

DEVELOPMENT OF AN EXPLAINABLE MACHINE LEARNING MODEL FOR HYPERTENSION RISK PREDICTION USING BASIC CLINICAL PARAMETERS

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DOI10.51459/jostir.2026.2.2.0271

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ABSTRACT

Hypertension is one of the major contributors for gravid women and unborn child' death especially in the developing countries where access to innovative diagnostic technologies is not common. The study used explainable machine learning algorithm to predict hypertension risk using basic clinical attributes. Pregnant women records in the Mother and Child Hospital in Akure was collected and preprocessed to address missing values, regulate the features, and enhance overall data quality. The data partitioning at 80% for training and 20% for testing was carried out to confirm a balanced representation of the target variable. Predictive models were developed using random forest and logistic regression algorithm and evaluation was carried out to measure their forecasting performance. Random Forest model achieved 90% accuracy and was able to classify both "HIGH and "LOW" risk level. In addition, SHapley Additive exPlanations (SHAP) analysis was adopted to select the most influential predictors in the model and the result identify systolic Bp, Temperature, Diastolic and weight as most factors contributing to hypertension risk. In conclusion, the developed model can serve as an intelligent clinical decision support tool to assist healthcare professionals in the early detection of hypertension risk using readily available clinical data.

Keywords: Hypertensive disorder, Machine learning algorithm, SHapley Additive Explanation, Foetal Mobility and mortality

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History

Received: 02-04-2026
Accepted: 04-06-2026
Published: August, 2026



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1. | Introduction

Hypertension occurs when an individual blood is pushing too forcefully against the artery walls and this condition at the advanced stage causes heart attack and other disease in the body (Abubakar, 2024). It should be attended to when diagnose early to reduce complications especially in a pregnant woman.

Early diagnosis of hypertension during pregnancy especially in the developing countries using simple and readily available clinical parameters

can significantly control mortality and foetal morbidity (Okitkpi, 2025).

The world health organization gave a world estimate of over one billion people at the middle age that are living with hypertension and many of them are from the developing countries. Majority of the affected individual are not aware of their health status because of the limited diagnostic facilities and level of awareness. The prevalence of hypertension by 2030 is a target of reduction to 33% compare with the baseline level (Unger *et al.*, 2020, Kario *et al.*, 2024).

The death of a pregnant woman is devastating for her family and the society. Many pregnant women, particularly in low-income countries, suffer from hypertensive disorders that often go undetected or are diagnosed too late. In many cases, a lot of women have limited access to quality healthcare services and as a result prevents them from regularly monitoring their health status during pregnancy and after birth (WHO, 2018; WHO, 2025)

Therefore, improving early detection and monitoring of hypertensive condition during pregnancy is essential to reduce health risks and improve the overall quality of maternal healthcare. Hence, this study employs two algorithms to support the early detection of hypertension in pregnant women. Also, the feature importance ranking analysis was conducted to identify the most influential predictors contributing to hypertension risk.

Abubakar, *et al.*, (2024) built a predictive model for early prediction of hypertension using machine learning algorithm. The diabetes prediction dataset is rebranded and preprocessed to address data imbalance and normalization. Predictive model was built using Transfer learning techniques and the result shows accuracy of 81.34% and other evaluation metrics were used for the model performance. Feature importance analysis was done using, Pearson's correlation coefficient and the relationships between features and outcomes selected for the training was calculated. During the course of this research, the deep neural network architecture was restructured to accommodate hypertension prediction by adding two new hidden layers and removing the last hidden layer.

Zhong, *et al.*, (2023) predicted the risk level of early cognitive impairment in hypertensive individuals using three learning classifiers. Records of 733 patients with hypertension were collected and divided into training and testing at the ratio of 70:30. Three machine learning classifiers were adopted for

the model implementation and evaluation and the result shows that XGB model outsmart other models in the area of performance. Feature importance selection was done using Shape Additive explanation (SHAP) analysis and those features identified has the ability to predict the risk of cognitive impairment in hypertensive clinical settings.

Nbaakee, (2025) analyse hypertension risk using a deep learning classification algorithm. Dataset consist of 5000 patient records was sourced from a publicly available health database and was pre-processed to address normalization and data imbalance. The data split was done into 80:20 to represent training and testing respectively. The model implementation and evaluation were done using Multilayer Perceptron algorithm and the result shows that the model achieved 91.3% accuracy, 89.5% precision, 92.7% recall, and 91.0% F1-score. This result validated the model's usefulness in classifying individuals at risk of hypertension.

Elizabeth, *et al.*, (2026) used classification algorithm to forecast the individual risk of hypertension. The dataset from Kaggle repository was preprocess to address missing values. The dataset was partitioning into 70% training and 30%. The implementation was done using Random Forest algorithm and the result achieved an impressive performance. Features importance was carried out by SHapley additive explanation (SHAP) to show systolic Bp as the highest contributing feature to the model's prediction performance.

Jonathan, *et al.*, (2024) investigated hypertensive disorders in pregnancy (HDP) using machine learning algorithm. Dataset of Mothers-to-Be (nuMoM2b) was collected, preprocessed to address missing values and divided into training and testing in the ratio of 80:20. Random Forest algorithm was used for the implementation and the result showed an impressive performance.

Panel (2024) investigated early hypertensive disorders in pregnancy. In this study, records of pregnant women were collected and preprocessed to address missing values using chain equation and distribution conversion. Five machine learning algorithms were used for the implementation and the result revealed 0.93 value for an area under the receiver operating characteristic curve, which implies that the developed model demonstrated that the early pregnancy prediction models has retain sufficient performance in hypertensive disorders. Recursive feature elimination (RFE) was also used for feature selection to avoid overfitting to improve the performance of the prediction model.

Campero-Jurado, *et al.*, (2024) predicted hypertensive disorders in pregnancy. Records of pregnant women were collected and preprocessing was done for data balancing using a random sub-sampling technique to adjust the dataset class distribution and also eliminate the problem of data imbalance. Five algorithms were used for the implementation and T-S and FCM has the highest predictive ability than the other three models.

Okitikpi, *et al.*, (2025) forecasted the risk of Hypertension Disorder in Pregnancy (HDP) using ML.NET in an ASP.NET web application

framework to provide a machine learning-based way to find high blood pressure early in pregnancy. Patient record (250), 75 real-time clinical entries and 30 Wearable Device Records were collected and preprocessed to address missing value. Decision Tree classification algorithm was adopted for the model classification with clinical factors like age, blood pressure, BMI, proteinuria, and diabetes status. The model that was developed was serialised and added to a web-based Patient Predictive Health Record System that was made with ASP.NET C# and linked to Microsoft SQL Server to handle patient information and user interactions. For the system evaluation, standard machine learning metrics were adopted and the results showed that the model was very good at making predictions, with an average cross-validation accuracy of 83.5%, an F1 score of 84.4%, and an AUC of 89.7%. In some folds, the accuracy reached 92.9%. These results confirm that the system is effective for clinical decision support in identifying HDP risk.

3. | Materials and Methods

Figure 1 explains the system architecture and the interact among all the modules from data sources to the implementation.

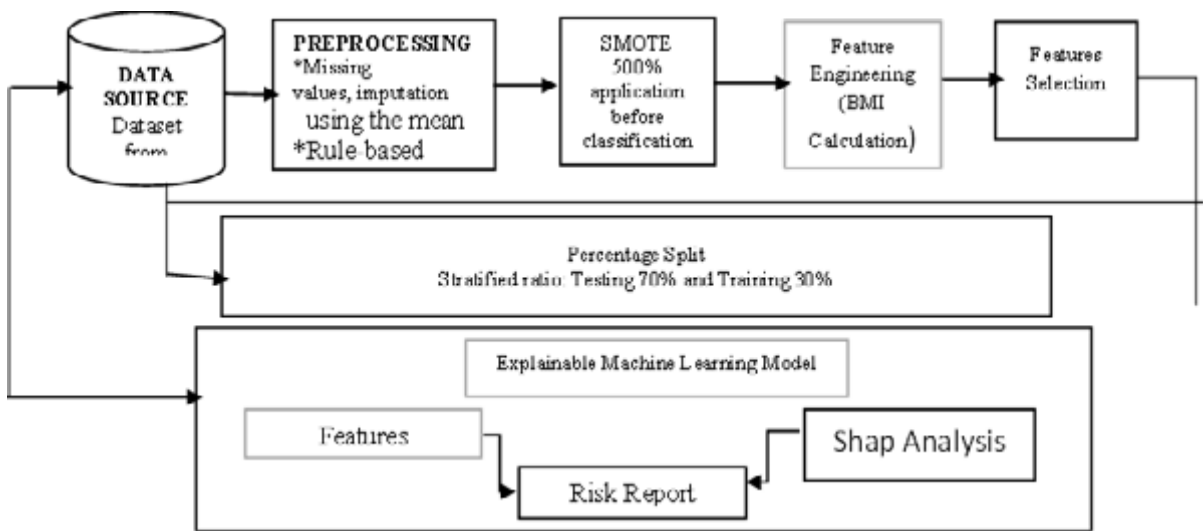


Figure 1 | System Architecture for Hypertension Risk Prediction model

3.1 | Ethical Clearance

Ethical clearance was obtained from the hospital management before the commencement of data collection. This process was done in accordance with approved ethical guidelines.

3.1.1 | Data Acquisition

Pregnant women 148 unlabeled records from the mother and child Hospital in Akure was collected. The rules used to generate class labels for similar dataset obtained from Kaggle.com were adopted to assign class labels to the newly collected dataset. Below are the set of predefined rules generated

- i. when the body temperature is greater or equal to 100 and Diastolic Bp is also greater and equal to 66.6
- ii. when Diastolic BP is greater or equal to 92.5 and Heart Rate is also greater than or equal to 66.5.
- iii. when Body Temp is greater than or equal to 100, Age greater than or equal to 22 and Diastolic BP is lesser than or equal to 75
- iv. when Heart Rate is greater than or equal to 79 and Age is greater than or equal to 22.5
- v. when Age is lesser and equal to 50 and Diastolic BP is equal 80
- vi. when Systolic BP is equal to 120 and (Diastolic BP equal to 75 OR Diastolic BP equal to 85 OR Diastolic BP equal to 90) and Body Temp equal to 98
- vii. when Systolic BP is greater than or equal to 129.5
- viii. when Body Temp is greater than or equal to 100 and Heart Rate is lesser or equal to 66.7

Table 1 | Dataset View

Age	StytolicBp	DiastolicBp	BodyTemp	Heart Rate	Weight	Height
24	97	59	98	91	59	1.59
24	110	70	98	88	65	1.74
28	140	70	98	74	68	1.85
29	100	70	98	80	59	1.58
34	110	70	97	92	64	1.45
29	100	70	98	104	75	1.96
34	120	70	99	100	63	1.54
28	140	100	99	74	78	2.12
26	120	70	98	96	80	2.34
31	100	60	98	80	69	2.1
32	140	100	98	88	71	1.91
40	110	80	98	80	75	1.96
28	100	60	100	92	53	1.63
31	120	70	97	88	60	2.1
31	120	80	97	74	70	2.65

28	140	80	97	96	65	2.4
37	110	70	98	98	68	1.84
29	120	80	98	60	76	1.87
21	120	80	98	84	79	2.1
35	150	100	98	72	69	2.3

Table I shows the view of dataset collected from Mother and Child hospital in Ondo state. It consists of pregnant women age, systolic Bp, diastolic Bp, body temperature, heart rate and their weight. Table 2 represents the description of the feature.

Table 2 | A summary of Dataset Description

Features	Description
Weight	The human body mass measurement
Diastolic	lower value of blood pressure in millimeters of mercury (mmHg)
Age	The age of the pregnant woman
Temperature	The body internal heat balance
Risk level	Hypertension (1 = Yes, 0 = No)
Systolic	Blood pressure value at the upper measured in millimeters of mercury (mmHg)
Heart Rate	The number of times the heart beats per minutes (bpm)
Height	Measure of vertical distance of the body

Table 3 | Statistical Analysis of the Dataset Features to Address Missing Variables

Mean Deviation	Standard Deviation	Minimum	25%	50%	75%	Maximum	Missing	Mean Deviation
Age	29.77027	16.999054	18	27	30	32.25	41	1
Systolic	118.1081	16.999054	80	110	120	120	180	1
Diastolic	74.35811	11.712549	50	70	70	80	120	3
Temperature	36.58	0.4560702	34.5	36.375	36.6	36.8	38.6	13
Heart Rate	86.55405	10.334069	60	80	84.5	92	128	3
Weight	75.11486	17.749015	48	64.75	74	78.25	163	21
Height	1.961689	0.9441365	1.13	1.59	1.67	1.96	7.2	21

Table 3 presents the statistical analysis to handle missing data in the collected dataset across all features. The dataset has features like age, diastolic blood pressure, systolic blood pressure, temperature, heart rate, weight and height. Descriptive statistical measures, such as mean, standard deviation, minimum value, 20th, median, 75th percentile and maximum value were used to evaluate the distribution of the data and also address the missing variables.

3.1.2 | Preprocessing

Data cleaning and normalization of pregnant women records at the mother-child hospital was done and prepared in a format suitable form for modelling. Rules used to determine the class label of the dataset from Kaggle is adopted to categorize records into High and Low risk groups because the dataset collected from Mother and Child lacked predefined class labels.

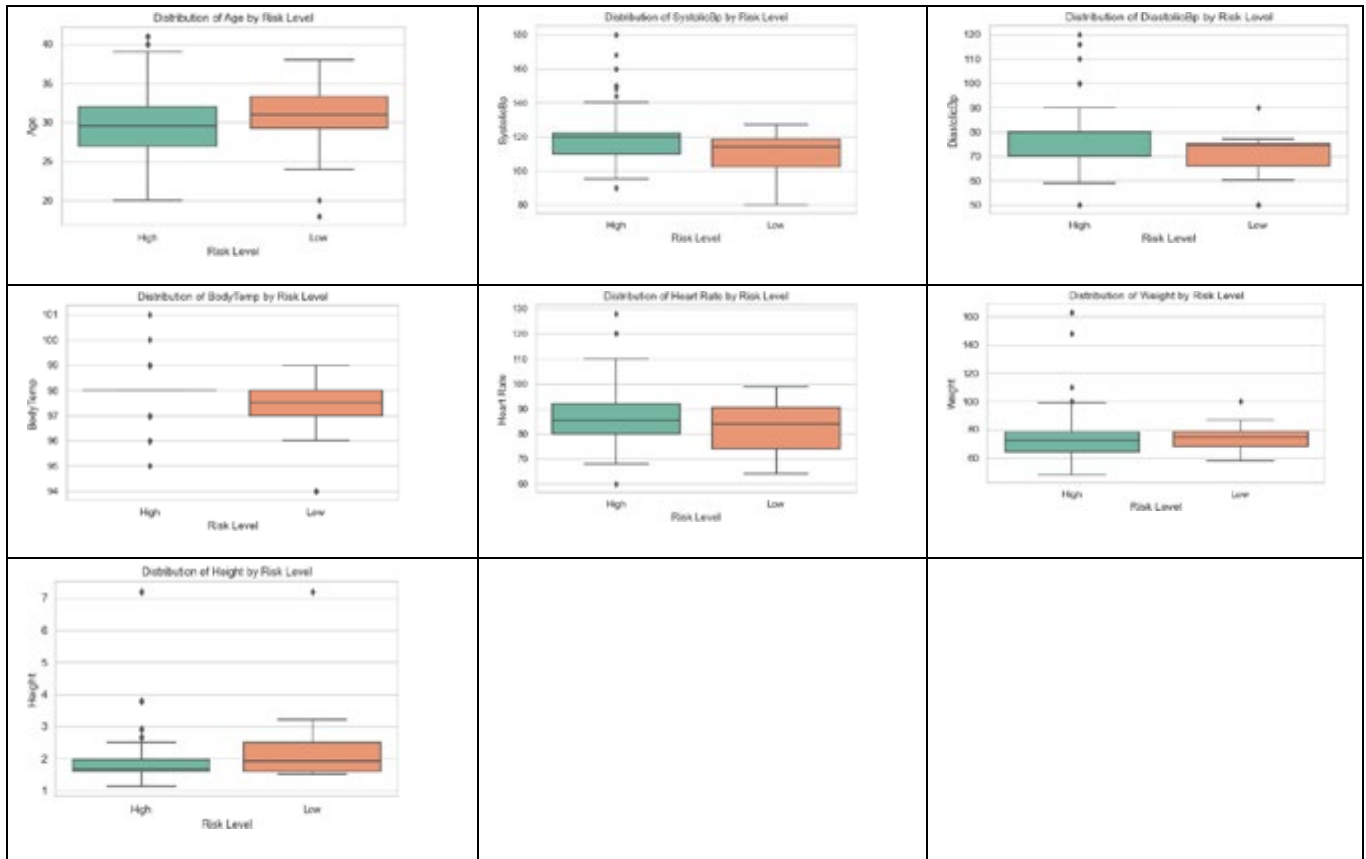


Figure 2 | Features Distribution Plots

3.1.3 | Class Imbalance and Percentage Split

In this study, SMOTE was used to address data misbalancing and the result actually increase the number of Low-risk instances and stable distribution output. The dataset split into training and testing at ratio 80:20 was done.

3.1.4 | Prediction Models

i. Random Forest

The mathematical model of Random Forest classifier is described in equation (1)

$$\hat{y} = \arg \max_c \sum_{i=1}^T I(h_i(x) = c) \quad (1)$$

Where:

$\hat{y}$ is final predicted class

T is total number of trees

$h_i(x)$ is prediction from the i th tree for input x

c is class label

$I(\cdot)$ is indicator function that equals 1 if the condition is true and 0 otherwise

$\arg \max$ is selects the class with the highest number of votes

Each decision tree in equation (1) forecast a class for the input data and the random forest counts the votes from all trees and assigns the class that receives the highest votes as the overall prediction.

ii. Logistic Regression

The logistic regression model is expressed in equation (2):

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1x_1 + \beta_2x_2 + \cdots + \beta_nx_n$$

(2)

Where:

P represents the positive class probability

β_0 is intercept

$\beta_1, \beta_2, \dots, \beta_n$ is model coefficients while

$x_1, x_2, \dots, x_n$ are input features

3. | Results and Discussion

3.1 | Evaluation of Models: Performance Metrics

Logistic Regression model achieved accuracy of approximately 83.33% which is slower than the Random Forest. The Logistic Regression

Regression model performed very well for the “HIGH” risk class (precision: 0.86, recall: 0.96, fi-score: 0.91), indicating it correctly identified all “HIGH” cases. However, it completely failed to identify any “LOW” risk cases (precision: 0.50, recall:0.20, fi-score: 0.29). this suggests that the model might be biased towards the majority class (HIGH) and is unable to correctly classify the minority (LOW) risk cases.

Random Forest Classifier achieved accuracy of 90.00% which indicated a strong overall performance in classifying hypertension risk. The Random Forest showed excellent performance for the High-risk class while its performance for the LOW-risk class was lower.

Figure 3 and 4 shows the confusion matrix for both logistic regression and random forest model. In Figure 3, twenty-four (24) were classified as high and actually high and one (1) classified as high but

Table 4 | Model Performance Comparison

Model	Risk Cases	Precision	Recall	Fi-score	Accuracy%
Logistic Regression	High risk cases	0.86	0.96	0.91	83.33
	Low risk cases	0.50	0.20	0.29	
Random Forest	High risk cases	0.89	1.00	0.94	90
	Low risk cases	1.00	0.40	0.57	

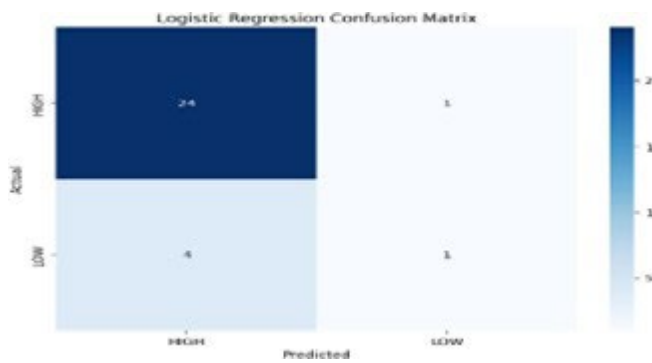


Figure 3 | Logistic Regression Confusion Matrix

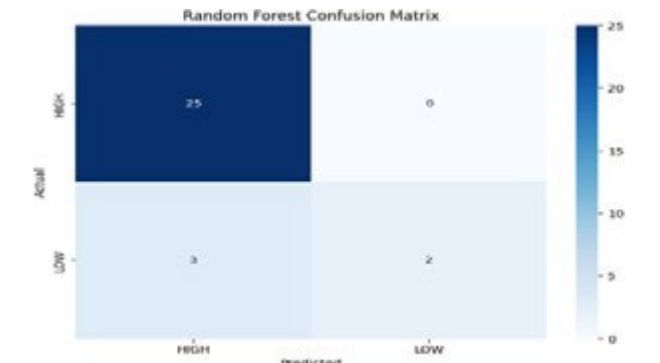


Figure 4 | Random Forest Confusion Matrix

actually low. Also, four (4) were classified as low and actually high and one classified as low and actually low. Twenty-five (25) instances were correctly predicted as high risk and were actually high. Zero instances were incorrectly classified as high but actually low. In addition, three (3) instances were incorrectly classified as low risk but were actually as high, while two (2) instances were correctly classified as low risk and were actually low.

3.2 | Model Interpretability with SHAP

Shapley Additive explanation values were adopted for the two model to know each features contribution in the prediction:

- i. Random Forest (TreeExplainer): Random Forest model provides features that were most influential in determining the hypertension risk. Typically, features like Heart Rate, temperature and systolicBp are the strongest predictors in such medical contexts.
- ii. Logistic Regression (LinearExplainer): The SHAP summary plot for Logistic Regression and it shows that the output of the model's struggle with the "LOW" risk class, the SHAP values might highlight that the features' linear relationships were not sufficient to differentiate this minority class effectively.

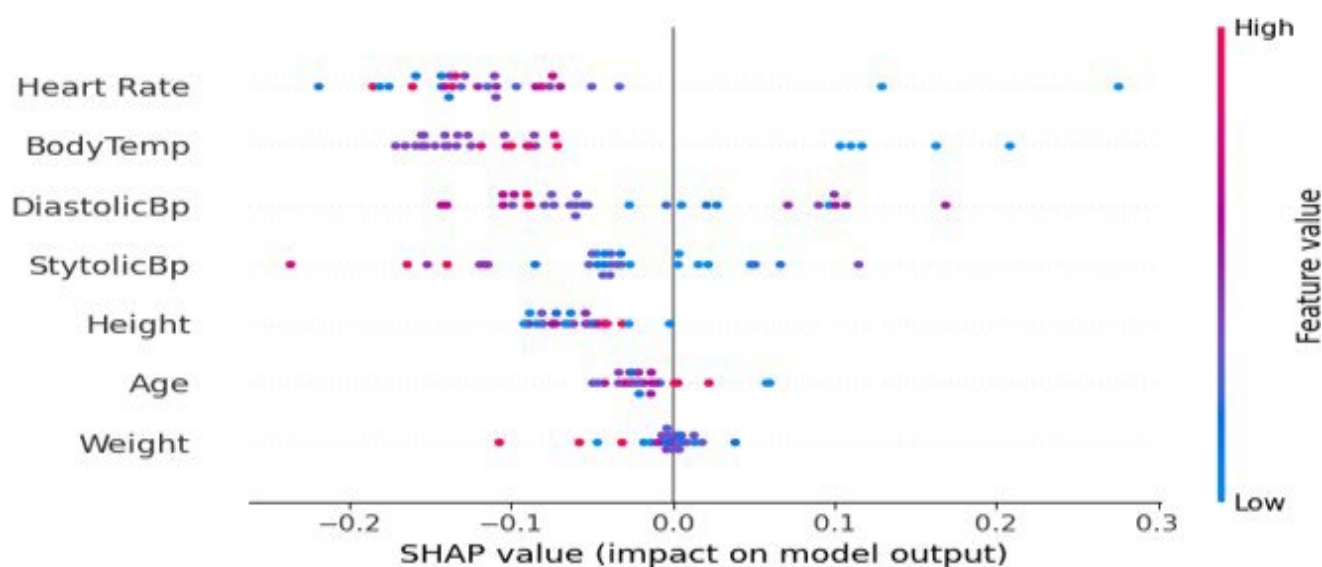


Figure 5 | SHAP value output on the model

Figure 5 is the SHAP summary plot, which explains how each feature contributes to the prediction of hypertension risk in Random Forest model. SHAP values show how much each feature pushes the model prediction toward higher risk or lower risk. The pink colour represents high feature while the blue presents the low feature value. Each dot represents patient in the dataset and features at the top are generally more important in influencing predictions. Heart rate is seen as the highest influential predictor of hypertension risk. Higher values of these features generally increased the possibility of hypertension prediction, while lower values reduced the model output. In contrast, height, age,

and weight showed minimal influence on the prediction outcome.

4. | Conclusion

SHapley Additive exPlanations (SHAP) was employed to explain the predictions and identify the most important features contributing to hypertension risk. The SHAP analysis revealed that heart rate, body temperature, and blood pressure measurements were the most significant predictors of hypertension in pregnant women, while other features like height,

age, and weight had reasonably lower influence on the prediction outcome.

Overall, the study demonstrates that combining machine learning models with explainable artificial intelligence techniques can provide accurate and

interpretable predictions for hypertensive disorder. This developed model can assist healthcare professionals in the early identification of pregnant women at risk of hypertension, thereby enabling timely intervention and improved maternal healthcare outcomes.

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