

A Percentile Rank-Based Multi-Criteria Decision-Making Algorithm for Interpretable Hypertension Risk Stratification in Clinical Decision Support Systems

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ABSTRACT

Hypertension risk prediction remains a critical challenge in data-driven healthcare systems, particularly in low- and middle-income countries (LMICs). In many of these settings, timely monitoring and diagnosis remain difficult. Machine learning (ML) methods have been applied for hypertension risk prediction; however, their complexity and “black box” nature limit their integration into clinical decision support systems. This study presents a Percentile Rank-Based Multi-Criteria Decision Making (PRBMCDM) model for hypertension monitoring and risk stratification. Hypertension-related data were collected from public and private hospitals in the Kogi Eastern Senatorial District of Nigeria. The data were used to develop and validate the proposed model. The proposed algorithm calculates risk scores based on the percentile ranking of multiple risk criteria of each patient. The model is designed as a lightweight and interpretable framework suitable for deployment in resource-constrained digital health environments. A drop column method was used to rank features. The model performance was evaluated using 5-fold cross-validation. PRBMCDM achieved an AUC of 0.75, 0.70 and 0.72 high, medium, and low-risk respectively. The model demonstrated high interpretability, making it well-suited for deployment in clinical settings. The PRBMCDM algorithm offers a transparent, simple, and clinically relevant framework for hypertension risk stratification model. Key limitations of existing ML models were addressed. Future work will focus on validating PRBMCDM against established risk scores on larger and more diverse dataset to further strengthen its clinical applicability.

Keywords: Hypertension, Decision Support Systems, Multi-Criteria Decision Making, Percentile Ranking, Healthcare Analytics, Explainable AI.

INTRODUCTION

The increasing availability of healthcare data has enabled the development of computational models for hypertension risk prediction, which remains a major contributor to cardiovascular disease (CVD) and premature mortality worldwide [1]. Each year, it is estimated to contribute to more than 10 million deaths, with LMICs bearing most of this burden [2]. Despite decades of progress in developing effective medications and lifestyle-based interventions, the global prevalence of uncontrolled hypertension remains high, particularly in resource-limited regions [3].

The emerging trend of machine learning (ML) models to make prediction using many clinical characteristics mined from health related data- has gained prominence in hypertension monitoring and risk stratification. Techniques such as ensemble learning, Random Forest and deep learning models have shown promising results in identifying patients at high risk [4]–[6]. However, their clinical applications are limited due to complexity and interpretability issues [7], [8]. Most machine learning models are often considered “black boxes” because their internal decision-making processes are difficult to interpret, even when predictions are accurate [7], [8]. This lack of transparency makes clinicians hesitant to rely on them, especially that healthcare decisions demand both accuracy and interpretability [9], [10]. From a computational perspective, there is a growing need for models

that balance predictive performance with interpretability and low computational complexity, especially in resource-limited healthcare environments where deployment constraints exist.

To address this critical issue, Multi-Criteria Decision Making (MCDM) methods, a decision-support framework can be an alternative to enhance model interpretability. This method allows the integration of multiple risk factors in a transparent and structured manner [11]. Though, the major limitation of traditional MCDM methods is their reliance on static weighting schemes or subjective expert assessments, which limit their dynamic applicability in evolving clinical contexts. This study proposes a Percentile Rank-Based Multi-Criteria Decision-Making (PRBMCDM) algorithm as an interpretable and computationally efficient framework for hypertension monitoring and risk stratification. Percentile rank is a statistically grounded techniques mostly used in clinical reference interpretation [12], [13]. When this is combined with the principle of MCDM can be a viable technique of developing a low-complex, interpretable, and data-driven risk stratification model. In contrast to ML models, PRBMCDM allows clinicians to assess feature importance of hypertension risk factors and adapt risk scoring based on evolving patient data. This makes the deployment of hypertension monitoring and risk stratification model in resource-limited healthcare environments.

By addressing the limitations of ML-based models and enhancing model interpretability through structured percentile-based decision-making, this work contributes a framework for hypertension risk monitoring focusing on clinical decision support systems.

METHODOLOGY

Ethical Approval

For this study, the authors formally applied to Kogi State Ministry of Health Lokoja, Nigeria for permission to carry out the study. The application was approved by the Health Research Ethics Committee of the ministry following the invitation of the lead author and clarification regarding the study and its objectives. An ethical clearance certificate was issued.

System Architecture

The proposed PRBMCDM framework is structured as a modular decision-support system comprising data acquisition, preprocessing and feature selection, and a risk stratification engine. Clinical input data are processed through feature importance evaluation and percentile-based ranking to generate individualized risk scores. The architecture is designed to support integration with electronic health record systems and remote monitoring platforms. Figure 2.1 presents the architecture of the proposed PRBMCDM-based hypertension risk stratification system.

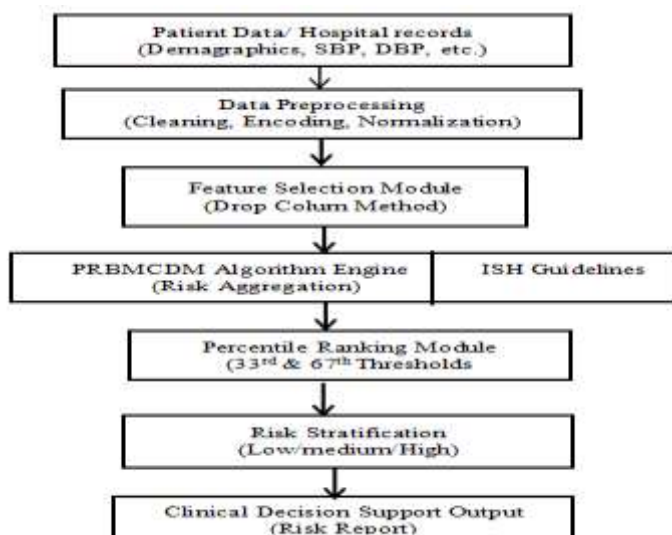


Figure 1. Architecture of the proposed PRBMCDM-based hypertension risk stratification system

Study Design and Data Source

This study employed a retrospective design using hypertension-related health records extracted from hospitals case files in private and public hospitals in the Kogi Eastern Senatorial District of Nigeria. The dataset comprises of demographic, clinical, and lifestyle variables including age, sex, location, family history of hypertension, systolic and diastolic blood pressure (SBP, DBP), diabetes status, cholesterol levels, and smoking status. The target outcome was hypertension risk levels, classified into low, medium, and high risk based on expert clinical explanations.

The dataset was cleaned and pre-processed to address duplicate records and missing values. Categorical variables were encoded, and continuous variables were standardized where necessary. To ensure generalizability and model robustness, k-fold cross-validation ($k=5$) was used in performance evaluation.

Feature Importance Determination and Selection

A model-agnostic feature importance technique based on the drop-column approach was employed to evaluate the contribution of each feature to model performance. The Percentile Rank-Based Multi-Criteria Decision-Making (PRBMCDM) algorithm was then applied to determine the importance score of each feature. The algorithm is present in algorithm 1.

Algorithm 1: Algorithm for feature importance determination

<i>Input: Tabular dataset S where $S \in (N, P)$ with N instances and P features</i>
<i>Fit a model $f(x)$ using all P features on the dataset S</i>
<i>Output: Features with higher value</i>
1. <i>Begin</i>
2. <i>Calculate the accuracy A of $f(x)$ in S using all P features on the dataset S.</i>
3. <i>For each feature (p_i) in P:</i>
<i>a. Remove p_i from the dataset S, resulting in reduced dataset $S-\{p_i\}$</i>
<i>b. Fit the classification model $f(x)$ to $S-\{p_i\}$</i>
<i>c. Calculate the accuracy $A-\{p_i\}$ of the model on $S-\{p_i\}$</i>
<i>d. Calculate the importance score x_i for feature p_i the drop in accuracy:</i>
$x_i = A - (A - \{p_i\})$
4. <i>Repeat step (3) for all features p_i in P until all features have been evaluated</i>
5. <i>Sort the feature importance score x_1 in descending order to get the feature ranking.</i>
$x_{sort} = x_1 > x_2 > x_3 > \dots > x_p$
6. <i>To select the feature subset</i>
<i>a. Select the predetermined number of top features based on the ranking.</i>

<i>b. Exclude features that have low importance measure values.</i>
<i>c. Select the features that have higher importance values</i>
<i>d. compared to the rest.</i>
<i>7. End</i>

Description of PRBMCDM Aalgorithm

Hypertension grade

The Hypertension Grade (HG) is based on the International Society of Hypertension (ISH) guidelines. PRBMCDM Algorithm assigns rating to each risk factor ranging from zero (0) to one (1). The function returns (1) if the specified condition is true and (0) otherwise. This is presented in equation 1.

$$HG=g(SBP,DBP) \begin{cases} g_1 \text{ if } (140 \leq SBP < 160 \text{ or } 90 \leq DBP < 100) \\ g_2 \text{ if } (160 \leq SBP < 180 \text{ or } 100 \leq DBP < 110) \\ g_3 \text{ if } (SBP \geq 180 \text{ or } DBP \geq 110) \end{cases} \quad (1)$$

Where, g = grade, SBP = systolic blood pressure, DBP = diastolic blood pressure.

Gender-specific age classification

The gender-specific age classification assigns risk points based on age and gender. This is presented in equation 2.

$$A = \begin{cases} 1 \text{ if Gender is 0 and Age } \geq 65 \\ 1 \text{ if Gender is 1 and Age } \geq 55 \end{cases} \quad (2)$$

Where, A = gender- specific age classification, Gender = 0 represents female and Gender = 1 represents male.

Risk weight calculation

The total risk factor is calculated as a function that sums all the individual risk factors, represented as $\hat{\alpha}$, such that:

$$\alpha_i = g_i + a_1 + a_2 + \dots + a_n$$

$$\alpha_i = g_i + \sum_{i=1}^n a_i \quad (3)$$

Where, α_i is the sum of all the risk factors, α_i = specific risk weight of individual instance in the dataset with Index, i , g_i = specific grade point of individual instances in the dataset with index i

The set of risk weights are sorted in an ascending order such that

$$\alpha_{sort} = \alpha_1 < \alpha_2 < \alpha_3 < \dots < \alpha_n \quad (4)$$

Percentile rank thresholds

Percentile boundaries are denoted as β_1 (33rd percentile) and β_2 (67th percentile), which help in stratifying the hypertension risk levels based on the distribution of risk factors in the dataset.

$$\beta_1 = \frac{p_1}{100} [N+1] \quad (5)$$

$$\beta_2 = \frac{p_2}{100} [N+1] \quad (6)$$

Where, β_1 = the lower limit of the risk weight, β_2 = the upper limit of the risk weight

p_1 = (33%) , p_2 =(67%) and N = the total number of instances in the dataset

If either β_1 or β_2 is not an integer, the midpoint between the floor and ceiling values of β_1 and β_2 respectively is calculated to establish an accurate threshold.

$$\beta_1 = \frac{p_1}{100} [N+1] \longrightarrow \frac{\text{floor}(\beta_1) + \text{ceil}(\beta_1)}{2} \quad (7)$$

$$\beta_2 = \frac{p_2}{100} [N+1] \longrightarrow \frac{\text{floor}(\beta_2) + \text{ceil}(\beta_2)}{2} \quad (8)$$

Stratification of hypertension risk level

Hypertension Risk Stratification (HRS) is a function of Hypertension Grade Point (g) and risk weight (α) such that

$$HRS = hrs(g, \alpha) = \begin{cases} 1 & \text{if } g=1 \text{ and } \alpha=0 \\ 2 & \text{if } g=2 \text{ and } \alpha \leq 2 \\ 3 & \text{if } (g=3 \text{ and } \alpha=0) \text{ or } (1 \leq g \leq 2 \text{ and } \alpha \geq 3) \end{cases} \quad (9)$$

The HRS stratifies the risk of hypertension to return Low Risk (1), Medium Risk (2) or High Risk (3) respectively.

To determine Hypertension Risk level (R), the following conditions hold.

$$R = \begin{cases} 1 & \text{if } \alpha \leq \beta_1 \\ 2 & \text{if } \beta_1 < \alpha \leq \beta_2 \\ 3 & \text{if } \alpha > \beta_2 \end{cases} \quad (10)$$

Table 2 presents PRBMCDM algorithm.

<i>Input: Input tabular dataset S containing hypertension record $HG_i, A_i, a_1, a_2, a_3, \dots, a_n$</i>	
<i>Output: Hypertension Risk Level value</i>	
1. Begin	
2. For each individual i: $HG =$	
i.	$g1 \text{ if } (140 \leq SBP < 160 \text{ or } 90 \leq DBP < 100)$
ii.	$g2 \text{ if } (160 \leq SBP < 180 \text{ or } 100 \leq DBP < 110)$
iii.	$g3 \text{ if } (SBP \geq 180 \text{ or } DBP \geq 110)$
3. For each individual i: $A_i =$	

i.	1 if (Gender =0 and age ≥ 65) or (Gender=1 and age ≥ 55)
ii.	0 otherwise
4.	For each individual i: $\alpha_i = HG_i + A_i + a_1, a_2, a_3, \dots, a_n$
5.	Sort the risk weight $\alpha_{sort} \alpha_1 < \alpha_2 < \alpha_3 < \dots < \alpha_n$
6.	Calculate the 33 rd percentile (β_1) and 67 th percentile (β_2) of the sorted risk weights:
	$\beta_1 = p_1 * 100 / (N+1), \beta_2 = p_2 * 100 / (N+1)$
7.	Find average points between floor and ceil of β_1 and β_2 if β_1 or β_2 is not integer
8.	For each individual i: R_i : 1 if $\alpha \leq \beta_1$, 2 if $\beta_1 < \alpha \leq \beta_2$, 3 if $\alpha > \beta_2$
9.	End

The PRBMCDM algorithm operates with low computational complexity, making it suitable for real-time implementation in resource-constrained environments

Model Implementation

The PRBMCDM algorithm was implemented in Python 3.10 using a modular computational approach. Key libraries include NumPy for numerical operations, Pandas for data processing, and Scikit-learn for validation. The implementation supports reproducibility and potential deployment as a clinical decision support module

Evaluation Metrics

The performance of PRBMCDM algorithm was assessed using the following performance metrics:

$$Accuracy = \frac{TN+TP}{TN+FN+TP+FP} \quad (11)$$

$$Precision \quad (12)$$

$$Recall = \frac{TP}{TP+FN} \quad (13)$$

$$F-Score = \frac{Precision * Recall}{Precision + Recall} \quad (14)$$

The computation of true vs. predicted classifications was carried out using confusion matrix.

RESULTS AND DISCUSSION

This section presents the computational performance and evaluation results of the proposed PRBMCDM algorithm. The evaluation is based on classification metrics obtained through 5-fold cross-validation.

Descriptive Statistics

The dataset consisted of 1793 patients from the Kogi Eastern Senatorial District of Nigeria. The important features obtained from the drop column approach were used for the analysis. Approximately 29.17 % of patients were classified as high-risk, 65.81 % as medium-risk, and 3.46 % as low-risk based on clinical records.

A summary of feature distributions and correlations with hypertension risk is presented in Table 1.

Table 1: Summary of Descriptive Statistics across Hypertension Risk Factors

Risk Factor	Category	Total Cases (%)	High Risk (%)	Medium Risk (%)	Low Risk (%)
Age	40–49	501 (27.94)	26 (5.19)	417 (83.23)	58 (11.57)
	50–59	700 (39.04)	196 (28.00)	502 (71.71)	2 (0.28)
	60–69	448 (24.99)	143 (31.92)	303 (67.63)	2 (0.44)
	≥70	144 (8.03)	33 (22.92)	111 (9.78)	0(0.00)
Gender	Female	593 (33.07)	79 (13.32)	58 (9.78)	456 (76.90)
	Male	1200 (66.93)	217 (18.08)	46 (3.83)	937 (78.08)
Local Government Area	Ankpa	429 (23.93)	74 (17.25)	23 (5.36)	332 (77.39)
	Bassa	229 (12.77)	56 (24.45)	9 (3.93)	164 (71.62)
	Dekina	319 (17.79)	35 (10.97)	18 (5.64)	266 (83.39)
	Idah	351 (19.58)	51 (14.53)	31 (8.83)	269 (76.64)
	Igalamela	139 (7.75)	27 (19.42)	9 (6.47)	103 (74.10)
	Olamaboro	224 (12.49)	43 (19.20)	10 (4.46)	171 (76.34)
Location	Rural	517 (28.83)	98 (18.96)	3 (0.58)	416 (80.46)
	Urban	1276 (71.17)	198 (15.52)	101 (7.92)	977 (46.73)
Family History (F.H.H)	No	756 (42.00)	43 (5.69)	103 (13.62)	610 (80.69)
	Yes	1037 (57.84)	253 (24.40)	1 (0.10)	783 (75.51)
Diabetes (DBM)	No	1192 (66.48)	85 (7.13)	103 (8.64)	1004 (84.23)
	Yes	601 (33.52)	221 (35.11)	1 (0.17)	389 (64.73)
Smoking Status (S.S)	Non-Smoker	1667 (92.97)	236 (14.16)	104 (6.24)	1327 (79.60)
	Smoker	126 (7.03)	60 (47.62)	0 (0.00)	66 (52.38)
Total Cholesterol (TCH)	≤149 mg/dL	144 (8.03)	26 (18.10)	5 (3.70)	113 (78.43)
	150–199 mg/dL	1528 (85.22)	192 (12.57)	99 (6.48)	1237 (80.96)
	200–249 mg/dL	121 (6.74)	78 (64.50)	0 (0.00)	43 (35.50)

Hypertension Grade (HG)	Grade 1	1235 (68.88)	196 (15.87)	103 (8.34)	936 (75.79)
	Grade 2	509 (28.39)	52 (10.22)	1 (0.20)	456 (89.59)
	Grade 3	49 (2.73)	48 (97.96)	0 (0.00)	1 (2.04)

Feature Importance Analysis

The feature importance selection techniques used in this study successfully identified the most significant risk factors for hypertension. The top seven most important risk factors identified were: diabetes mellitus, family history of hypertension, age, smoking status, hypertension grade, total cholesterol, and gender. The calculated importance scores and corresponding drops in accuracy are summarized in Table 2 and visualized in figure 1.

Table 2: Feature importance ranking based on drop in accuracy

Rank	Feature	Accuracy without Feature	Drop in Accuracy (Importance Score)
1	Diabetes mellitus	83.4%	4.9
2	Family history of hypertension (FHH)	85.2%	3.1
3	Age	85.4%	2.9
4	Smoking status	85.8%	2.5
5	Hypertension grade	86.1%	2.2
6	Total cholesterol	86.7%	1.6
7	Gender	87.4%	0.9
8	Local government area	87.5%	0.8
9	Location	87.5%	0.8

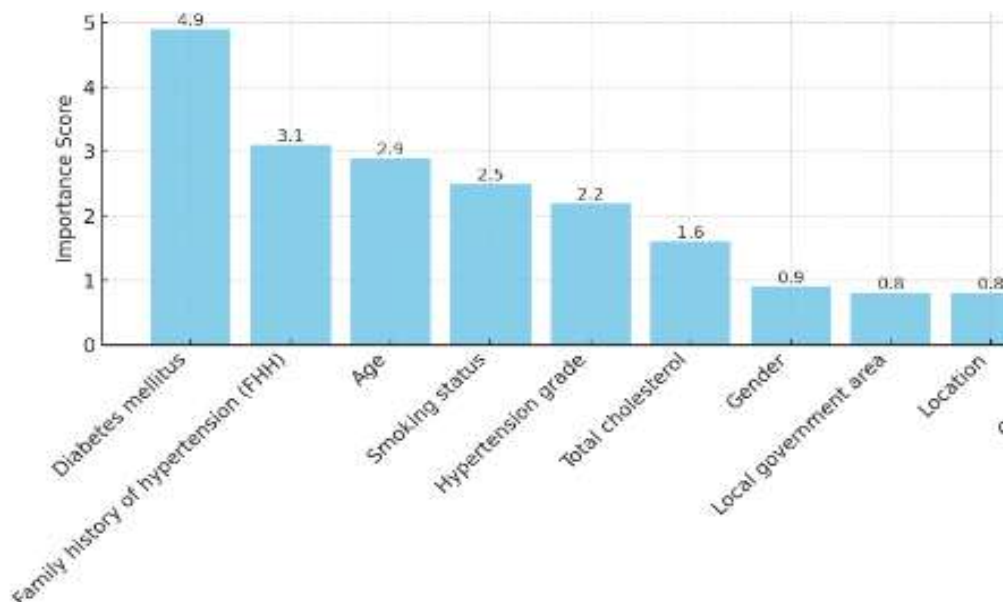


Figure 1: Feature importance score

The result from feature importance scores revealed the relative significance of each feature in the context of hypertension risk prediction.

Model Performance Evaluation

The classification performance of the PRBMCDM based hypertension risk stratification model is summarized in Table 2.

Table 2: Model performance

Risk Level	Accuracy	F-score	Precision	Recall	Specificity
High Risk	0.987	0.977	0.966	0.990	0.985
Medium Risk	0.986	0.989	0.995	0.984	0.991
Low Risk	0.994	0.931	0.925	0.939	0.997

Confusion Matrix and ROC Analysis

The confusion matrix of the PRBMCDM model (table.3) indicates high true positive and true negative rates, with minimal false classifications across all risk categories.

Table.3: Confusion matrix of PRBMCDM on test data.

	High Risk	Medium Risk	Low Risk
High Risk	523	3	2
Medium Risk	16	1180	3
Low Risk	2	2	62

In addition, the Receiver Operating Characteristic (ROC) curve in Figure 4 shows the model's trade-off between sensitivity and specificity, with an AUC of 0.75, 0.70, and 0.72 for high, medium and low risk respectively. The AUC values obtained from this study fall within the same range.

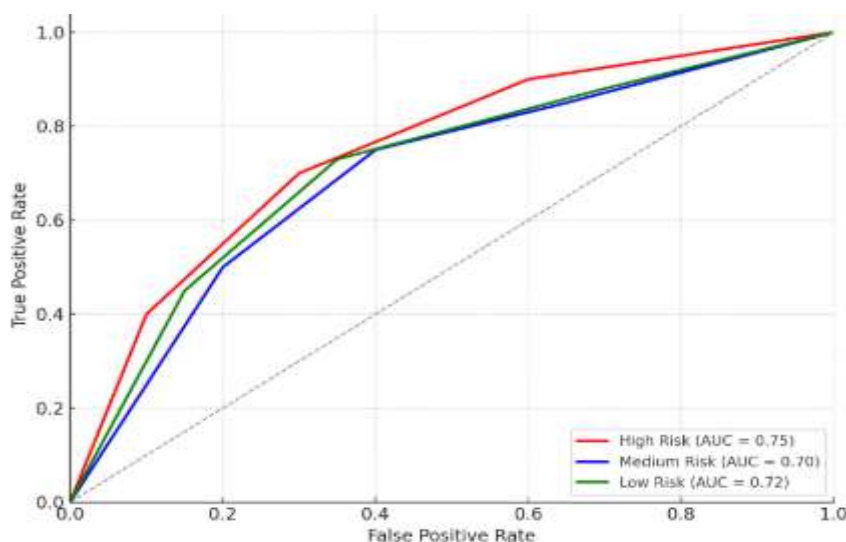


Figure 2: ROC curve for PRBMCDM

DISCUSSION

This study presents a PRBMCDM algorithm for hypertension monitoring and risk stratification model using hypertension related data. Finding from feature importance rank indicate seven top influential hypertension risk factors. This aligns with existing literature on hypertension risk factors.

The findings revealed that the PRBMCDM model achieved an AUC of 0.75, 0.70, and 0.72 for high, medium, and low risk respectively. These values suggest the model performs reasonably well. These results, when compared with widely used cardiovascular risk models, are encouraging. For instance, QRISK3 typically reports AUC values in the range of 0.74-0.79 in the United Kingdom [14], while SCORE2 achieves around 0.72-0.76 in European cohorts [15].

The primary strength of the PRBMCDM model lies in its interpretability, low computational overhead, and structured decision-making capability. The process risk calculation is transparent due to the summing of individual risk factors to compute the total risk weight (α). This makes it more straight forward for clinicians to explain and apply it in clinical settings. However, some limitations must be acknowledged. The model relies on a well-characterized reference population for accurate percentile calculations. This may require frequent updates to percentile distributions.

This study did not carry out a direct numerical comparison with traditional cardiovascular risk score, since those models were developed on different populations. Instead, the focus was on showing how PRBMCDM provides a more flexible, multi-criteria, and interpretable approach compared to the single-criterion methods commonly used. Future work will focus on validating PRBMCDM against established risk scores on larger and more divers dataset to further strengthen its clinical applicability.

CONCLUSION

The primary strength of the PRBMCDM model lies in its interpretability, low computational overhead, and structured decision-making capability. Our findings show that the algorithm can accurately classify patients into low, medium, and high-risk groups, while highlighting important factors such as diabetes, family history of hypertension, age, and smoking status. Unlike complex “black box” machine learning models, this approach is transparent and easy for clinicians to interpret and apply in practice. Its simplicity and use of routinely collected clinical data make it especially suitable for resource-limited healthcare settings. The proposed framework provides an interpretable, scalable, and computationally efficient solution suitable for integration into clinical decision support systems.

REFERENCES

1. Unger T. et al. 2020 International Society of Hypertension global hypertension practice guidelines. *Hypertension*. 2020;75 (6): 1334-1357. [https://doi.org/ 10.1161/HYPERTENSIONAHA.120.15026](https://doi.org/10.1161/HYPERTENSIONAHA.120.15026).
2. Chaturvedi A, Zhu A , Gadela N V , Prabhakaran D, and Jafar T H. Social determinants of health and disparities in hypertension and cardiovascular diseases. *Hypertension*. 2024; 81(3): 387-399. [https://doi.org/ 10.1161/HYPERTENSIONAHA.123.21354](https://doi.org/10.1161/HYPERTENSIONAHA.123.21354).
3. Mills KT, Stefanescu A, and He J. The global epidemiology of hypertension. *Nature Reviews Nephrology*. 2020; 16(4): 223-237. [https://doi.org/ 10.1038/s41581-019-0244-2](https://doi.org/10.1038/s41581-019-0244-2).
4. Cheng Y B. et al. Risk stratification by cross-classification of central and brachial systolic blood pressure. *Hypertension*. 2022;79 (5): 1101-1111. [https://doi.org/ 10.1161/HYPERTENSIONAHA.121.18773](https://doi.org/10.1161/HYPERTENSIONAHA.121.18773).
5. Boutilier JJ, Chan T C Y, Ranjan M, and Deo S. Risk stratification for early detection of diabetes and hypertension in resource-limited settings : machine learning analysis. *Journal of Medical Internet Research*. 2021; 23:20123. [https://doi.org/ 10.2196/20123](https://doi.org/10.2196/20123).
6. Forte C. et al. Development and validation of decision rules models to stratify coronary artery disease , diabetes , and hypertension risk in preventive care : cohort study of returning UK Biobank participants. *Journal of personalized medicine*. 2021;11(2); [https://doi.org/ 10.3390/jpm11121322](https://doi.org/10.3390/jpm11121322).

7. Rudin C, Chen C, Chen Z, Huang H, and Semenova L. Interpretable machine learning : fundamental principles and 10 grand challenges. *Statistical Surveys*. 2021; 16: 1-85. <https://doi.org/10.1214/21-SS133>
8. Tonekaboni S, Joshi S, McCradden MD, and Goldenberg A. What clinicians want: contextualizing explainable machine learning for clinical end use. *Proceeding of Machine Learning Research*. 2019; 106:359-380. <https://doi.org/10.48550/arXiv.1905.05134>.
9. Ahmad M A, Eckert C, and Teredesai A. Interpretable machine learning in healthcare. *IEEE Intelligent Informatics Bulletin*. 2018; 9(1): 559-560. <https://doi.org/10.1145/3233547.3233667>.
10. Kolyshkina I, and Simoff S. Interpretability of machine learning solutions in public healthcare : The CRISP-ML Approach. *Frontiers in Big Data*. 2021; 4. <https://doi.org/10.3389/fdata.2021.660206>.
11. Drnovšek R, Kapun MM, Šteblaj S, and Rajkovič U. Multicriteria risk evaluation model: utilizing fuzzy logic for improved transparency and quality of risk evaluation in healthcare. *Risk Management. Healthcare Policy*. 2025; 637-653. <https://doi.org/10.2147/RMHP.S490598>.
12. Pollock BD, Ubl DS, Devkaran S, and Dowdy SC. Simulating the overall hospital quality star ratings with random measure weights. *JAMA Network Open*. 2025; 8 (7): 1-8. <https://doi.org/10.1001/jamanetworkopen.2025.19029>.
13. Wu Y, Li S, Yuan J, Zhang H, Wang M. and Zhang Z. Benchmarking : a novel measuring tool for outcome comparisons in surgery. *International Journal of Surgery*. 2023;: 419-428. <http://doi.org/10.1097/JS9.0000000000000212>
14. Parsons RE, Liu X, Collister JA, Clifton DA, Cairns BJ, and Clifton L. Independent external validation of the QRISK3 cardiovascular disease risk prediction model using UK Biobank. *Heart*. 2023; 109 (22); 1690-1697. <https://doi.org/10.1136/heartjnl-2022-321231>.
15. Van Trier TJ. et al. Validation of systematic coronary risk evaluation 2 (SCORE2) and SCORE2-Older Persons in the EPIC-Norfolk prospective population cohort. *European. Journal of Preventive Cardiology*. 2024; 31(2): 182-189. <https://doi.org/10.1093/eurjpc/zwad318>.