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ORIGINAL ARTICLE

Medicine Science International Medical Journal

Medicine Science 2024;13(4):866-72

# Prediction of cardiovascular disease from factors associated with waist hip ratio by machine learning

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Received 22 August 2024; Accepted 08 October 2024
Available online 01 December 2024 with doi: 10.5455/medscience.2024.08.094



**Abstract**

Early risk factor detection is essential for managing and treating cardiovascular disease (CVD), a global health issue. Studies have shown that waist circumference (WC) and waist hip ratio (WHR) are better at identifying CVD than BMI. The study uses Random Forest (RF) machine learning to identify characteristics that affect WHR, an indication of CVD. Isfahan Cardiovascular Research Centre in Iran provided the dataset, which includes sex, family history, diabetes, WHR, smoking, systolic blood pressure, and total cholesterol. Statistical analyses employed Yates' correction and Pearson chi-squared tests. Modeling with RF yielded accuracy, balanced accuracy, sensitivity, specificity, PPV, NPV, and F1 score from performance metrics. Finally, variable significance values determined the dependent variable's most relevant variables. WHR and other variables are statistically significantly correlated. Random Forest machine learning predicts high WHR with high accuracy, sensitivity and specificity. The most important variables of the prediction model are female sex, smoking status and blood pressure ranges. In conclusion, the global burden of CVD and the necessity of early diagnosis are underlined. The role of WHR along with BMI and waist circumference in the assessment of cardiovascular risk is emphasised. The study concludes that the machine learning model can effectively predict high WHR, aid CVD risk management and facilitate personalised treatment plans. The results contribute to a better understanding of the factors influencing high WHR and can guide healthcare professionals in the comprehensive assessment and management of cardiovascular risks.

**Keywords:** Cardiovascular disease, risk factor, waist hip ratio, machine learning

## Introduction

The enormous morbidity and death caused by cardiovascular diseases (CVD) makes them a major international health problem [1]. The risk factors for CVD are complex and may have been undervalued in terms of their significance. Some of the risk factors encompassed in this list are hypertension, hypercholesterolemia, diabetes mellitus, and chronic renal disease [2]. There is still uncertainty about the prevalence of CVD in many parts of the world, highlighting the importance of gaining a more comprehensive understanding and improving the management of this condition [3]. Inflammation has been recognized as a prognosticator of CVD occurrences, underscoring the potential significance of medications that target inflammation in the management of CVD risk [4]. Moreover, oxidative stress has been linked to the underlying mechanisms of CVD, indicating the potential effectiveness of antioxidant therapies in managing CVD [5]. In addition, chronic renal disease has been recognized as a significant risk factor for mortality from cardiovascular and all-cause causes, highlighting the importance of an all-encompassing approach to the management of comorbid illnesses in patients who have cardiovascular disease [6]. It is crucial to focus on preventing and treating hypertension, which is a significant risk factor for CVD, in order to decrease the risk of CVD, especially in women [7]. To summarize, the therapy of cardiovascular illnesses

**CITATION**
Kucukakcali Z, Balikci Cicek I. Prediction of cardiovascular disease from factors associated with waist hip ratio by machine learning. Med Science. 2024;13(4):866-72.

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DOI: 10.5455/medscience.2024.08.094

necessitates a comprehensive strategy that tackles several risk factors, such as hypertension, hypercholesterolemia, diabetes mellitus, chronic renal disease, and non-alcoholic fatty liver disease. Moreover, the possible contributions of inflammation, oxidative stress, and phosphate metabolism to the development of cardiovascular disease emphasize the necessity for comprehensive and focused therapies to efficiently address this worldwide health problem.

It becomes very important to establish early diagnosis and prevention strategies for such a disease in which many factors affect its formation. For this reason, some measurements that can be considered as determinants of CVD are used. Although body mass index (BMI) is the traditionally chosen method, there are also measurements such as waist circumference (WC) [8,9] and WHR [10,11]. Studies have shown that these measurements are superior to BMI in the detection of CVD. Compared to BMI, it has been suggested that waist circumference and waist:hip ratio, which define body fat distribution more accurately, are more closely related to morbidity and mortality [12].

Recent studies have suggested the use of clinical decision support systems to address missed opportunities in the prevention and treatment of CVD and emphasised the importance of evidence-based practices in the management of this condition. For this reason, in this study, it is aimed to determine the factors affecting the WHR measurement used in the determination of CVD with artificial intelligence-based machine learning methods, and indirectly, the parameters that will play a role in the development of CVD will be determined with the results obtained. For this purpose, Random Forest (RF), one of the machine learning methods, which is a subfield of artificial intelligence, was used to determine the factors associated with the WHR variable using an open access dataset.

## Material and Methods

### The Data Set Included in The Study And Its Characteristics

The data set used in the study was obtained from Isfahan Cardiovascular Research Centre, a clinic in Iran. The data set was created to determine CVD. This dataset used in the current study was shared as an open access dataset and made available for researchers to use in their research. The dataset can be accessed directly from the address 'https://figshare.com/articles/dataset/CVD_risk_assessment_sample_dataset/5480224?file=9477889'. The data set was accessed via the internet and does not require an ethics committee decision. High WHR rate was defined as follows while creating the dataset: High WHR was defined as WHR≥0.80 in women and ≥0.95 in men. The data set included age, sex, family history of CVD, diabetes mellitus, high WHR, smoking status, systolic blood pressure (SBP), total cholesterol (Tch) variables [13]. The variables are qualitative variables and the definitions of the variables are given in Table 1.

**Table 1.** Definitions of the variables

| Variables | Categories |
|---|---|
| **Sex** | Male |
| | Female |
| **Family history of cardiovascular disease** | No |
| | Yes |
| **Diabetes mellitus** | Diabetes |
| | Non-diabetes |
| **High waist-to-hip ratio** | No |
| | Yes |
| **Smoking status** | Non-smoker |
| | Smoker |
| **Systolic blood pressure** | <120 mmHg |
| | >=160 mmHg |
| | 120-139 mmHg |
| | 140-159 mmHg |
| **Total cholesterol** | <150 mg/dL |
| | >=300 mg/dL |
| | 150-200 mg/dL |
| | 200-250 mg/dL |
| | 250-300 mg/dL |

### Machine Learning and Random Forest

Machine learning is a crucial element of artificial intelligence and computer science, having extensive applications in diverse fields. It entails the creation of algorithms and statistical models that allow computer systems to enhance their performance on a particular task by analyzing data, without requiring explicit programming. Data-intensive machine-learning methods have been widely used across several fields, resulting in evidence-based decision-making in domains including healthcare, manufacturing, education, financial modeling, policing, and marketing [14]. In the area of healthcare, machine learning has showed promise in improving the categorization and treatment of heart diseases through applications in echocardiography and health information databases [15]. Moreover, machine learning has expedited the identification and diagnosis of several ailments, such as cardiovascular illness and COVID-19, permitting swifter and more precise evaluations [16]. Machine learning is a versatile and complex science that has significant

DOI: 10.5455/medscience.2024.08.094

ramifications in various fields, such as healthcare, oncology, big data analytics, and algorithmic fairness. The applications of algorithmic decision-making are always growing due to the pursuit of enhanced prediction accuracy, comprehensibility, and fairness.

The Random Forest algorithm is a highly effective and extensively utilized machine learning technique that falls under the category of ensemble learning. Leo Breiman introduced the proposal in 2001, and it has since been widely popular because of its adaptability and strong performance in other fields [17]. The algorithm relies on decision trees and functions by creating numerous decision trees in the training phase. It then determines the class that appears most frequently among the trees for classification, or calculates the average prediction for regression [18]. The random forest algorithm constructs each tree by utilizing a random portion of the training data and a random subset of the features. This approach enhances the model's capability to handle high-dimensional data and intricate relationships among variables [19]. Random forests exhibit a notable advantage in their capability to effectively manage missing data and uphold accuracy even when confronted with noisy data. This quality renders them a resilient option for practical applications [20]. Moreover, the algorithm's exceptional precision and user-friendly nature have rendered it a favored option for classification tasks [21]. To summarize, the random forest method is a very flexible and potent tool in the machine learning arsenal, providing strong performance, versatility across different domains, and the capability to tackle intricate data obstacles.

### Biostatistical Analyses And Modelling Phase

The variables in the data set used in the study are categorical variables and the variables are summarised using number (percentage). Chi-squared test with Yates' correction and Pearson chi square test were used in the statistical analyses of the dependent variable WHR and other variables. $p<0.05$ was considered statistically significant. Analyses were performed using IBM SPSS 26.0.

In the modelling phase, the relationship between the dependent variable WHR and other variables was examined using the RF method. Firstly, the data set was divided into training and test data sets in a ratio of 70 to 30 in order to ensure internal validity using the hold out method. 5-fold cross validation method was used to validate the results. Cross validation method is a technique used to evaluate the performance of machine learning models and to measure their generalisation capabilities. The results obtained as a result of modelling are given with performance metrics. At this stage, the results are given separately for training and test dataset and the results are given with accuracy, balanced accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), F1 score performance metrics.

## Results

When the data set used in the study is analysed, the data of 500 patients were included in the study and 266 (53.20%) of the patients were male and 234 (46.80%) were female. 55 (11.00%) patients had family history of cardiovascular disease while 445 (89.00%) patients did not have family history of cardiovascular disease. While 151 (30.20%) of the patients did not have high waist-to-hip ratio, 349 (69.80%) had high waist-to-hip ratio. Descriptive statistics of all variables are given in Table 2.

**Table 2.** Descriptive statistics of all variables

| Variables | Categories | Count (%) |
|---|---|---|
| Sex | Male | 266 (53.20) |
| | Female | 234 (46.80) |
| Family history of cardiovascular disease | No | 445 (89.00) |
| | Yes | 55 (11.00) |
| Diabetes mellitus | Diabetes | 125 (25.00) |
| | Non-diabetes | 375 (75.00) |
| High waist-to-hip ratio | No | 151 (30.20) |
| | Yes | 349 (69.80) |
| Smoking status | Non-smoker | 388 (77.60) |
| | Smoker | 112 (22.40) |
| Systolic blood pressure | <120 mmHg | 142 (28.40) |
| | >=160 mmHg | 86 (17.20) |
| | 120-139 mmHg | 177 (35.40) |
| | 140-159 mmHg | 95 (19.00) |
| Total cholesterol | <150 mg/dL | 38 (7.60) |
| | >=300 mg/dL | 37 (7.40) |
| | 150-200 mg/dL | 136 (27.20) |
| | 200-250 mg/dL | 200 (40.00) |
| | 250-300 mg/dL | 89 (17.80) |

According to the statistical analyses performed for the dependent variable high waist-to-hip ratio and the other variables sex, family history of cardiovascular disease, diabetes mellitus, smoking status, systolic blood pressure, and total cholesterol, there is a statistically significant relationship between the dependent variable and all other categories of variables. Statistical results and descriptive statistics of these relationships are given in Table 3.

DOI: 10.5455/medscience.2024.08.094

**Table 3.** Statistical results of the dependent variable and other variables

| Variables | Categories | High waist-to-hip ratio: No Count (%) | High waist-to-hip ratio: Yes Count (%) | p |
|---|---|---|---|---|
| **Sex** | **Male** | 147 (97.35) | 119 (34.10) | <0.001* |
| | **Female** | 4 (2.65) | 230 (65.90) | |
| **Family history of cardiovascular disease** | **No** | 142 (94.04) | 303 (86.82) | 0.027* |
| | **Yes** | 9 (5.96) | 46 (13.18) | |
| **Diabetes mellitus** | **Diabetes** | 21 (13.91) | 104 (29.80) | <0.001* |
| | **Non-diabetes** | 130 (86.09) | 245 (70.20) | |
| **Smoking status** | **Non-smoker** | 94 (62.25) | 294 (84.24) | <0.001** |
| | **Smoker** | 57 (37.75) | 55 (15.76) | |
| **Systolic blood pressure** | **<120 mmHg** | 57 (37.75) | 85 (24.36) | <0.001** |
| | **>=160 mmHg** | 11 (7.28) | 75 (21.49) | |
| | **120-139 mmHg** | 60 (39.74) | 117 (33.52) | |
| | **140-159 mmHg** | 23 (15.23) | 72 (20.63) | |
| **Total cholesterol** | **<150 mg/dL** | 24 (15.89) | 14 (4.01) | <0.001** |
| | **>=300 mg/dL** | 4 (2.65) | 33 (9.46) | |
| | **150-200 mg/dL** | 57 (37.75) | 79 (22.64) | |
| | **200-250 mg/dL** | 50 (33.11) | 150 (42.98) | |
| | **250-300 mg/dL** | 16 (10.60) | 73 (20.92) | |

The values of the performance metrics obtained in the modelling between the dependent variable and other variables using the RF method are given separately for the test and training data set and the results of these values are given in Table 4.

**Table 4.** Performance metrics for test and training data set

| Metric | Training set Value (%) | Test set Value (%) |
|---|---|---|
| **Accuracy** | 87.5 | 83.9 |
| **Balanced accuracy** | 86.5 | 78.4 |
| **Sensitivity** | 89.0 | 92.3 |
| **Specificity** | 84.0 | 64.4 |
| **PPV** | 92.8 | 85.7 |
| **NPV** | 76.7 | 78.4 |
| **F1 score** | 90.8 | 88.9 |

When the performance metrics for the test and training data set are analysed, the accuracy, balanced accuracy, sensitivity, specificity, positive predictive value, negative predictive value and F1 score obtained for the test data are 83.9%, 78.4%, 92.3%, 64.4%, 85.7%, 78.4%, 88.9% respectively. When the performance metrics are analysed, it is seen that the model exhibits a high success in general. The accuracy of the model on the test data is quite high and most of the predictions are correct. In particular, the model's success in recognising the positive class is quite good, i.e. true positives are correctly identified to a large extent. However, the recognition rate of the model for the negative class is lower than for the positive class, indicating that the correct prediction rate of the negative class is more limited. A measure of how accurate the positive predictions are also gives a very positive result, while the accuracy of the negative predictions is also acceptable. As a result, the performance of the model on the positive class is said to be impressively high. Overall, the model performs strongly in terms of both sensitivity and stability.

Variable significance values are a metric that measures how effective certain input variables are in the predictions of a model. The significance values calculated for each attribute are used to understand the complex internal structure of the model and to explain the predictions of the model. The variable importance values obtained as a result of the modelling are given in Table 5.

**Table 5.** Variable importance values obtained as a result of modelling

| Variables | Variable importance value |
|---|---|
| **sexFemale** | 100 |
| **smokingstatusSmoker** | 16.281 |
| **sbp120-139 mmHg** | 9.402 |
| **diabetesmellitusDiabetes** | 8.456 |
| **tch200-250 mg/dL** | 2.756 |
| **tch>=300 mg/dL** | 2.442 |
| **familyhistoryofcvdYes** | 1.693 |
| **sbp>=160 mmHg** | 1.109 |
| **tch150-200 mg/dL** | 0.769 |
| **sbp140-159 mmHg** | 0.704 |

The variable importance graph of the modelling is given in Figure 1.

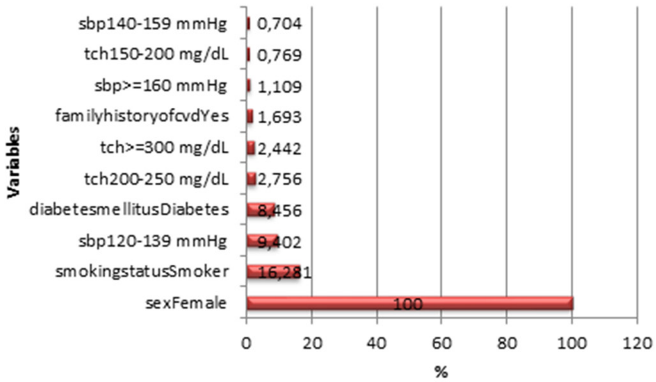


**Figure 1.** Variable ımportance graph

According to the variable significance values obtained as a result of modelling, the variables most associated with WHR are sex (Female), smokingstatus (Smoker), sbp120-139 mmHg, diabetesmellitus (Diabetes), tch200-250 mg/dL, tch>=300 mg/dL, familyhistoryof (cvdYes), sbp>=160 mmHg, tch150-200 mg/dL, sbp140-159 mmHg. This ranking provides an important guide in identifying the main factors and risk factors that impact on WHR.

## Discussion

CVD imposes a significant burden, impacting 40% of women and 50% of men during their lives [22]. Cardiovascular disease is the primary global cause of mortality, accounting for 31% of all fatalities [23]. Cardiovascular disorders account for roughly 33% of global mortality [24]. Obesity, along with hypertension and CVD, is increasingly becoming a significant factor in the worldwide disease burden [25]. Projections suggest that CVD will persist as a significant worldwide health issue, necessitating the development of novel approaches for prevention, diagnosis, and treatment [26]. Therefore, early diagnosis plays an important role in the management of the disease. Early diagnosis is critical in mitigating the effects of cardiovascular disease, initiating treatment and preventing disease progression. Early intervention can stop or slow the progression of the disease.

There is a need for some basic measures that can be used as a marker of disease without any procedure and that can reveal the disease. BMI is the most important of these. In many studies, high values of BMI have been found to be associated with obesity and cardiovascular disease risk. Waist circumference measurement, which is one of the similar and less commonly used measurements compared to BMI, evaluates fat accumulation in the abdominal region. This measurement is used to assess abdominal obesity, which is associated with cardiovascular disease risk. Finally, waist hip ratio is a measurement used for obesity and cardiovascular disease risk in the same way as BMI and waist circumference measurement. Although this measurement is not widely used, it gives better results than the other two measurements [27-29].

A comprehensive examination of existing research literature conducted a combined analysis of 58 prospective studies and revealed a substantial correlation between waist-to-hip ratio and the likelihood of developing cardiovascular disease for the first time [29]. Similarly, they found that a high waist-to-hip ratio was the most accurate anthropometric indicator of mortality in their group of older women [30]. Additionally, it was discovered that a high waist-to-hip ratio was autonomously linked to an elevated likelihood of coronary heart disease in both males and females [31]. The study provided evidence that waist-to-hip ratio had a stronger and more consistent correlation with the risk of coronary heart disease in both men and women, compared to waist circumference or BMI [32].

In the present study, it was aimed to determine the factors that may be associated with WHR and to determine the factors indirectly associated with CVD by considering the relationship between WHR and CVD. For this purpose, statistical analyses and modelling with RF were performed between the dependent variable WHR and other independent variables. As a result of the statistical analyses, a statistically significant relationship was found between the categories of WHR and the categories of other variables such as sex, family history of cardiovascular disease, diabetes mellitus, smoking status, systolic blood pressure, and total cholesterol ($p<0.05$). As a result of the modelling, performance metrics were obtained for the training and test data sets and the performance metrics for the test data were obtained as accuracy, balanced accuracy, sensitivity, specificity, positive predictive value, negative predictive value and F1 score as 83.9%, 78.4%, 92.3%, 64.4%, 85.7%, 78.4%, 88.9%, respectively. With the modelling, "yes" and "no" categories of high WHR were predicted by the independent variables with high accuracy and it can be said that the modelling can be used in prediction. In addition, when the variable importance values obtained at the end of the model are examined, it is said that "female" among the categories of gender variable, "smoker" among the categories of smoking status variable, and "120-139 mmHg" among the categories of systolic blood pressure variable are most related to high WHR. In other words, these are the first three variables that explain the dependent variable highWHR the most and the others are diabetes, cholesterol 200-250 mg/dL, cholesterol over 300, CVD family history, systolic blood pressure greater than 160, cholesterol 150-200 and systolic blood pressure 140-159, respectively.

## Conclusion

In conclusion, it can be said that modelling can be used with good results in such problems and CVD risk can be managed by managing the factors associated with high WHR. Successful modelling for CVD management allows for accurate identification of risk factors associated with high WHR and development of an effective intervention strategy. Modelling is an important tool for assessing the effects of WHR on cardiovascular health. The advantages of modelling include more precise determination of cardiovascular risk profiles of individuals and identification of potential risk factors. In particular, a better understanding of the factors associated with high WHR through modelling can play an important role in developing individualised treatment plans and health management strategies. These modelling results guide healthcare professionals to more effectively assess and manage individuals' cardiovascular risks. Beyond high WHR, modelling provides integrity by bringing together various risk factors such as blood pressure, cholesterol levels, sugar metabolism, genetic predisposition and lifestyle factors. Preventive health services play an important role in identifying and managing individuals' cardiovascular risks. In this context, the information provided by modelling provides a valuable resource for health professionals and individuals to develop and implement individual health plans.

**Conflict of Interests**
*The authors declare that there is no conflict of interest in the study.*

**Financial Disclosure**
*The authors declare that they have received no financial support for the study.*

**Ethical Approval**
*Ethics committee approval is not required for this study.*

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