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ORIGINAL RESEARCH

Determinants of blood pressure control in hypertensive individuals using histogram-based gradient boosting: findings from 1114 male workers in South Korea

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Abstract

Hypertension is a significant public health concern, particularly among workers, due to its association with increased risk of cardiovascular and cerebrovascular diseases. This study aimed to identify key factors influencing blood pressure control in hypertensive male workers aged 40 and above using the Histogram-based Gradient Boosting (HGB) algorithm. Data were drawn from the 2017–2020 Korean National Health and Nutrition Examination Survey (KNHANES), including 1114 male participants who reported being diagnosed with hypertension by a physician. The HGB model was compared with five other machine learning models: Random Forest, XGBoost, LightGBM, CatBoost and AdaBoost. The HGB model demonstrated superior performance with an accuracy of 82.3%, precision of 80.5%, recall of 78.9% and F1-score of 79.7%. Feature importance analysis revealed that age, Body Mass Index (BMI) and physical activity were the most significant factors influencing blood pressure control. Other notable factors included sodium intake, stress levels and medication adherence. The study's findings underscore the importance of targeted interventions focusing on these key factors to improve hypertension management strategies. By employing advanced machine learning techniques, this research provides valuable insights into the determinants of blood pressure control, offering a foundation for developing effective strategies to reduce hypertension-related complications and mortality among Korean male workers.

Keywords

Hypertension; Blood pressure control; Machine learning; Gradient boosting; Male worker

1. Introduction

Cerebrovascular and cardiovascular diseases rank as the second and third leading causes of death in South Korea, following cancer as a major cause of mortality [1]. Hypertension, a significant risk factor for these diseases, is closely associated with metabolic syndrome [2] and substantially increases the risk of mortality due to cardiovascular complications [3]. Given its critical impact on public health, both prevention and effective management of hypertension are emphasized. However, data from the 2021 Korean National Health and Nutrition Examination Survey (KNHANES) indicated that the prevalence of hypertension among adults aged 30 and above was 30.5%, an increase from 24.6% in 2007. This prevalence was particularly high among individuals aged 70 and above, at 65.1%, marking a 6.4% increase over the same period [4]. The rate of hypertension control in Korea stood at 45.9%, significantly lower than the rates in Canada (64.6%) and the United States (50.1%) [5].

Effective management of hypertension generally involves lifestyle modifications such as reduced alcohol consumption, smoking cessation, regular physical activity and dietary adjustments, alongside the management of obesity, hyperlipidemia and diabetes [6]. Additionally, the use of antihypertensive medication is a key component in controlling hypertension [7]. Despite these general recommendations, the literature presents inconsistent findings regarding the impact of these factors on hypertension control. Some studies suggest that moderate alcohol consumption can help control hypertension [8], while others report lower control rates among drinkers compared to non-drinkers [9]. Similarly, the relationship between smoking and hypertension control is ambiguous, with some studies indicating no significant association [10], whereas others highlight improved control rates with smoking cessation [9].

Regular physical activity is widely believed to aid in blood pressure control [6], although some research suggests that for Koreans, regular exercise, regardless of intensity, does not significantly affect hypertension control [11]. Sodium intake is another controversial factor; while some studies link high sodium intake to poor hypertension management [12], others find no significant relationship between low-sodium diets and hypertension control. The roles of obesity, hyperlipidemia

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and diabetes in hypertension control also remain debated, with studies both supporting and refuting their significance as risk factors [10]. These inconsistencies highlight the need for further research into the interactions between lifestyle factors, chronic diseases and hypertension control. Hypertension is classified as a manageable condition, emphasizing the importance of identifying determinants that influence its control.

Recent advancements in machine learning provide new opportunities to enhance the predictive accuracy and interpretability of hypertension management models. Histogram-based Gradient Boosting (HGB) is one such advanced algorithm that has shown promise in various predictive modeling scenarios. HGB builds on the strengths of traditional gradient boosting algorithms by employing a histogram-based approach to improve computational efficiency and model performance. This study aims to apply the Histogram-based Gradient Boosting (HGB) algorithm to identify key factors influencing blood pressure control among hypertensive male workers aged 40 and above, and to compare its performance with five other well-established machine learning models—Random Forest, XGBoost, LightGBM, CatBoost and AdaBoost. By incorporating these models, the research seeks to provide a comprehensive analysis of hypertension control determinants and offer insights into effective management strategies, ultimately developing targeted interventions to reduce hypertension-related complications and mortality among Korean male workers.

2. Materials and methods

2.1 Study design and population

This research adopts a cross-sectional design, utilizing data collected from the 2017–2020 Korean National Health and Nutrition Examination Survey (KNHANES). By rigorously following these methodologies, this study aims to provide a comprehensive analysis of factors influencing blood pressure control among hypertensive male workers, utilizing advanced machine learning techniques to derive actionable insights for effective hypertension management strategies. The study focuses on hypertensive male workers aged 40 and above who reported having been diagnosed with hypertension by a healthcare professional. A total of 1114 male participants were selected based on their responses to the health survey, clinical assessment and nutritional survey components of KNHANES.

2.2 Data collection

2.2.1 General characteristics

The general characteristics of the participants were gathered to provide a comprehensive demographic and socioeconomic profile. Age was segmented into four categories: 40–49, 50–59, 60–69 and 70 years and above. Residential area classification distinguished between urban (dong) and rural (eup/myeon) settings. Participants' gender was recorded as marital status was defined by the presence or absence of a spouse.

Educational attainment was categorized into elementary school or below, middle school, high school and college or higher. Household income was assessed based on monthly earnings, categorized into high (above 3 million Korean Won, KRW), middle-high (2–3 million KRW), middle-low (1–2 million KRW) and low (below 1 million KRW). Occupational roles were classified into managerial/administrative, clerical, sales/service, agriculture/fishery, technical/assembly, simple labor and others (including housewives, students and military personnel).

2.2.2 Health-related characteristics

Health-related characteristics were meticulously evaluated. The duration of hypertension was calculated by subtracting the age at first diagnosis from the current age. Participants were categorized based on their current use of antihypertensive medication into medication users and non-users.

The receipt of hypertension management education was recorded, irrespective of the location or provider of the education. Alcohol consumption was assessed based on the frequency and quantity of alcohol intake over the past year, classifying participants into non-drinkers and various levels of drinkers.

Smoking status was determined by current smoking behavior, categorizing participants as current smokers or non-smokers. Physical activity was measured using the International Physical Activity Questionnaire (IPAQ), which quantified time spent on vigorous, moderate and walking activities over the past week. The metabolic equivalent tasks (MET) values were calculated for each activity type, with participants categorized into health-enhancing ($\geq$3000 MET-min/week), minimally active (600–2999 MET-min/week) and inactive ($<$600 MET-min/week) groups.

Dietary intake was evaluated using a 24-hour dietary recall method, calculating total daily caloric intake and sodium consumption. Participants were classified based on adherence to the Korean Dietary Reference Intakes (KDRI), with appropriate calorie intake defined by estimated energy requirements and appropriate sodium intake defined as $\leq$2000 mg/day.

Perceived stress levels were recorded, categorizing responses as high (experiencing a lot or very much stress) or low (experiencing little or no stress). Subjective health status was rated on a scale from very good to very poor. The presence of comorbid conditions such as hyperlipidemia and diabetes was determined by self-reported physician diagnosis. Obesity status was classified based on Body Mass Index (BMI), calculated as weight in kilograms divided by height in meters squared (kg/m^2), with categories defined as underweight ($<$18.5 kg/m^2), normal (18.5–24.9 kg/m^2) and obese ($\geq$25.0 kg/m^2).

2.2.3 Blood pressure measurement

Blood pressure was measured using a mercury sphygmomanometer following standardized protocols. Participants were seated and given a 5-minute rest period before measurements were taken. Blood pressure was measured three times, and the average of the second and third readings was recorded. To ensure accuracy, blood pressure readings were corrected for arm height relative to heart height, based on the following formula:

$$[Corrected \quad BP = Measured \quad BP \pm 0.7 \quad \times \quad (\frac{Arm \quad Height - Heart \quad Height}{1 \quad cm})]$$

Where (Measured BP) is the initial blood pressure reading, (Arm Height) is the height at which the blood pressure was measured, and (Heart Height) is the reference heart height (83 cm for men, 81 cm for women).

2.3 Statistical analysis

2.3.1 Data preprocessing

To address missing data, multiple imputation techniques were employed. Continuous variables were standardized to have a mean of zero and a standard deviation of one. Categorical variables were converted using one-hot encoding to facilitate their use in machine learning models.

2.3.2 Machine learning models

The study employed Histogram-based Gradient Boosting (HGB) as the primary model, along with five comparative models: Random Forest, XGBoost, LightGBM, CatBoost and AdaBoost. Each model was trained on 80% of the data, with the remaining 20% used for testing.

2.3.3 Model training and evaluation

Hyperparameter tuning was performed using grid search and cross-validation to optimize model performance. Models were evaluated using several metrics, including accuracy, precision, recall, F1-score, Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The performance metrics are defined as follows:

$$[Accuracy = TP + TNTP + TN + FP + FN]$$

$$[Precision = TPTP + FP]$$

$$[Recall = TPTP + FN][F1 - score = 2 \quad \times \quad Precision \quad \times \quad RecallPrecision + Recall]$$

$$[MAE = 1n\sum_{i=1}^{n}|y_i - \hat{y}i|]$$

$$[RMSE = \sqrt{1n\sum i = 1^n(y_i - \hat{y}_1)}^2]$$

Where (TP) represents true positives, (TN) represents true negatives, (FP) represents false positives, (FN) represents false negatives, and ($\hat{y}_i$) represents the predicted value.

2.3.4 Feature importance

Feature importance for the HGB model was calculated to identify key factors influencing blood pressure control. The importance of feature (j) is given by:

$$[Importance(j) = \sum_{t=1}^{T} \frac{\Delta I(t)}{I_{total}}]$$

Where (ΔI(t)) is the improvement in the splitting criterion brought by feature (j) at node (t) and (I_{total}) is the total improvement in the splitting criterion over all nodes.

3. Results

3.1 Participant characteristics

The study included 1114 hypertensive workers aged 40 and above. The demographic characteristics of the participants are summarized in Table 1. The majority of participants was aged between 50–59 years (37.8%). Most participants resided in urban areas (64.2%), and a significant proportion were married (75.4%). Educational attainment varied, with 29.1% having completed high school and 24.5% having a college degree or higher. Regarding household income, 32.4% fell into the middle-high income category.

3.2 Health-related characteristics

Health-related characteristics are presented in Table 2. The average duration of hypertension was 12.3 years. A significant portion of participants (62.6%) were on antihypertensive medication. Regarding hypertension management education, 38.0% had received some form of education. Alcohol consumption varied widely, with 18.7% reporting no alcohol intake and 12.0% consuming more than ten drinks per occasion. The majority of participants were non-smokers (59.8%). Physical activity levels indicated that 27.5% were health-enhancing active, while 31.3% were inactive. Dietary assessment showed that 33.4% adhered to the recommended calorie intake and 29.8% to the sodium intake guidelines. High stress levels were reported by 36.6% of participants, and the subjective health status was rated as poor or very poor by 21.2%.

3.3 Model performance

The F-1 score of the HGB model and the comparative models is summarized in Table 3. The HGB model outperformed the other models across most metrics, achieving an accuracy of 82.3%, a precision of 80.5%, a recall of 78.9% and an F1-score of 79.7%. The Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for the HGB model were 0.18 and 0.23, respectively (Figs. 1,2,3,4,5).

3.4 Feature Importance

The feature importance analysis for the HGB model is illustrated in Fig. 6. Age (0.25), BMI (0.20) and physical activity (0.18) were identified as the most significant factors influencing blood pressure control, followed by sodium intake (0.15), stress levels (0.12) and dietary adherence (0.10). The

TABLE 1. Demographic characteristics of the participants.

Characteristic	Category	Frequency (%)
Age (yr)		
	40–49	250 (22.4%)
	50–59	421 (37.8%)
	60–69	304 (27.3%)
	70+	139 (12.5%)
Residential Area		
	Urban	715 (64.2%)
	Rural	399 (35.8%)
Marital Status		
	With Spouse	840 (75.4%)
	Without Spouse	274 (24.6%)
Education Level		
	Elementary or Below	278 (25.0%)
	Middle School	238 (21.4%)
	High School	324 (29.1%)
	College or Higher	273 (24.5%)
Household Income		
	High	222 (19.9%)
	Middle-High	361 (32.4%)
	Middle-Low	283 (25.4%)
	Low	248 (22.3%)
Occupation		
	Managerial/Administrative	98 (8.8%)
	Clerical	154 (13.8%)
	Sales/Service	218 (19.6%)
	Agriculture/Fishery	114 (10.2%)
	Technical/Assembly	178 (16.0%)
	Simple Labor	262 (23.5%)
	Others	89 (8.0%)

importance scores indicate the relative contribution of each feature to the model's predictions.

4. Discussion

The results indicate that the HGB model provides superior performance in predicting blood pressure control among hypertensive male workers compared to other machine learning models. In this paper, main factors such as age, BMI and physical activity play a crucial role in managing hypertension. The findings suggest that the Histogram-based Gradient Boosting (HGB) model outperforms other machine learning models in predicting blood pressure control among hypertensive male workers. This study identifies key factors such as age, BMI and physical activity as critical in managing hypertension. Previous research supports the importance of these variables, highlighting salt intake, habitual coffee consumption, higher BMI and non-adherence to antihypertensive medications as independent predictors of uncontrolled blood pressure among

TABLE 2. Health-related characteristics of the participants.

Characteristic	Category	Frequency (%)
Hypertension Duration		
	<5 yr	168 (15.1%)
	5–10 yr	355 (31.8%)
	11–20 yr	411 (36.9%)
	>20 yr	227 (20.4%)
Medication Use		
	Yes	697 (62.6%)
	No	340 (30.5%)
Management Education		
	Yes	423 (38.0%)
	No	697 (62.6%)
Alcohol Consumption		
	Non-drinker	208 (18.7%)
	1–2 drinks	237 (21.2%)
	3–4 drinks	164 (14.7%)
	5–6 drinks	180 (16.2%)
	7–9 drinks	203 (18.2%)
	10+ drinks	133 (12.0%)
Smoking Status		
	Smoker	378 (33.9%)
	Non-smoker	666 (59.8%)
Physical Activity		
	Health-enhancing	306 (27.5%)
	Minimally active	443 (39.8%)
	Inactive	348 (31.3%)
Dietary Adherence		
	Calorie (yes)	373 (33.4%)
	Sodium (yes)	331 (29.8%)
Stress Level		
	High	407 (36.6%)
	Low	647 (58.1%)
Subjective Health		
	Very good	103 (9.2%)
	Good	268 (24.1%)
	Fair	522 (46.8%)
	Poor	164 (14.8%)
	Very poor	71 (6.4%)
Comorbidities		
	Hyperlipidemia	554 (49.7%)
	Diabetes	308 (27.6%)
Obesity		
	Underweight	84 (7.6%)
	Normal	554 (49.7%)
	Obese	401 (36.0%)

TABLE 3. F-1 score of models.

Model	F1-score (%)
HGB	79.7
Random Forest	75.5
XGBoost	77.3
LightGBM	78.1
CatBoost	77.6
AdaBoost	75.0

HGB: Histogram-based Gradient Boosting.

hypertensive patients [13]. Additionally, fluctuating BMI has been recognized as a potential predictor of decreasing blood pressure in middle-aged individuals with hypertension, further underscoring its role in hypertension management [14]. The TyG-BMI index, influenced by physical activity and diet, has also been linked to an increased risk of hypertension, suggesting its utility as a clinical index for the early diagnosis of hypertension [15]. Other influential factors in managing hypertension among male workers include age, sex, comorbidities such as diabetes mellitus and lifestyle choices, including physical activity and tobacco smoking [16]. These findings underscore the importance of targeted interventions focusing on these significant factors to improve hypertension management strategies. Future research should investigate the potential benefits of combining Histogram-based Gradient Boosting with other machine learning techniques and the impact of emerging health-related data sources to further enhance the management and prediction of hypertension.

Another finding of this study is the superior performance of the Histogram-based Gradient Boosting (HistGBDT) model. Specifically, HistGBDT exhibited superior predictive performance compared to other boosting models such as Adaboost and XGBoost. Through numerous preceding studies [17–21], Histogram-based Gradient Boosting (HistGBDT) has demonstrated significant efficacy in predictive modeling, particularly in accurately predicting the severity of outcomes with high recall and precision. For instance, by its application in predicting the severity of car accidents with remarkable accuracy, recall, and precision [17]. Similarly, its utilization in water distribution networks for leak localization showed high accuracy in identifying true leak locations, emphasizing its potential in complex prediction scenarios [18]. Moreover, the effectiveness of ensemble techniques in enhancing predictive modeling through techniques like bagging and stacking has also been noted [19]. In the sphere of hypertension management, while some studies have compared the performance of HGB with other machine learning algorithms and conventional models, indicating minimal differences in predictive accuracy for hypertension incidence [20], the broader context of machine learning's application in healthcare suggests a significant impact on predictive accuracy and management strategies [21]. Future research should explore the integration of Histogram-based Gradient Boosting with other advanced machine learning techniques to further enhance predictive accuracy and application in diverse healthcare scenarios.

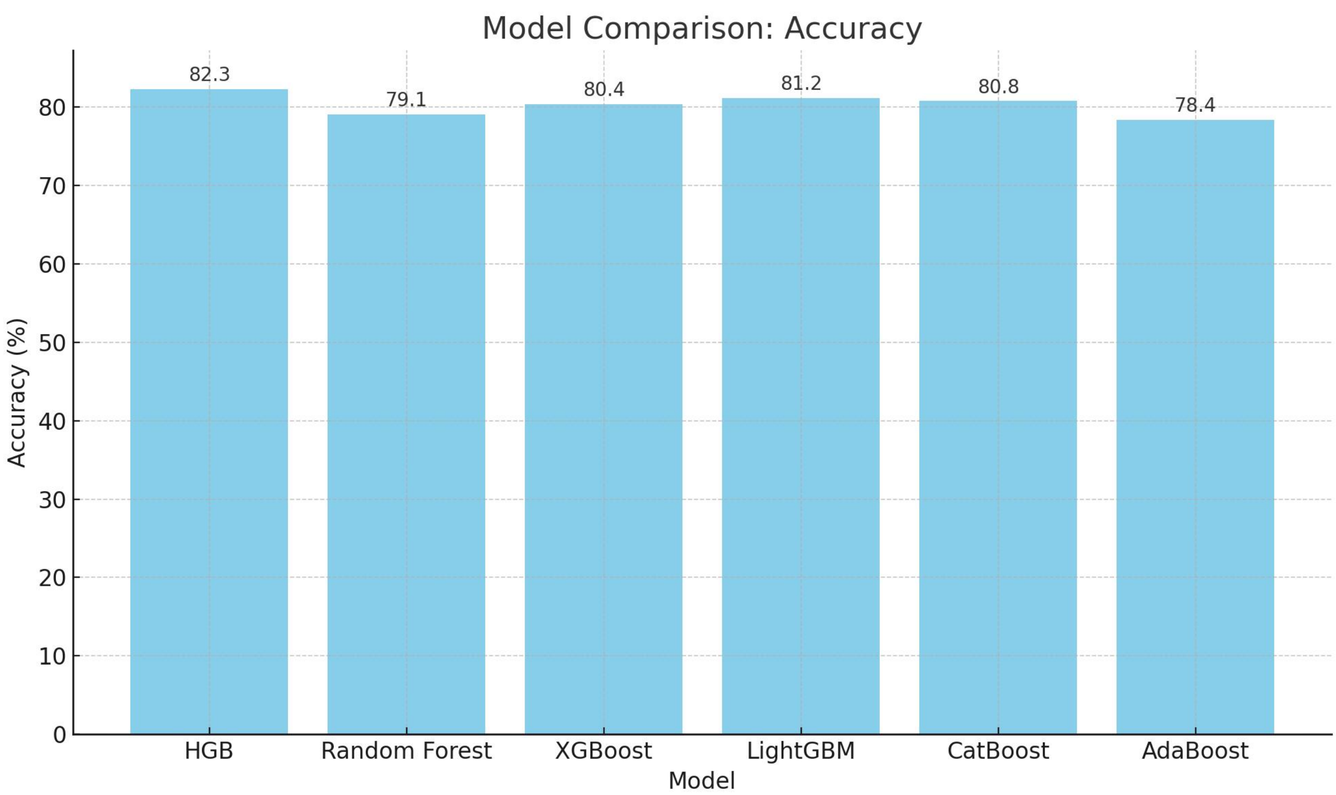
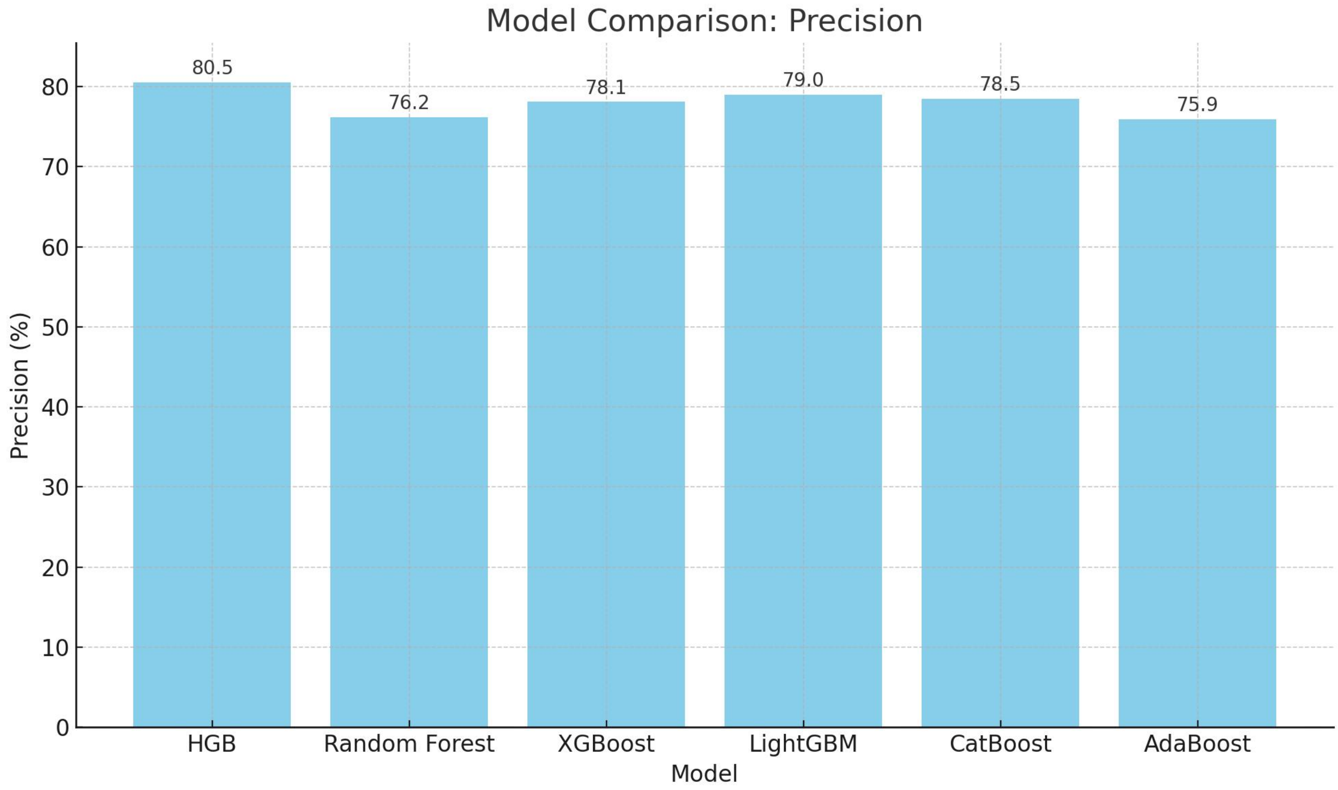
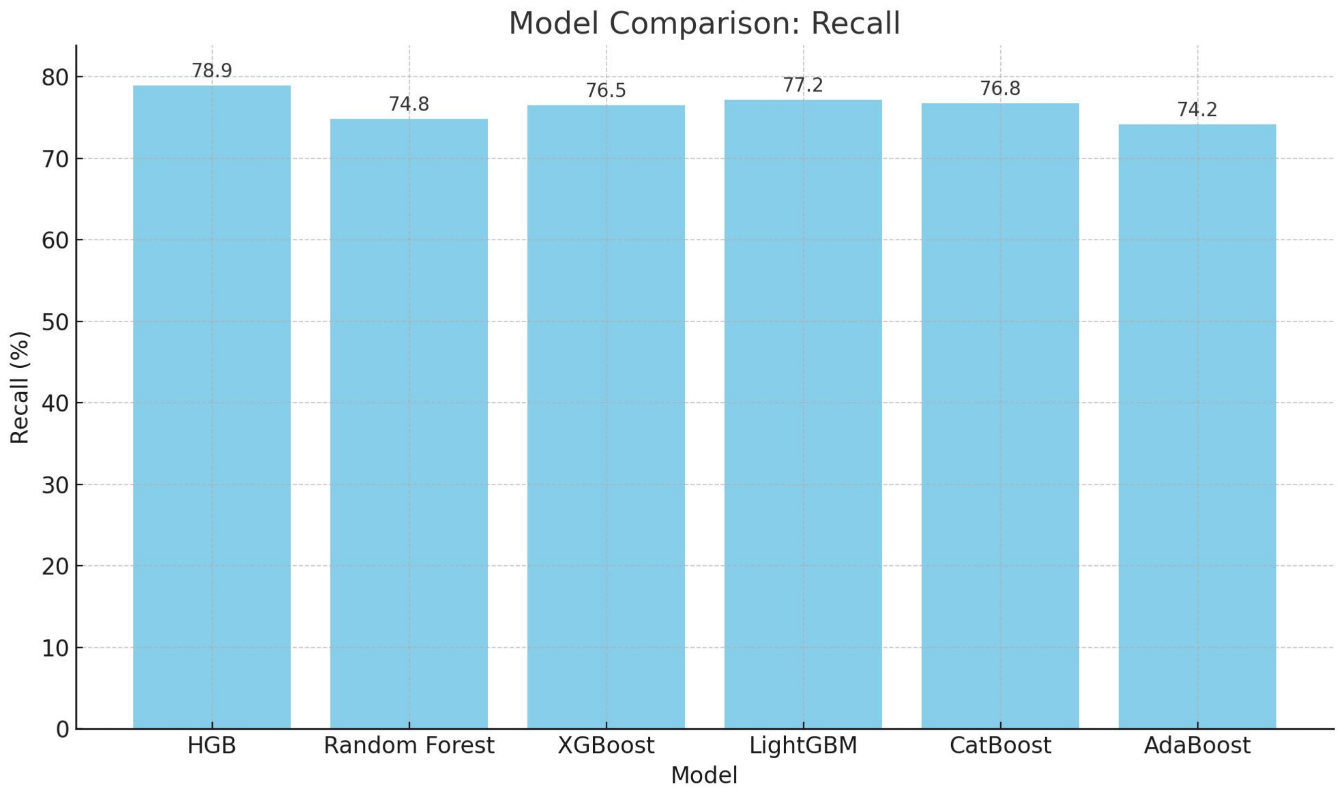


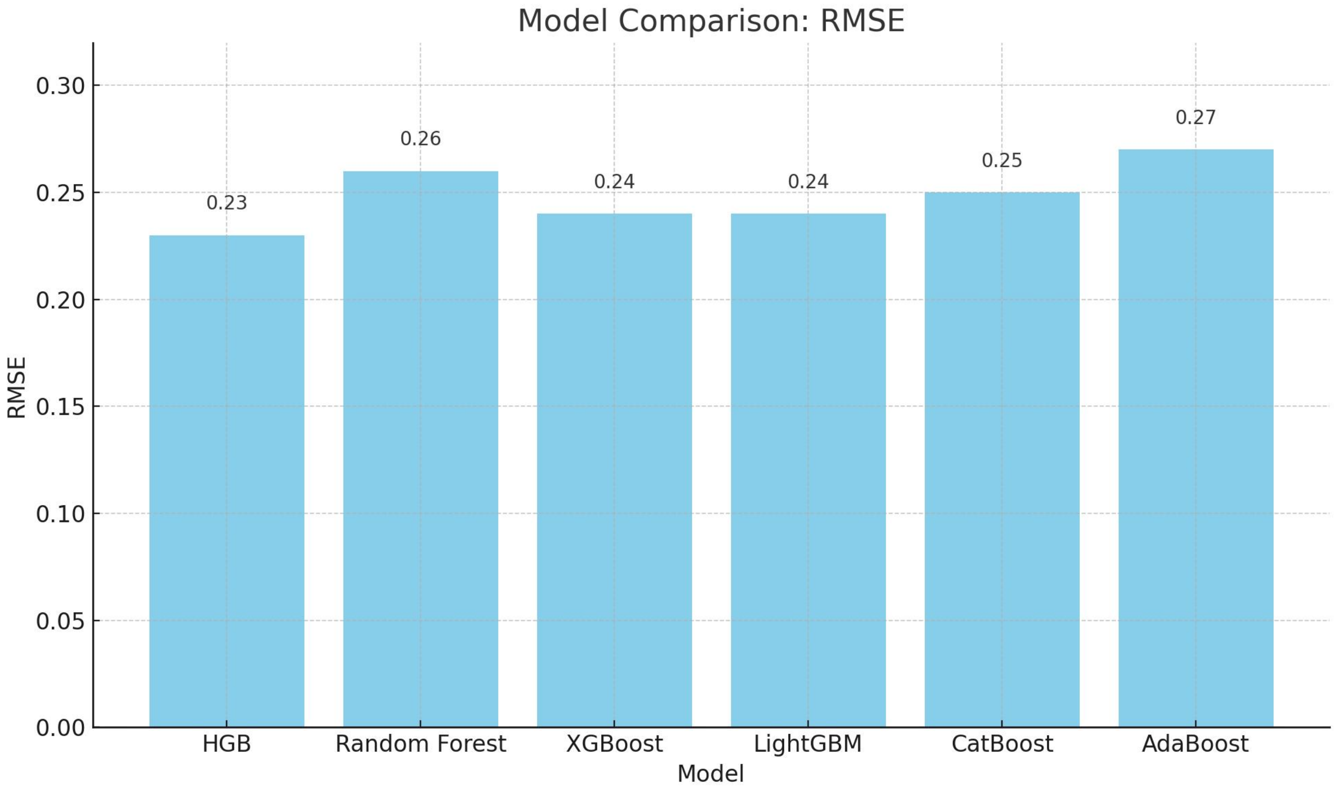
FIGURE 1. Comparison of model accuracy. HGB: Histogram-based Gradient Boosting.



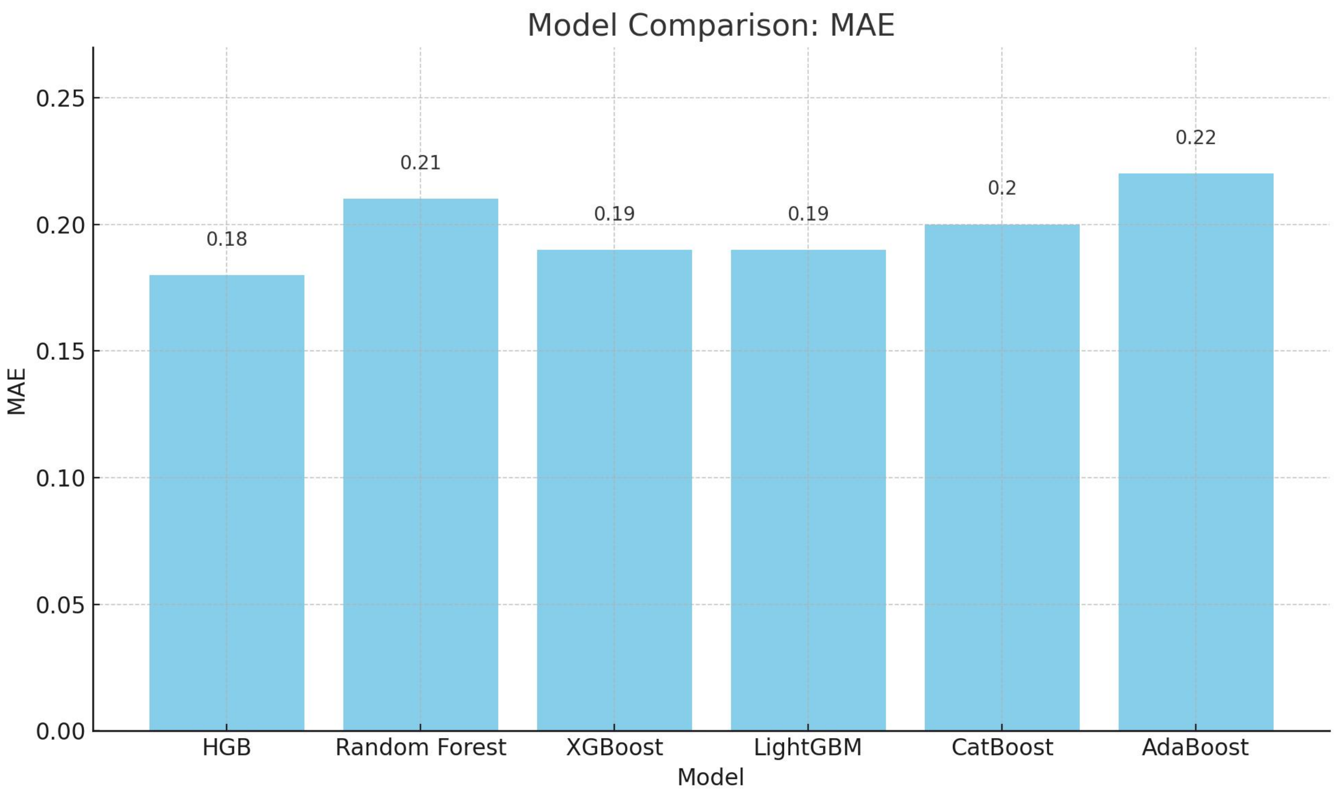
F I G U R E 2. Comparison of precision of model. HGB: Histogram-based Gradient Boosting.



F I G U R E 3. Comparison of recall rates of models. HGB: Histogram-based Gradient Boosting.



F I G U R E 4. Comparison to RMSE of models. HGB: Histogram-based Gradient Boosting; RMSE: Root Mean Squared Error.



F I G U R E 5. Comparison of MAEs of models. HGB: Histogram-based Gradient Boosting; MAE: Mean Absolute Error.

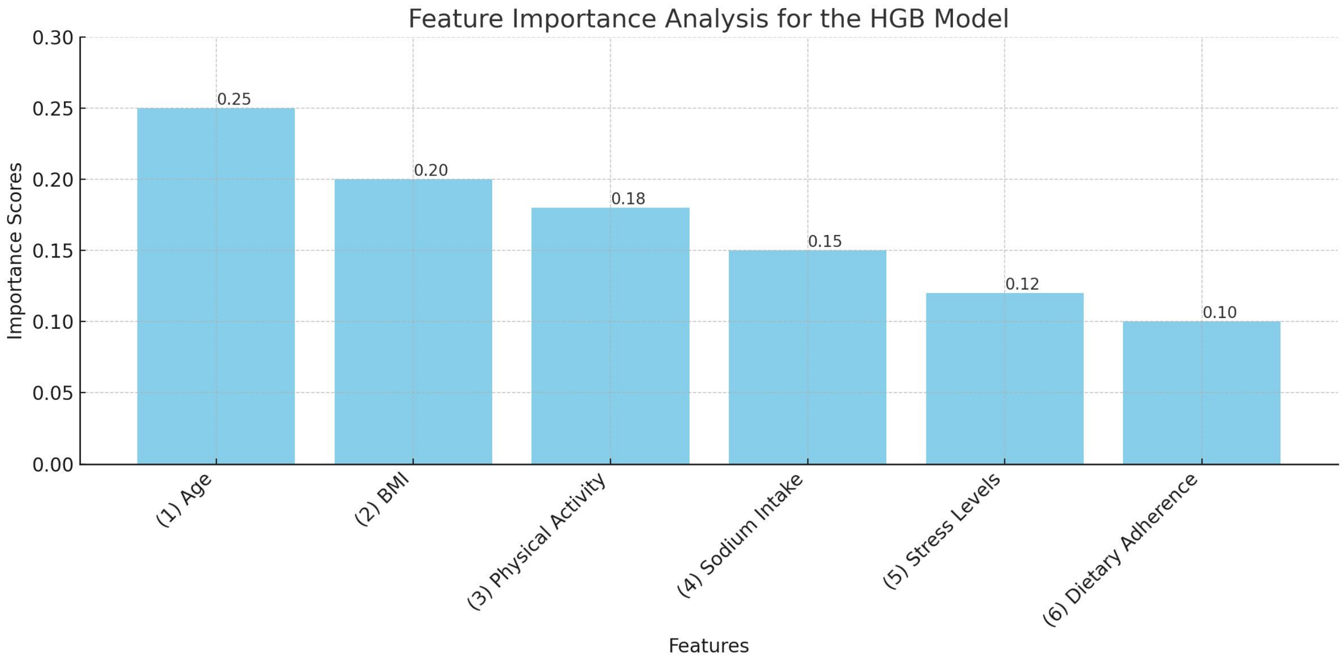


FIGURE 6. Feature Importance in the HGB Model. HGB: Histogram-based Gradient Boosting; BMI: Body Mass Index.

The limitations of the study are as follows. First, this study employs a cross-sectional design, which limits the ability to infer causality between the identified factors and blood pressure control, necessitating longitudinal studies to establish causal relationships. Second, several variables, such as alcohol consumption, smoking status and physical activity, rely on self-reported data, which may be subject to recall bias or social desirability bias, potentially affecting the accuracy of the findings. Third, the study sample is limited to hypertensive male workers aged 40 and above in South Korea, which may restrict the generalizability of the results to other populations or age groups.

5. Conclusions

This study highlights the effectiveness of the Histogram-based Gradient Boosting (HGB) model in predicting blood pressure control among hypertensive male workers, outperforming other machine learning models. Key factors influencing blood pressure control were identified, including age, BMI and physical activity. These findings emphasize the importance of targeted interventions focusing on these significant factors to improve hypertension management strategies. By leveraging advanced machine learning techniques, this research provides valuable insights into the determinants of blood pressure control, contributing to the development of effective strategies to reduce hypertension-related complications and mortality among Korean male workers. Future research should explore the longitudinal effects of these key factors and the integration of HGB with other advanced techniques to further refine hypertension management strategies.

AVAILABILITY OF DATA AND MATERIALS

The data presented in this study are provided at the request of the corresponding author. The data is not publicly available because researchers need to obtain permission from the Korea Centers for Disease Control and Prevention. Detailed information can be found at: http://knhanes.cdc.go.kr.

AUTHOR CONTRIBUTIONS

HB—conceptualization, software, methodology, validation, investigation, formal analysis, writing–original draft preparation, writing–review and editing, visualization, supervision, project administration, funding acquisition; contributed to editorial changes in the manuscript; read and approved the final manuscript.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Before conducting the survey, written informed consent was acquired from all participants. This study employed only pre-existing, anonymized data. It adhered to the principles outlined in the Declaration of Helsinki. The protocol for the Panel Study of Worker's Compensation Insurance received approval from the Institutional Review Board (IRB) of the KNHANES (IRB approval numbers: 2018-01-03-5C-A). All study participants provided written informed consent.

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CONFLICT OF INTEREST

The author declares no conflict of interest. Haewon Byeon is serving as the Guest Editor of this journal. We declare that Haewon Byeon had no involvement in the peer review of this article and has no access to information regarding its peer review. Full responsibility for the editorial process for this article was delegated to XXY.

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