Interpreting the Smart Healthcare Model Using Shapley Values

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Abstract

Data analysis and treatment specifications are important in healthcare, but there are many challenges, such as specifying metrics to measure and monitor patient health. Machine learning appears to improve the prediction of patients' outcomes at the lowest cost in healthcare systems. The machine learning used real data collected by Internet of Things (IoT) devices and analyzed them to detect potential future risks. There are many techniques for detecting potential future risks, but the random forest model was the strongest. Unfortunately, its results were complex and difficult to interpret. Therefore, this study used Shapley values, a powerful analysis method that helps interpret the ambiguity in ML results, often referred to as a black box. This led to the development of the random forest model, which interprets its outcomes by assigning equal importance to features based on their contribution to the results. This study is divided into two steps. Firstly, the random forest model classifies the data based on relationships among feature attributes to predict the outcome. Secondly, interpreting the prediction results from the previous step using Shapley Tree Interpreter (SHAP) values to distribute importance across attributes based on their contributions to the prediction. The proposed method showed that the age, ID, and AP-LO are the most important attributes in predicting diastolic blood pressure. Where age had (-157), id (+17.53), and ap-lo (-213.03) effects. Gender, height, and glu were the most important predictors of systolic blood pressure. Where gender had (-4.41), height (+2.78), and glu (+2.48) effects.

1. Introduction

The Internet of Things (IoT) has become a hot and important topic; its development has driven the digital field forward. It consists of several devices connected together to achieve a process. The IoT acts to develop several fields such as healthcare, industry, agriculture, etc. The IoT contributes to the development of smart cities by collecting data from diverse sources to improve people's lives. The IoT devices and sensors collect data from other events and conditions, including temporal and geographical. These gadgets are becoming more intelligent, with faster communication and the ability to perform more complex and mysterious tasks [1]. The IoT is represented as a network of devices that connect and communicate with one another to solve problems [2, 3].

The IoT concept is applied to cities, where different types of sensors share relevant data about the town in question with the Internet. The objective is to qualify the city, optimize resources, present data to support better city management, and provide real-time, high-quality information to populations, thereby improving the city's

sustainability [4-6], as shown in Figure 1. However, healthcare budgets are limited, requiring optimal use of resources. Artificial intelligence (AI) and Machine learning methods have enormous potential to effectively use healthcare resources [7].

Fig. 1 *Smart city*

Machine learning is the study of computer algorithms that can improve automatically through experience and by the use of data. It is seen as a part of artificial intelligence. Recent studies have shown that machine learning and artificial intelligence are essential and promising technologies for creating future predictions by using available data. They are characterized by expansion, processing speed, and reliability, and sometimes exceed human capabilities [8, 9]. Healthcare systems require good-quality medical services with higher availability, reliability, and security. The time sensitivity of medical services is very high, and the quality of service (QoS) should be ensured to provide data communication without delay, noise, latency, or interruptions to save lives and handle emergencies [10]. Data privacy and confidentiality are basic needs for providing a secure IoT health service. IoT medical devices must be robust and diverse, requiring different application software and legal acceptance by a medical expert panel [11]. Shapley values are a tool for analyzing results that specify the magnitude of the importance of the data used to obtain predictions for machine learning techniques [12].

This study contributes to solving the problem of data processing, interpretation, and decision tracking in healthcare in smart cities using the RF model, which in turn provides reliable predictions of clinical outcomes for the datasets used for prediction. The RF model is highly effective in healthcare. However, the fuzzy nature on which this model operates makes the results fuzzy and difficult for healthcare providers and physicians to interpret and manage, leading to decreased clinical confidence and increased bias in diagnosing based on the available features. To solve all these problems, Shapley values are used with the SHAPTREE algorithm, which helps to determine the contribution of each feature that led to the final prediction results and makes the results easy to interpret and deal with by providing strong justifications for each individual feature in the datasets, which in turn enhances clinical confidence, identifies bias, and develops a random forest model.

2. Related Works

Pregnant women suffer from hypertensive disorders during pregnancy. For this reason, clinical guidelines for blood pressure monitoring are established. Mean arterial blood pressure (MAP) is calculated using the maximum amplitude algorithm (MAA). The Random Forest algorithm then uses this average and manually entered weight data to predict systolic and diastolic blood pressure [13].

A random-forest-based prediction model was investigated using geochemical parameters to classify mafic and ultramafic rocks encountered in drilling samples. This model demonstrated accuracy ranging from 86% to 94%, with an F1-score of 96%. Shapley values are also used to interpret and clarify the model [14].

A robust statistical method was used to identify unique biomarker patterns that could predict IHCA. Despite the limitations, the results suggest that monitoring specific biomarker trajectories, especially low systolic blood pressure and its variability, high and fluctuating heart rate, persistent hypothermia, recurrent tachypnea, and low oxygen saturation and its variability, may improve the early identification of patients at high risk for IHCA [15].

A human activity recognition (HAR) system using image classification based on histograms generated from raw accelerometer and gyroscope data from a smartwatch. A pre-trained ResNet50 deep neural network within the ML.NET framework powers this system [16]. A decision support system (DSS) to predict student attentiveness during online learning using EEG signals recorded by a Neurosky device. The system uses machine learning to classify EEG data into "attentive" and "inattentive" states. Clustering algorithms (K-means and hierarchical clustering) further analyze these key bands to refine classification [17]. Two techniques have been proposed to improve interpretability. The first is Shapley values, which stipulate a fair distribution between features based on their contribution to prediction. The second technique is feature packing, which combines more than one similar feature into a single feature to facilitate understanding the model without needing reconstruction. The results showed that the techniques are interpretable for machine learning models [18].

Exploring spatial variables is important for understanding their impact on the economy and spatial justice. Using machine learning techniques, the best model for predicting economic mobility in a region based on its spatial variables yields an accuracy of 86%. Factors affecting this ratio include job availability, space, medical facilities, and groundwater resources. Some of these factors have a negative impact, while others have a positive impact, enabling a suitable analysis for comparing different regions to achieve spatial justice [19].

Leveraging the integration of deep networks with Shapley values to explore multivariate relationships of neuroimaging and cognitive functions, such as Alzheimer's disease (AZ) and mild cognitive impairment (MCI), and to provide solutions for the mechanisms specific to each pattern common to MCI and AZ [20]. Combining linear regression with kernel shape improved the model and reduced variance, making it universally suitable for cooperative games and more efficient and reliable. However, it will suffer from a slight increase in bias, leading to uncertainty in estimation [21]. Table 1 shows key points of previous research and its results.

Table 1 *Previous research and its results*

Ref.	Method	Aim	Merits	Demerits
[13]	RF	monitoring of blood pressure during pregnancy	Non-invasive early detection of hypertension uses different data	Manually enter weight data and use limited data, and a Non-integrated system
[14]	Tree SHAP	Develop a stochastic forest-based prediction model.	High accuracy and robustness, effective with high-dimensional datasets, and versatility	Complexity and lack of interpretability
[15]	GBTM	Identifying clinical subtypes at risk for IHCA	Accuracy, discovery of unexpected patterns, and analysis of extensive data	Limited internal verification and work on the exclusion criteria
[16]	HAR	develop and evaluate a real-time, cloud-deployable HAR system	Simplicity, accuracy, data processing, and real-time workability	Slow and increase training (computational cost)
[17]	DSS	Improve engagement between online learners in real time.	High accuracy, real-time monitoring, and non-invasive.	Complexity, non-generalization, and changeable accuracy
[18]	Tree SHAP	Analyze the ML models	Enhanced interpretability	Use a single dataset
[19]	Tree SHAP	Explore the problem of spatial injustice	Effective handling of complex data	Computational intensity
[20]	Deep SHAP	Uncovering the relationships between neuroimaging and cognitive functions	Accurate prediction is computationally	expensive when dealing with large datasets.
[21]	Kernel SHAP, Linear SHAP	Reconsidering the Kernel SHAP method for estimating Shapley values using linear regression	Providing rapid capabilities for global interpretations	Difficulty in rapid assessment and increased bias

Previous studies have relied on multiple methods for classifying and analyzing data, such as Deep SHAP, which was used with neural network and deep learning models, Kernel SHAP that takes samples to appreciate Shapley's values, Linear SHAP designed for interpreting linear models to calculate SHAP value, and Tree SHAP that creates decision trees to calculate SHAP value more accurately and faster than Kernel SHAP. consequently, this study proposes a new model for data classification and analysis based on random forests and Tree SHAP values. This model generates multiple decision trees to predict and assist in classifying data. The results are then analyzed using the SHAP tree explainer to identify the most important features that contributed to these results.

3. Methodology

This discusses the components and functions of each layer of the proposed model and describes the architecture of the IoT-based smart city health system. First, information collected by IoT sensors is sent to the cloud, where important vital parameters, such as systolic and diastolic blood pressure, are obtained using health sensors. For the model's practical applicability, the real data used is a dataset of patient samples focused on detecting cardiovascular problems [22]. This information is stored in the cloud using intermediate devices. After the data is taken from the cloud, it is processed in two stages. The first stage involves predicting the correlation between features using a random forest model. In the second stage, the results are analyzed using a SHAP tree explainer to fairly distribute importance among contributing features based on their contributions to the prediction values, making the model easier to interpret, as shown in Figure 2.
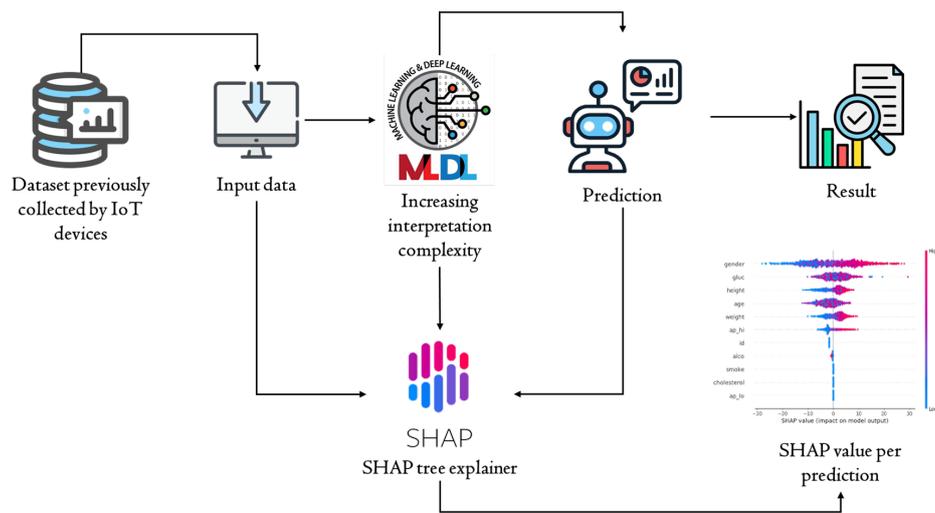

Fig. 2 *SHAP value with machine learning and IoT devices architecture*

3.1 Random Forest

This study used the Random Forest technique in healthcare, an effective machine learning technique implemented through two operations (training and testing). This algorithm creates an ensemble of decision trees in the training phase (each decision tree is built from a random subset of data to measure the characteristics of each section of the tree). This randomness creates variation among individual trees, which in turn improves the general prediction. At the testing level, the algorithm collects the results from all sub-trees and uses them either for classification or for decline. Then, it extracts accurate and stable results through the process of decision-making by utilizing different trees with their results [18]. The random forest algorithm is characterized by its ability to handle complex data, reduce overfitting, and provide accurate and reliable results across diverse environments, making it one of the best techniques for healthcare data.

3.2 Interpret the Model with SHAP Value

SHAP values can be described as a cooperative tool among features that are used in the model. This model works by distributing rewards, which represent the importance of the feature in the final prediction results according to its attributions. This outcome contributes to explaining and clarifying somewhat ambiguous and complex machine learning models. The following basic equation can give it:

$$\vartheta_i(n) = \sum_{K \in W}^{\{i\}} \frac{|K|! \, (|W| - |K| - 1)!}{|W|!} \, (n(K \cup \{i\} - n(K)) \tag{1}$$

Where: $\vartheta_i(n)$ is SHAP value for feature (i), (W) is all features, (K) is a subgroup of feature not constant feature (i) To use this equation to explain the prediction of the model $f(g)$ for a group of features (g), the SHAP value for one feature is defined as:

$$\vartheta_i(g) = \sum_{K \in W}^{\{i\}} \frac{|K|! \, (|W| - |K| - 1)!}{|W|!} \, (f(g_K \cup g_i) - f(g_K)) \tag{2}$$

Where: $\vartheta_i(g)$ is the SHAP value for feature (i) in group (g), $(f(g_K \cup g_i) - f(g_K))$ is the model output when the feature in group (K) and feature (i) has its actual value of (g).

After calculating the SHAP value, the summation of the SHAP value with the base value must be equal to the actual model prediction.

$$f(g) = E[f(G)] + \sum_{i=1}^{X} \vartheta_i(g) \tag{3}$$

Where: $f(g)$ is the actual prediction of the model for group (g), $E[f(G)]$ is the base value of SHAP, and $\vartheta_i(g)$ SHAP value for feature (i) in group (g).

Algorithm: SHAP value
Input:
- f: the prediction model
- x: the input instance to explain
- M: number of features in x
- x_baseline: baseline value(s) for features (e.g., all zeros or mean input)
Output:
- phi: SHAP values for each feature
Initialize:
phi = [0 for i in 1 to M]
For each feature i in 1 to M:
phi[i] = 0
For each subset S of {1, ..., M} excluding i:
weight = (|S|! * (M - |S| - 1)!) / M!
x_S = x_baseline.copy()
For j in S:
x_S[j] = x[j]
x_S_with_i = x_S.copy()
x_S_with_i[i] = x[i]
marginal_contribution = f(x_S_with_i) - f(x_S)
phi[i] += weight * marginal_contribution
Return phi

The SHAP value could provide several interpretations that can be classified under the term (local and general) where the local interpretations give the reason behind the random prediction access and the way features impact whether it is positive or negative. It provides several figures, such as Force plots and waterfall plots, and the local interpretations also apply to individual data statuses.

The general interpretations reveal the model's overall behavior on a set of data and how the features affect the predictions. Several figures, such as (Summary plots, Bar plots, and Bee swarm) and (Dependence plots), affect the general interpretations, and SHAP values can be calculated by different algorithms, for instance (Kernel SHAP, Tree SHAP, Deep SHAP, and Linear SHAP) [19-21].

The dataset, evaluation metrics, and the problem of processing and analyzing healthcare data in smart cities were discussed to identify the important features and how they contribute to obtaining the resulting metrics.

3.3 Dataset

There are three types of input features: Objective: factual information; Examination: results of medical examination; Subjective: information provided by the patient. All dataset values were collected at the time of the medical examination. The features can be described in Figure 3 as follows:

```
Age | Objective Feature | age | int (days)
Height | Objective Feature | height | int (cm)
Weight | Objective Feature | weight | float (kg)
Gender | Objective Feature | gender | categorical code
Systolic blood pressure | Examination Feature | ap_hi | int
Diastolic blood pressure | Examination Feature | ap_lo | int
Cholesterol | Examination Feature | cholesterol | 1: normal, 2: above normal, 3: well above normal
Glucose | Examination Feature | gluc | 1: normal, 2: above normal, 3: well above normal
Smoking | Subjective Feature | smoke | binary
Alcohol intake | Subjective Feature | alco | binary
Physical activity | Subjective Feature | active | binary
Presence or absence of cardiovascular disease | Target Variable | cardio | binary
```

Fig. 3 *The features of the dataset*

3.4 Evaluation Metrics

Automatic evaluation criteria are used to evaluate the performance of the proposed system. There are many metrics used to evaluate the model's performance. In this study, the following parameters were used:

- Mean Squared Error (MSE): Mean squared difference between the resulting values and the original values, and is calculated using the following equation:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_{(i)} - \widehat{y_{(i)}})^2 \tag{4}$$

- Mean Absolute Error (MAE): Average absolute difference between the resulting values and the original values, and is calculated using the following equation:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_{(i)} - \widehat{y_{(i)}}| \tag{5}$$

4. Analysis and Results

The Systolic and diastolic blood pressure data were analyzed. Results were obtained using the RF model and the Kaggle dataset, and mean squared error (MSE)and mean absolute error (MAE) were measured [13], as shown in Table 2. Given that the algorithm used is one of the machine learning models which, despite its accuracy in prediction, is considered to produce ambiguous and difficult-to-interpret results, especially when dealing with healthcare data, where specialists such as doctors and healthcare providers need clear and explicit explanations to understand the reason for the prediction and the features that influenced the achievement of these predictions in order to avoid bias and increase the reliability of the results, the need arose to use models to interpret these cases. In this study, since a random forest model was used to obtain predictions, Shapley values were computed using the algorithm, which assigns importance to each feature in the dataset, each according to its contribution to the final predictions of the machine learning model. Thus, it provides interpretable, clear, and reliable results on clinical outcomes, free from biases that may arise (e.g., giving undue importance to an unimportant feature), and easy to understand for healthcare professionals and doctors.

**Table 2** *Evaluation results of RF without SHAP value*

Parameters	Systolic Blood Pressure	Diastolic Blood Pressure
MSE	43.133	13.467
MAE	3.215	1.550

In Figure 4, Shapley values are calculated for the arterial diastolic blood pressure feature from the dataset, and the SHAP summary plot illustrates the importance of each feature and its impact on the model's predictions for the test dataset. This plot shows that the model relies heavily on systolic blood pressure (ap_hi), age (age), and diastolic blood pressure (ap_lo) to make its decisions. Higher ap_hi and ap_lo drive the model's outputs toward lower values, while higher age drives them toward higher values. The other features are much less critical in this model's predictions.
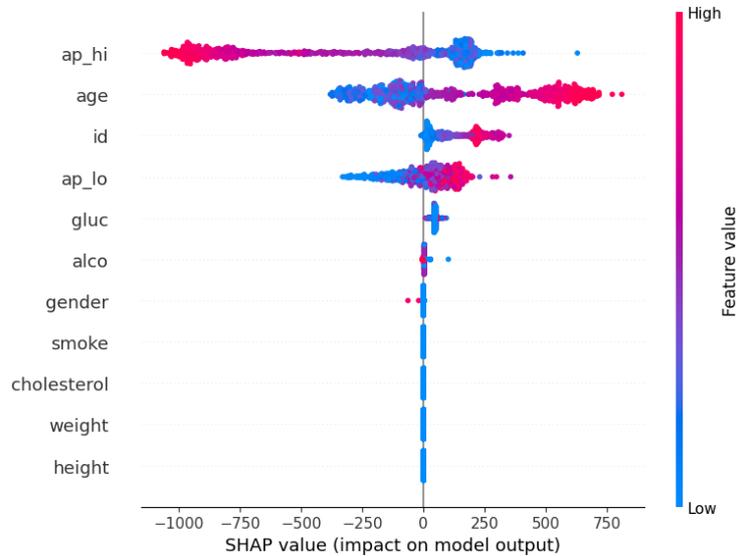

Fig. 4 *SHAP Summary plot for impacts of input features for Diastolic blood pressure*

In Figure 5, the model starts with a baseline prediction of 96.421. To predict the final value of 83.26 for this particular instance, the following happened: ap_hi was the most significant positive contributor (significantly raising the prediction). ap_lo and age were the most critical negative contributors (significantly lowering the prediction). Other features (such as gluc and alco) had more minor effects, either increasing or decreasing, ultimately leading to the predicted value of 83.26. This chart helps explain why the model arrived at this particular prediction for a single instance, and highlights which features played the most significant role.
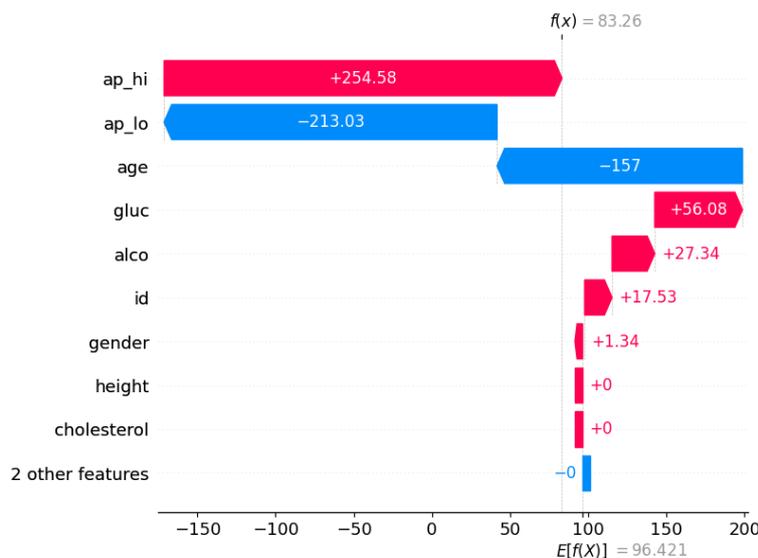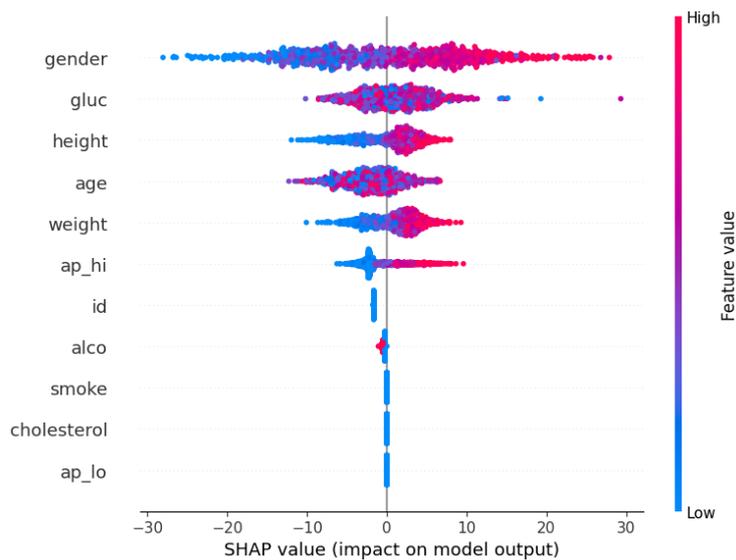

Fig. 5 *SHAP waterfall plot for the most important features for Diastolic blood pressure*

In Figure 6, this chart confirms that systolic blood pressure (ap_hi) and age (age) are the two most important features for the model being analyzed, followed by diastolic blood pressure (ap_lo) and glucose level (gluc). Other features, such as alcohol, gender, smoking, and cholesterol, play a very marginal role in this model's predictions.
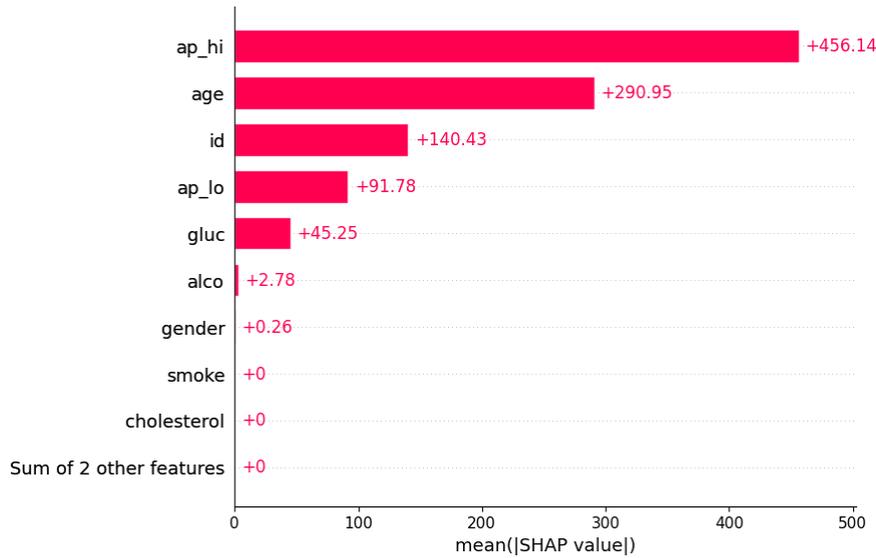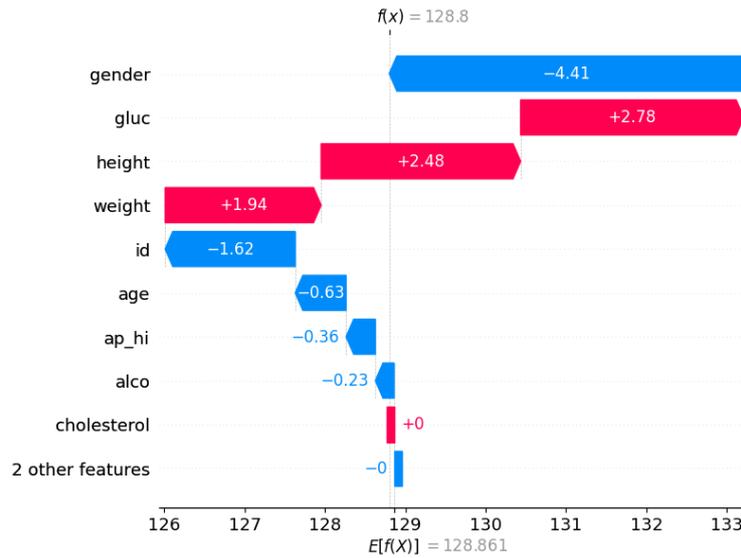
Fig. 6 *SHAP bar plot for the most important features for Diastolic blood pressure*

Figure 7 shows Shapley values for the arterial systolic blood pressure feature from the second dataset, indicating that the model relies heavily on gender, glucose level, height, age, and weight to make decisions. High values of these features (except for gender, where the effect depends on how it is encoded) tend to raise the model's output, whereas low values tend to lower it. Features such as id, alcohol, smoking, cholesterol, and diastolic blood pressure (ap_lo) play a much less critical role in this model's predictions. The importance of blood pressure (especially ap_lo) is much lower in this model than in previous plots, suggesting that it is trained on a different task: systolic blood pressure.


Fig. 7 *SHAP summary plot for impacts of input features for Systolic blood pressure*

In Figure 8, the model starts with a baseline prediction of 128.861. To predict the final value of 128.8 for this particular instance, the following occurred: Gender was the most significant negative contributor, significantly lowering the prediction. Glucose level, height, and weight were the most important positive contributors, increasing the prediction. Other features, including age and systolic blood pressure, had more minor effects, either increasing or decreasing, ultimately resulting in a predicted value of 128.8.

Fig. 8 *SHAP waterfall plot for the most important features for Systolic blood pressure*

Figure 9 confirms that gender is the dominant feature in this model. It is followed by glucose level (gluc), height (height), age (age), and weight (weight), all of which play essential roles. Compared to some previous plots, the ap_hi feature (systolic blood pressure) shows a relatively minor impact in this model. Features such as alcohol, smoking, and the remaining features have minimal effect on this model's predictions.
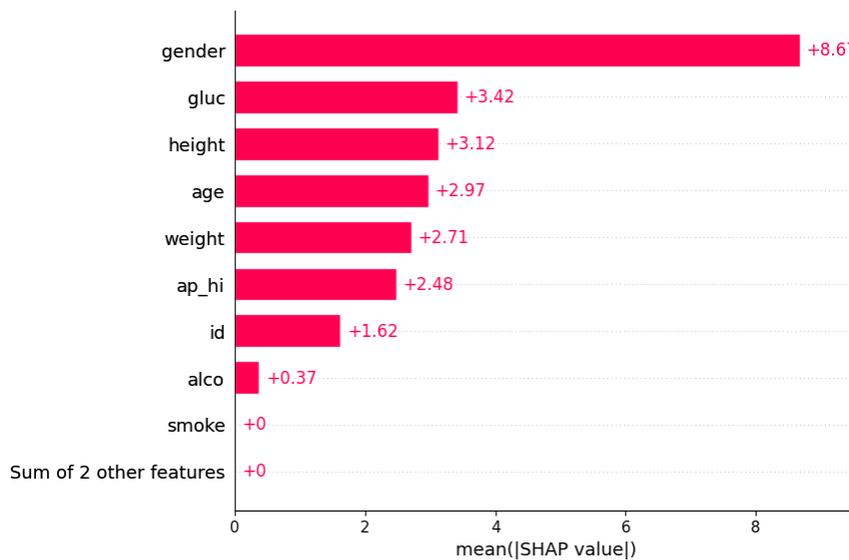

Fig. 9 *SHAP bar plot for the most important features for Systolic blood pressure*

Based on Shapley's values, features that are irrelevant or negatively affect the results were identified. This allowed for improving the model's performance and reducing the values of (MAE) and (MSE), as shown in Table 3. This demonstrates the importance of Shapley's values in interpreting models, making them more explanatory, manageable, and optimized.

**Table 3** *Evaluation results of RF with SHAP value*

Parameters	Systolic Blood Pressure	Diastolic Blood Pressure
MSE	11.680	11.716
MAE	0.109	0.180

Penerbit
UTHM

Figure 10 shows the model's performance when predicting diastolic blood pressure using the actual values from the second data set. The closer the blue dots are to the red dashed line, the better the proposed model's prediction. However, if the dots are spread out, this indicates data dispersion and the presence of prediction errors. Values far from the line represent extremes in the data, and the difference between the predicted and actual values in the data set used.
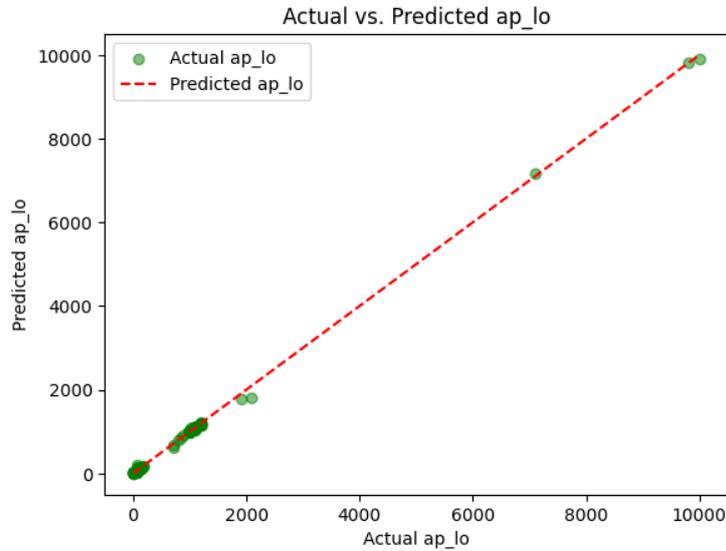
Fig. 10 *Diastolic blood pressure vs. actual data by using RF*

Figure 11 shows the model's performance when predicting systolic blood pressure using the actual values in the data set. The closer the green dots are to the red dashed line, the better the prediction of the proposed model. However, if the dots are spread out, this indicates data dispersion and the presence of errors in the prediction. Values far from the line represent extremes in the data, and the difference between the predicted and actual values in the data set used.
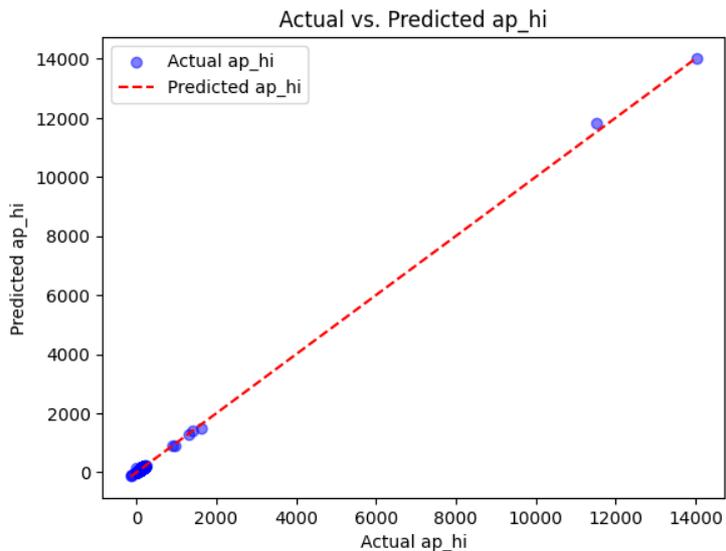
Fig. 11 *Systolic blood pressure vs. actual data by using RF*

The RE model is important because it contains decision trees and is able to deal with non-linear data. It is presented as a set to reduce variation by collecting several predictions from the decision trees, which in turn yields more stable results and makes it less susceptible to distortion and extreme values. Because the data used is healthcare data, it is necessary to understand how to predict outcomes, analyze the model, and how it works. Therefore, it is necessary to use shape values, which simplify the understanding of the model by creating a histogram that assigns appropriate importance to the features used, each according to its contribution to the

model's results, such as diastolic blood pressure. Figures 4-6 show a strong dependence on systolic blood pressure and age, with the latter being a stronger predictor of decline. The shape summary and bar charts, Figures 4 and 5, further illustrate that these main features are more important to the model's decision-making process.

The waterfall diagram (Figure 5) shows how these features contribute to the final prediction: Ap-hi had a strong positive effect, while Ap-lo and age had negative effects in this phase. In contrast, systolic blood pressure figures 7-9 show a different set of main influencing factors. The model's predictions are largely affected by gender, glucose level, height, age, and weight. Figures 7 and 9 confirm that gender is the most influential feature, followed by glucose, height, and weight. The waterfall diagram in Figure 8 confirms that gender is a negative factor, and that glucose, height, and weight are positive factors in the final prediction. The differences in the important features between the two models are highlighted. Ap-hi is very important for predicting Ap-lo, while gender, demographics, and physical characteristics are essential for predicting Ap-hi. The relationships between variations are related to the aimed prediction. This clarifies the importance of shape analysis in providing transparency into how to learn the different models and the characteristics the models prioritize for different tasks, emphasizing that the models might differ substantially depending on the data and the prediction aim. Figure 10 shows good predictive performance, with several data points near the perfect dashed red line, indicating that the model predictions match the actual values. The scatter in Figure 11 shows good performance, with the data largely following the perfect line despite some distractions.

5. Conclusion and Feature work

In this study, the Shapley values were used to interpret the predictions of the random forest model trained on the healthcare dataset. The study specifies the positive and negative features that impact the prediction outcome. The MSE and MAE are achieving 11.680 and 0.109, respectively, in systolic blood pressure, while the MSE and MAE are achieving 11.716 and 0.180, respectively, in diastolic blood pressure. The analysis by Shapley shows that the most influential features for systolic blood pressure prediction are age, ID, and ap-lo. At the same time, gender, height, and gluc are the most influential features for predicting blood pressure, both positively and negatively. This study aims to specify the functioning of algorithms in a machine learning model and transform it from a complex, ambiguous model into an easy-to-understand one. Understanding the result and how it's generated leads to making the model more flexible. These interpretations make the model trustworthy and easy to use. For future studies, we can apply the Shapley values to multiple real datasets, use more than one model for prediction and classification, and then analyze these models using SHAP values.

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Conflict of Interest

The Authors declare that there is no conflict of interest regarding the publication of this paper.

Author Contribution

The authors confirm contribution to the paper as follows: **study conception and design:** *Nejood Faisal Abdulsattar Abdulsattar;* **analysis and interpretation of results:** *Hassan Khotanlou;* **draft manuscript preparation:** *Hatam Abdoli. All authors reviewed the results and approved the final version of the manuscript.*

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