosing high blood pressure using bioelectrical signal parameters and a swarm-based support vector machine algorithm is presented in [127]. The results show that in the diagnosis of hypertension, swarm-based SVM has a better performance than various machine learning algorithms. Also, swarm-based SVM using electrocardiogram (ECG) and photoplethysmogram (PPG) shows a good performance for the diagnosis of hypertension, and its F1 score is 96.49%. However, the diagnosis of hypertension using only PPG has shown a low performance.

C) Bidirectional Long Short-Term Memory

Bidirectional long short-term (BiLSTM) memory network is a type of recurrent neural network that addresses the limitations of traditional recurrent neural networks. This architecture is used in tasks that require prediction based on past and future states [128].

Bidirectional processing allows the network to consider both the preceding and following context when making predictions. For scenarios where only past information is needed, long short-term memory (LSTM) is ideal, whereas bidirectional long short-term memory shines in applications where understanding the full context of the sequence is required. The choice between these two approaches depends on the specific requirements of the task at hand [129]. The flowchart showing bidirectional long short-term memory and flowchart is shown in Fig. 9. In [130], the authors detail a blood pressure estimation model based on a two-way short-term memory network. Following the generalization process using the leave-one-subject-out approach, the model undergoes fine-tuning. The results indicate a mean absolute error of 2.05 mm Hg for the diastolic phase and 2.56 mm Hg for the systolic phase of blood pressure.

A method for blood pressure classification using a two-way short-term memory network is proposed in [131], where time-frequency analysis is used based on photo-plethysmography signals. The classification performance is improved, as well as the training time is reduced. Based on the outcomes of the suggested approach, the blood pressure classification's accuracy, sensitivity, and specificity are, respectively, 97.33, 100, and 94.87%.

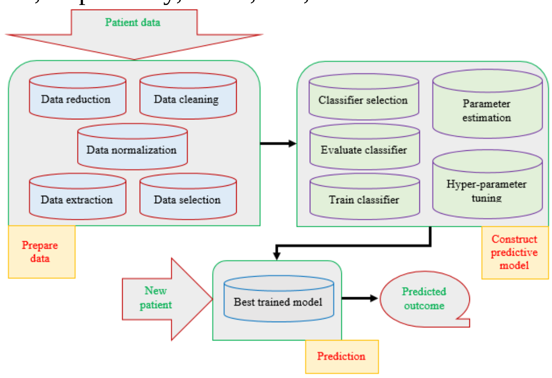


Fig. 7. Typical steps in developing a support vector machine to solve a classification or regression problem

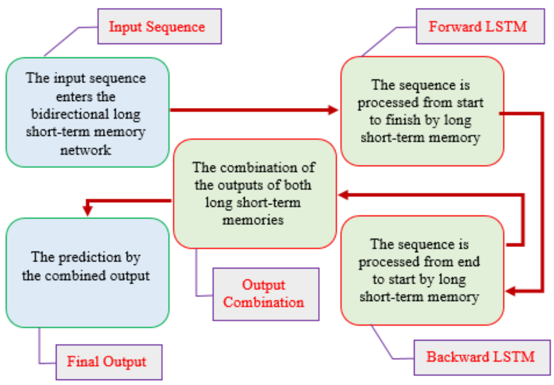


Fig. 8. Flowchart of bidirectional long short-term memory operation

An examination of characteristic extraction strategies for blood pressure estimation employing photo plethysmography signals is provided in [132]. Feature extraction methodologies can be classified into three subgroups: time-based features, statistics-based features, and frequency domain-based features. The analysis of these approaches involves the utilization of various machine learning methods to assess their performance from diverse perspectives. Results from experiments conducted on two datasets suggest that employing time-based group-based feature sets is a more reliable approach compared to other strategies for blood pressure estimation.

D) K-Nearest Neighbour

The k-nearest neighbour (KNN) algorithm is a nonparametric, supervised learning classifier that utilizes proximity to categorize or predict the grouping of a given data point. The KNN algorithm is a pattern recognition method that can be used for classification and for regression prediction problems. In KNN algorithm, points with similar inputs have similar outputs. A typical k-nearest neighbour algorithm flowchart involves four steps: input, distance calculation, nearest neighbor selection, and classification/prediction [133-135].

Easy implementation, simple interpretation of output results, very high accuracy, and versatility are some of the advantages of the k-nearest neighbor algorithm. Also, the need for a lot of memory, a long average calculation time, sensitivity to data scale, and limitations in choosing the value of k are some of the disadvantages of this algorithm [136,137]. Therefore, the flowchart in Fig. 10 can be considered a working example for the k-nearest neighbor algorithm.

A deep learning system is introduced in [138] for the purpose of classifying and predicting hypertension based on blood pressure-related parameters. The k-nearest neighbour algorithm is employed to identify the k samples closest to the selected sample in the feature space. Empirical evidence shows that deep neural networks outperform decision trees. Unlike conventional machine learning algorithms such as decision trees, deep neural networks exhibit optimal performance in scenarios where energy usage is not subject to regulation.

E) Random Forest

Random forest is a learning-based algorithm that builds upon the decision tree model. In this algorithm, the output of several decision trees is combined to reach a single result. This algorithm is an ensemble learning method, and can be used for classification and regression. The advantages of this method include its ease of use and flexibility, because it solves classification and regression problems [139-141].

A decision tree is a simple and intuitive model, and it makes predictions by dividing data into smaller subsets based on different features. However, a random forest is an ensemble learning method, which uses a combination of multiple decision trees to improve the accuracy and stability of the model [142,143].

Fig. 11 shows four key features of random forests. The two methods, random forest and decision tree, are compared based on different parameters in Table (4). As is clear, the random forest method is used in important cases and data dispersion.

Table.4.
Comparison between decision tree and random forest

Method Property	***Decision Tree***	***Random Forest***
Structure (Nature)	Single decision tree	Ensemble of multiple decision trees
Precision	Less	More
Stability	Less	More
Complexity	Less	More
Resistance to overfitting	Less	More
Interpretability	More	Less
Overfitting	More	Less
Training Time	Less	More
Predictive Time	Faster	Longer
Performance	Well	Well
Handling Outliers	More susceptible	More robust

The study in [144] explores the correlations between blood pressure and lifestyle factors and provides personalized and comprehensive suggestions for improving blood pressure levels. Data is autonomously gathered in the proposed approach. A random forest model is proposed, utilizing Shapley value-based feature selection, to create personalized blood pressure models. This model aims to identify the most influential lifestyle factors and offer comprehensive recommendations based on these aspects.

The study cited in [145] utilized data from Iran's cross-sectional technique to monitor risk factors. The distribution of patients across different stages was determined, and a random forest model was employed to identify specific attributes associated with the progression of each stage. Subsequently, the model underwent optimization, considering six crucial factors at each stage to demonstrate population-based marginal effects. The random forest model detected characteristics and provided insights into improving efficient inclusion. The findings suggest that individuals who are younger, male, have lower wealth, and are single are less likely to receive care at all levels.

F) Gaussian Process Regression

Gaussian process regression (GPR) is used in the prediction of blood pressure, especially hypertension, by analyzing multiple data points. This method is used for continuous estimation without the need for a blood pressure cuff. Its advantages include noise immunity, quantifying uncertainty and the ability to model uncertainty in blood pressure measurements.

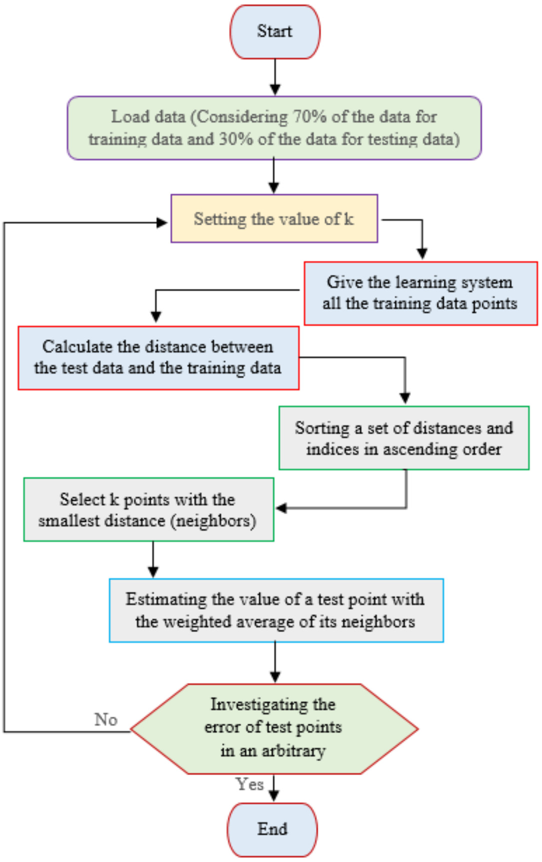


Fig. 9. Flowchart of the k-nearest neighbour algorithm

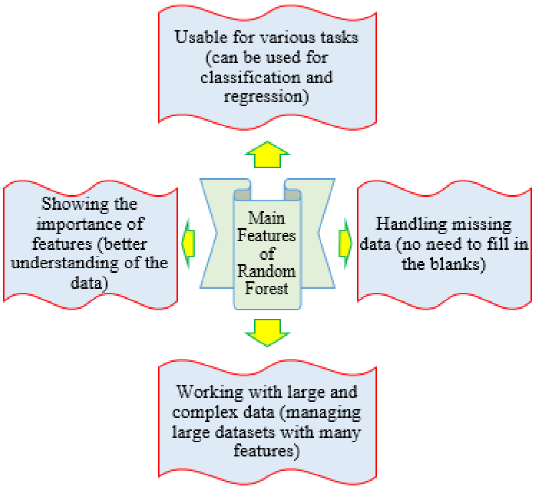


Fig. 10. Main features of random forest in machine learning

Gaussian functions are an example of exponential functions and are used to describe many phenomena [146]. Gaussian functions can be considered univariate or multivariate. Gaussian process regression (GPR) is a method used for regression and probabilistic modeling. It is well suited for handling complex and nonlinear relationships, and provides estimates of uncertainty for predictions made. Gaussian mixture regression combines the strengths of GPR to handle complex datasets with a mixture likelihood approach. A flowchart depicting this process typically involves several steps of data preprocessing, training the GPR model with kernel selection and hyper-parameter optimization, and prediction and evaluation with mixture likelihood [147-149].

A hybrid prediction method combining Gaussian process regression and a feature extraction step is presented in [150], which is applied to blood pressure estimation from cuff oscillometric waveforms. Seven performance metrics such as mean absolute error, agreement index, and mean absolute percentage error are used to evaluate the proposed method in terms of the performance of estimating systolic blood pressure and diastolic blood pressure values from cuff oscillometric waveforms.

A method for improving the reliability of blood pressure estimates and confidence intervals is presented in [151], in which a combined feature selection method and Gaussian process-based decision making are used. To accurately estimate blood pressure and confidence intervals, F-test and robust neighbor component analysis are used for feature selection methods.

G) Artificial Neural Network

Artificial neural networks (ANNs) are used to classify blood pressure and hypertension. By analyzing health-related measures, these models can classify patients into different stages of blood pressure, as well as predict the likelihood of high blood pressure. The benefits of using artificial neural networks include improved accuracy, early detection, and personalized care. Applications of artificial neural networks in blood pressure classification include high blood pressure diagnosis, blood pressure monitoring, and personalized treatment.

A comparison between the two methods, artificial neural network and SVM, is given in Table (5) for a number of parameters. The ANN method is similar to the SVM method in blood pressure classification, but they differ in performance and approach. ANNs can capture complex nonlinear relationships, which are suitable for more refined classifications as well as high accuracy.

Table.5.
Comparison between support vector machines and artificial neural networks

Method Property	*Support Vector Machines*	*Artificial Neural Networks*
Complexity	Simpler	More complex
Interpretability	More	Less
Training Speed	Fast	Slow
Accuracy	High	Very high
Computational Cost	Low	High

Comparing ANN with GPR, one can point out the handling of complex nonlinear relationships in ANN which may require larger data sets. It is worth noting that both techniques can be used for feature selection.

In blood pressure classification, KNN and ANN learning algorithms are used to classify data points. The ANN technique is a more complex algorithm than KNN, which uses interconnected nodes to learn complex patterns from the data [152-161]. A continuous convolutional neural network for blood pressure level classification is presented in [162], in which features extracted from PPG and ECG signals are integrated. Five-way cross-validation is used in the training process to select the best model with the highest classification performance. The results show that the proposed method has achieved the highest test accuracy of 94.56-95.15% with a 95% confidence interval in blood pressure level classification.

A neural network classification model is presented to estimate the association between some parameters such as age and gender with diabetes in patients with hypertension in [163]. An unbalanced dataset consisting of non-hypertensive patients and hypertensive patients was used. The results of the study show that the sensitivity is 40%, specificity is 87%, accuracy is 57.8% and area under the curve (AUC) is measured as 0.77.

4. Criteria Difference in Algorithms Types

Different machine learning algorithms will be evaluated by different metrics based on the type of learning task, such as classification, regression, and clustering, as well as the specific goals of the model. Typically, the metrics used are precision, accuracy, recall, and F1 score for classification. The metrics used are mean absolute error, mean square error for regression, and the metrics used are silhouette score and Davis-Bouldin index for clustering. Table (6) summarizes the evaluation of different learning algorithms. A number of specific considerations for the various algorithms that are most commonly used are given in Table (7).

5. Conclusion

High blood pressure stands as one of the prevalent health conditions, often lacking specific symptoms in many individuals, leading to potential confusion with other ailments. A considerable number of individuals with high blood pressure remain unaware of their condition. Machine learning, a subset of artificial intelligence reliant on pattern recognition, emerges as a powerful tool in addressing the challenges associated with high blood pressure.

Table.6.
Evaluation of different learning algorithms

Types of machine learning	*Difference in criteria*		
Supervised Learning	Classification	Accuracy	Accuracy in general predictions, and potential for misleading in unbalanced data
		Precision	Uncertainty of predicted samples as positive
		Recall	Uncertainty of predicted samples from all true positive samples
		F1-score	Usefulness of harmonic mean precision and recall based on importance
		AUC-ROC	Measurement of class distinction
	Regression	Mean Absolute Error	Mean absolute difference between predicted and actual values
		Mean Squared Error	Mean squared difference and penalizing larger errors
		Root Mean Squared Error	Root Mean Squared Error of the same units as the target variable
		R-squared	The proportion of variance in the dependent variable determined by the model
Unsupervised Learning (Clustering)	Inertia	Measures the compactness of clusters	
	Silhouette Coefficient	Measures the extent to which each data point is in its assigned cluster compared to other clusters	
	Davies-Bouldin Index	Measures the average similarity ratio of each cluster to its most similar cluster	
Reinforcement Learning	Reward Function	Numerical points received by an agent for performing certain actions	
	Episode Length	Number of steps for an agent to perform a task	
	Training Time	Time for an agent to learn the optimal policy	

Table.7.
Algorithm-Specific Considerations

Algorithm Name	***Algorithm Considerations***
Decision Trees	Evaluation using classification and regression metrics, Prone to overfitting
Random Forests	Evaluation using similar metrics to decision trees
Neural Networks	Accuracy, Precision, Recall, F1-score (for classification), MSE, RMSE (for regression)
Support Vector Machines	Area Under curve-Receiver Operating Characteristic, Accuracy, Precision, Recall, F1-score
Clustering Algorithms	Inertia, Silhouette Score, Davies-Bouldin index

The use of machine learning algorithms in the diagnosis and management of various diseases is increasing. The use of machine learning algorithms to analyze blood pressure data to predict high blood pressure, classify blood pressure categories, and identify potential risks is expanding. Factors such as specific data sets and the purpose of the research have an impact on the selection of the algorithm. Research studies consistently demonstrate the superior performance of deep learning models compared to traditional machine learning methods.

To choose the best algorithm for prediction, factors such as the nature of the problem, the type of data, and the unique requirements should be considered. Usually, SVM and random forest algorithms are better for prediction. Also, for processing long data, random forest and decision tree algorithms are faster.

SVMs are powerful classifiers, but GPR has a more flexible model, which can provide both prediction and uncertainty estimation.

Learning algorithms can improve early diagnosis, personalized treatment and even predict possible complications in some cases. The utilization of advanced technologies, such as deep learning, holds promise in enhancing our understanding, diagnosis, and management of high blood pressure, thereby contributing to more effective healthcare interventions. For algorithms, general considerations of time complexity, space complexity, hardware usage, and interpretability must be taken into account. Table (8) summarizes the key differences in a number of machine learning algorithms to compare their performance.

Table.8.
Key differences in applied algorithms

Alghorithm ***Feature***	***Random Forest***	***Bidirectional LSTM***	***Gaussian Process Regression (GPR)***	***Support Vector Machine (SVM)***	***Decision Tree Learning***	***K-Nearest Neighbors (KNN)***
Model type	A collection of decision trees	Recurrent neural network	Probabilistic	Discriminative	Single tree-based	Non-parametric and sample-based
Interpretability	Less interpretability compared to a single decision tree	Challenging interpretability due to complex network architecture	Greater interpretability, due to uncertainty estimates and probabilistic nature	Low interpretability, relies on finding the optimal hyperplane	More interpretability due to tree structure	High interpretability, especially for smaller data sets
Accuracy	Achieving high accuracy (especially with balanced datasets)	High in complex datasets and time series data	Resulting from the Bayesian approach to modeling training data	Varies based on kernel used and data characteristics	Low (especially with complex datasets)	Low (especially with noisy data or high-dimensional data)
Complexity	Complicated due to numerous trees	Complex due to the need for more computational resources	Complex and computationall y intensive	Simple and easy to interpret	Simple and understandable	Simple implementation and training
Classification Approach	Using decision trees for prediction	Training a deep neural network to classify sequence data	Assignment based on Gaussian distribution and probability estimation	Finding the optimal hyperpage	Tree-like structure based on feature-based decision rules	Assignment based on nearest neighbors

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