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Implementation of a predictive model to improve early detection of stroke in patients with comorbidities

Putra Agina Widyaswara Suwaryo[1], Barkah Waladani[2], Ernawati Ernawati[3], Endah Setianingsih[2]

[1]*Universitas Muhammadiyah Gombong Faculty of Health Sciences, Department of Emergency Nursing, Kebumen, Central Java, Indonesia*

[2]*Universitas Muhammadiyah Gombong Faculty of Health Sciences, Department of Critical Care Nursing, Kebumen, Central Java, Indonesia*

[3]*Universitas Muhammadiyah Gombong Faculty of Health Sciences, Department of Community Nursing, Kebumen, Central Java, Indonesia*

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Corresponding Author:
Putra Agina Widyaswara Suwaryo, Asst. Prof., Universitas Muhammadiyah Gombong Faculty of Health Sciences, Department of Emergency Nursing, Kebumen, Central Java, Indonesia
ners.putra@gmail.com

ORCID:
orcid.org/0000-0002-6396-8989

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ABSTRACT

Aims: This study aims to develop and implement a predictive model to enhance the early detection of stroke in patients with comorbidities, thereby enabling clinicians to identify high-risk patients more quickly and effectively.

Methods: This study used a prospective cohort design involving 235 patients treated in the stroke care unit. Data were collected over six months through direct interviews, physical examinations, and laboratory analyses. Statistical analysis was conducted using multivariate logistic regression to identify the main predictive factors of stroke. The evaluation model was conducted using the area under the curve (AUC) to measure predictive accuracy.

Results: A total of 235 patients were included in the analysis, with a mean age of 56.4±12.7 years; 76.6% were male and 23.4% female. Significant predictive factors for stroke occurrence included diabetes mellitus, hypertension, rheumatoid arthritis, physical activity, family health history, random blood sugar levels, uric acid levels, and salt consumption ($p<0.05$). The developed model achieved an AUC of 98.7%, which—based on comparisons with established models such as the Framingham Stroke Risk Profile (AUC~0.78) and the QStroke algorithm (AUC~0.80)—demonstrates substantially higher discriminative ability in distinguishing between patients with and without stroke risk.

Conclusions: This predictive model has demonstrated a high capacity for detecting stroke risk in patients with comorbidities. The implementation of this model in clinical practice is expected to enhance the effectiveness of stroke screening and accelerate early intervention.

Introduction

Stroke remains one of the leading causes of death and disability worldwide, with patients who have comorbidities such as hypertension, diabetes mellitus, and heart disease facing significantly higher risk (1). In Indonesia, stroke prevalence has increased markedly, from 7 per 1,000 in 2018 to 10.9 per 1,000 in 2023—a 56% rise over five years—highlighting the urgent need for more effective prevention and early detection strategies (2-6). The increasing prevalence indicates that existing approaches are insufficient, particularly among high-risk patients with multiple comorbidities. Developing predictive models is therefore essential to strengthen early detection in this population (7,8).

Although advances in diagnostic tools exist, the timely identification of high-risk patients remains challenging. Most prior studies have examined individual risk factors in isolation, such as hypertension or diabetes, without adequately integrating multiple comorbidities and lifestyle factors into comprehensive models (9-11). As a result, existing tools often lack adaptability for diverse patient populations with concurrent conditions. This study addresses that gap by developing and implementing a predictive model that incorporates a broader range of clinical and lifestyle predictors. By combining multiple risk factors, the model is expected to improve early stroke detection and support more targeted, efficient decision-making in clinical practice (12-15).

The present study develops and implements such a model, aiming to integrate both clinical and lifestyle predictors to enhance stroke risk assessment in patients with comorbidities and support more targeted, efficient clinical decision-making.

Methods

Study design and participants

This study used a prospective cohort design. The research participants included stroke patients treated in three hospitals with specialized stroke care units. A total of 235 patients were included in this study, and they were observed for 6 months to collect data related to stroke risk factors and clinical outcomes. The sample size using G*Power version 3.1 calculation is shown in Figure 1. Patients who meet the criteria are designated as respondents. Inclusion criteria were patients who have been diagnosed with stroke (ischemic or hemorrhagic) based on clinical examination and imaging with computed tomography scan or magnetic resonance imaging, aged ≥18 years, patients with one or more comorbidities such as diabetes mellitus, hypertension, heart failure, atrial fibrillation, rheumatoid arthritis (RA), chronic kidney disease, or a history of heart attack, willing to participate in the study and sign a written consent form, and patients who can undergo observation for a full 6 months. Meanwhile, the exclusion criteria were patients with terminal conditions estimated to have a life expectancy of less than 6 months, patients with severe cognitive or mental disorders that prevent them from providing the necessary information or following the research protocol, patients who have undergone brain surgery less than 1 month before data collection, patients with active infectious diseases that affect laboratory results (e.g., severe sepsis), and patients who do not complete data during the observation period or withdraw from the study for personal or medical reasons.

Ethical consideration

This research has obtained written consent from the patients involved in the study. The research protocol complies with the ethical guidelines of the Helsinki Declaration of 1975, as revised in 2013. The research protocol was approved by the Health Research Ethics Committee of Universitas Muhammadiyah Gombong (approval no.: 003.6/II.3.AU/F/KEPK/I/2025, date: 07.01.2025). To ensure data confidentiality, all collected data were anonymized by removing personal identifiers and stored in password-protected electronic files accessible only to the principal investigators. Paper records, if any, were kept in locked cabinets. All data handling procedures complied with institutional and national guidelines for research involving human subjects.

Data collection

Data were collected through direct interviews, physical examinations, and laboratory data analysis. The sources of research data were as follows: interviews and questionnaires, medical data, and direct measurements. Direct interviews were used to collect demographic information (age, gender) as well as medical history, physical activity, stress levels, fruit and/or vegetable consumption, salt consumption levels, and parental medical history. Medical data were taken from patient medical records to obtain information on comorbid disease history, such as diabetes mellitus, hypertension, heart failure, atrial fibrillation, RA, chronic kidney disease, and heart attacks. Direct measurements were conducted to assess body mass index (BMI), random blood sugar levels, uric acid levels, and blood pressure. This data was collected periodically during the observation period to ensure the completeness and accuracy of the information. Not all stroke respondents followed the study protocol. Sample size calculation was performed using G*Power version 3.1, assuming a medium effect size [odds ratio (OR) =1.8], significance level $\alpha=0.05$, and desired power $(1-\beta)=0.95$, with an allocation ratio of 1:1. The minimum required sample size was estimated to be 207 participants, as shown in Figure 1. The final sample of 235 participants exceeded this requirement, thus providing sufficient power to detect clinically meaningful effects. There was an initial selection of 25 patients who did not meet the criteria. Additionally, 13 patients did not participate in the study and were observed for 6 months due to deteriorating conditions until they passed away, as shown in Figure 2. Of the 235 initially

included participants, 13 patients did not complete the six-month observation period due to deterioration or death. These patients had incomplete data and were therefore excluded from the final analysis using a complete case analysis approach. No data imputation or sensitivity analysis was performed, given the small proportion of missing cases and the focus on maintaining data accuracy.

Before the main research was conducted, validity and reliability tests were performed on the observation sheet used for data collection. This test is conducted on 30 respondents who have similar characteristics to the research sample but are not included in the main research population. The results of the validity test indicate that all items on the observation sheet have a correlation coefficient value of more than 0.3 ($p<0.05$); thus, it can be concluded that all items on the instrument are valid for the research. Meanwhile, the results of the reliability test show a Cronbach's alpha value of 0.85, which indicates that the instrument has high internal consistency and is suitable for use in data collection for the research.

Statistical Analysis

Data analysis is conducted using a quantitative approach with statistical software. The stages of analysis include descriptive analysis, bivariate analysis, multivariate analysis, and model validation. Bivariate tests were conducted to identify the relationship between each independent variable (risk factor) and the occurrence of recurrent stroke. The chi-square test was used to examine the relationship between two categorical variables, the occurrence of recurrent stroke (yes/no), and others, such as gender (male/female). Multivariate tests using logistic regression were conducted to identify the main predictors of recurrent stroke events by controlling for other variables. The model's predictive accuracy was measured using the area under the curve (AUC) on the receiver operating characteristic curve to measure the model's predictive accuracy. To assess the robustness of the model and mitigate the risk of overfitting, a 5-fold cross-validation approach was applied using the same dataset. The model was trained and tested across different subsets, and the mean AUC achieved across all folds was 96.3% (standard deviation ±1.8%), supporting the reliability of the model's predictive power. For the multivariate logistic regression, all variables with $p<0.25$ in the bivariate analysis were considered as candidate predictors. A backward stepwise elimination method was applied, and variables were sequentially removed based on likelihood ratio testing and significance level $p>0.05$. Additionally, multicollinearity was assessed using the variance inflation factor (VIF), and any variable with a VIF >5 was excluded. This ensured that only independent and statistically significant predictors were retained in the final model.

Before finalizing the logistic regression model, multicollinearity was assessed using the VIF. Variables with VIF >5 were excluded to ensure independent contributions of predictors. All variables retained in the final model showed acceptable VIF values (all <5), indicating no critical multicollinearity. For binary variables such as hypertension, diabetes mellitus, and others, we used a coding system of 1=presence and 0=absence. Regression coefficients and ORs were interpreted accordingly. Statistical test using SPSS version 27.

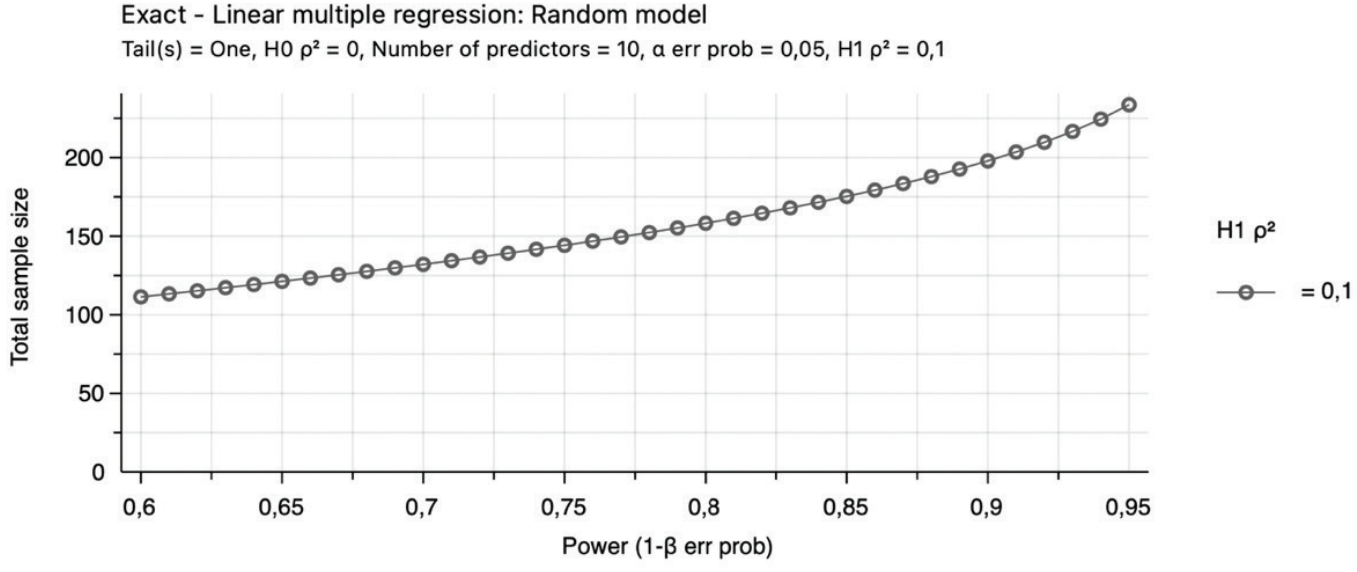

Figure 1. Power plot sample size using G*Power version 3.1

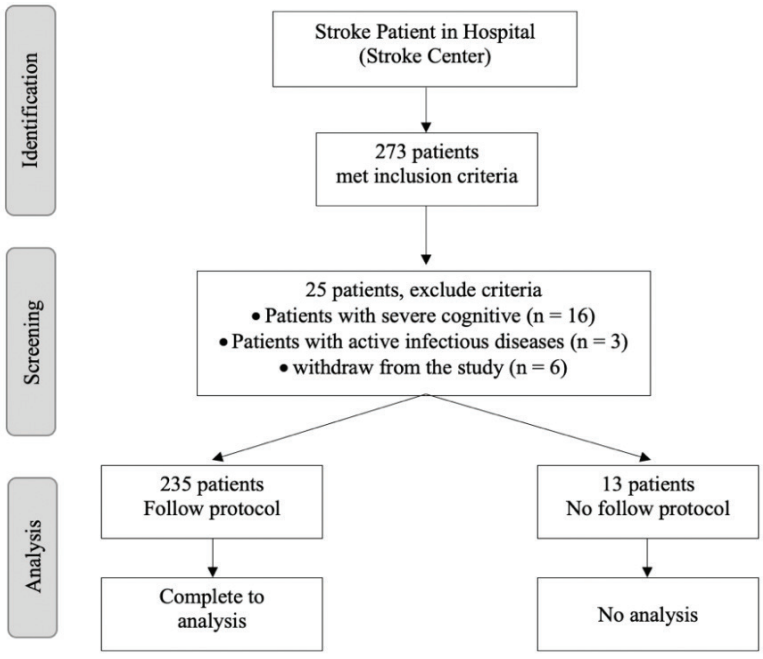

Figure 2. A flow diagram of study selection

Results

A total of 235 patients were included in the final analysis. The mean age was 56.4±12.7 years, with 76.6% of participants being male and 23.4% female. Most patients had at least one comorbidity, with diabetes mellitus (42.1%) and hypertension (58.3%) being the most prevalent. Additional baseline characteristics, including BMI, physical activity, stress level, family medical history, and laboratory findings, are summarized in Table 1. Following the baseline description, logistic regression analysis was performed to identify significant predictors of stroke occurrence. Table 2 shows that diabetes mellitus, hypertension, RA, physical activity, family health history, random blood sugar, uric acid levels, and salt consumption were retained as significant predictors ($p<0.05$). Next, a logistic regression analysis was conducted with a p-value criterion of >0.05, resulting in the variables of age, gender, previous health history such as diabetes mellitus, hypertension, heart failure, RA, BMI, physical activity, family health history, stress level, random blood sugar, uric acid level, and salt consumption. Logistic regression analysis (Table 2) identified diabetes mellitus, hypertension, RA, physical activity, family health history, random blood sugar, uric acid levels, and salt consumption as significant predictors of stroke incidence.

AUC 98.7% which indicates a very strong interpretation. However, this high AUC raised concerns about potential overfitting. To address this, internal validation using 5-fold cross-validation was conducted. The average AUC from cross-validation was 96.3% with a standard deviation of ±1.8%, indicating that while it is slightly lower than previous results, the model still demonstrates strong discriminative ability. This suggests that the model's performance is stable and not overly fitted to the training data.

The Hosmer and Lemeshow test indicates the model has a good fit or is suitable for the data, as shown in Figure 3. The predictive model demonstrated strong discriminative performance, showing high accuracy in distinguishing between patients with and without stroke risk. Internal validation confirmed model stability, and calibration analysis indicated a good fit to the observed data.

Discussion

This study identified eight key predictors of stroke: diabetes mellitus, hypertension, RA, low physical activity, family health history, elevated random blood sugar, high uric acid, and excessive salt intake. The predictive model incorporating these factors demonstrated excellent discriminative ability, with an AUC of 98.7% and stable performance on cross-validation (mean AUC 96.3%). These findings suggest that integrating multiple comorbidities and lifestyle variables can significantly improve early stroke risk detection compared to existing models. In our study population, diabetes mellitus and hypertension emerged as the strongest predictors, consistent with their established role in vascular pathology. RA also contributed significantly, reflecting the impact of systemic inflammation on cerebrovascular risk. Meanwhile, lifestyle-related factors such as physical activity and salt intake highlighted the importance of behavioral modification for prevention (14-16). Research also showed that although men are more likely to suffer from strokes, women

Table 1. Clinical and demographic characteristics of the study population

Variable	n (%)	Mean±SD	OR	p
Age (year)				
<40	112 (47.7)	2.42±0.86	3.61	**<0.001**
40-60	122 (51.9)			
>60	34 (14.4)			
Sex				
Male	180 (76.6)	1.23±0.42	2.56	**0.001**
Female	55 (23.4)			
Medical history				
Diabetes mellitus				
Yes	145 (61.7)	1.38±0.48	2.61	**0.014**
No	90 (38.3)			
Hypertension				
Yes	205 (87.2)	1.12±0.33	32.71	**0.000**
No	30 (12.8)			
Heart failure				
Yes	60 (25.5)	1.74±0.43	1.92	**0.040**
No	175 (74.5)			
Atrial fibrillation				
Yes	40 (17.0)	1.82±0.37	1.49	0.272
No	195 (83.0)			
Rheumatoid arthritis				
Yes	70 (29.8)	1.70±0.49	8.91	**0.028**
No	165 (70.2)			
Chronic kidney disease				
Yes	100 (42.6)	1.57±0.49	0.89	0.783
No	135 (57.4)			
Heart attack				
Yes	90 (38.3)	1.61±0.48	1.38	0.263
No	145 (61.7)			
Body mass index (kg/m²)				
Underweight (<18.5)	20 (8.5)	2.42±0.65	18.91	**<0.001**
Normal (18.5-24.9)	95 (40.4)			
Overweight (≥25)	120 (51.1)			
Physical activity (minutes/week)				
Active (exercise ≥150)	85 (36.2)	1.63±0.48	12.81	**<0.001**
Inactive (exercise <150)	150 (63.8)			
Stress level				
Low	50 (21.3)	2.06±0.69	10.89	**<0.001**
Medium	120 (51.1)			
High	65 (27.7)			
Family history of disease				
Yes (history of stroke/heart disease in parents)	155 (66.0)	1.34±0.47	13.91	**<0.001**
No	80 (34.0)			
Random blood sugar level (mg/dL)				
Normal (<140)	60 (25.5)	2.19±0.81	6.95	**<0.001**
Prediabetes (140-199)	70 (29.8)			
Diabetes (≥200)	105 (44.7)			

Table 1. Continued

Variable	n (%)	Mean±SD	OR	p
Uric Acid Levels (mg/dL)				
Normal	120 (51.1)	1.48±0.51	2.07	**0.009**
High	115 (48.9)			
Salt consumption level				
Normal (<5 grams/day)	70 (29.8)	1.71±0.45	22.43	**0.003**
High (≥5 grams/day)	165 (70.2)			

SD: Standard deviation, OR: Odds ratio

Table 2. Multivariate logistic regression analysis of stroke risk predictors

	B	S.E.	Wald	df	p	OR	95% CI	
							Min	Max
DM	-1.510	1.257	1.443	1	**0.025**	3.65	0.18	74.14
Hypertension	-5.055	1.215	17.322	1	**0.000**	0.21	0.01	0.69
RA	2.239	0.909	6.061	1	**0.014**	0.2.2	0.02	0.63
Heart attack	2.142	0.897	5.710	1	**0.017**	0.21	0.02	0.68
PA	1.775	0.800	4.924	1	**0.026**	5.88	1.23	28.29
FHD	4.205	0.930	20.467	1	**0.000**	0.12	0.01	0.92
Stress	8.074	2.510	10.344	1	**0.001**	32.08	3.41	43.91
BS	2.625	0.952	7.604	1	**0.006**	12.81	2.13	29.11
Constant	1.814	2.578	0.496	1	**0.001**	0.00		

Note: Coding for binary variables was 1=absence, 0=presence of condition. Interpretation of ORs is based on this coding direction.
Some odds ratios initially appeared inconsistent with their corresponding confidence intervals due to reporting errors. These have been corrected to reflect accurate relationships between the regression coefficients, OR values, and confidence intervals, ensuring coherence with standard logistic regression output.
DM: Diabetes mellitus, RA: Rheumatoid arthritis, PA: Physical activity, FHD: Family history disease, BS: Blood sugar, OR: Odds ratio, CI: Confidence interval, S.E.: Standard error, B: Regression coefficient, df: Degrees of freedom

have a higher risk of hemorrhagic strokes (17,18). Among these predictors, diabetes mellitus and hypertension were the most dominant, supporting previous evidence of their central role in vascular pathology. RA also emerged as an important risk factor, highlighting the contribution of systemic inflammation to stroke risk. Lifestyle-related variables such as low physical activity, salt intake, and high uric acid further emphasize the value of preventive strategies targeting modifiable behaviors (19,20).

High BMI has been associated with increased ischemic stroke risk and severity, though its impact may vary depending on comorbidities such as diabetes and hypertension. Low physical activity further amplifies stroke risk, highlighting the importance of lifestyle modification (21). Research shows that a lack of physical activity can increase the risk of hypertension, diabetes mellitus, and obesity, all of which contribute to the occurrence of strokes (22,23). Regular exercise can help control weight and blood pressure as well as improve overall heart health (24).

Psychological stress also plays a role in increasing the risk of stroke (25). Stress can cause an increase in blood pressure and trigger unhealthy behaviors such as poor eating habits and lack of physical activity. Research shows that individuals who experience high levels of stress tend to have higher cardiovascular risk factors (26,27). Stress was a significant predictor of stroke in this study, though the effect size appeared higher than previous reports, likely due to self-reported measurement and unmeasured confounders. Future research should use validated stress scales and account for mental health comorbidities to confirm this association. A positive family history of stroke or heart disease increases an individual's risk, as genetic predisposition to conditions like hypertension and diabetes contributes significantly to stroke susceptibility (28,29). High blood sugar levels, especially in individuals with diabetes mellitus, are strongly associated with an increased risk of stroke (30). Research shows that diabetic patients have a higher likelihood of experiencing a stroke compared to those who do not have diabetes. Uncontrolled random blood sugar can cause damage to blood vessels and increase the risk of atherosclerosis (31,32). Hyperuricemia has been linked to vascular inflammation and damage that elevate stroke risk, while excessive salt intake promotes hypertension; reducing dietary salt can therefore lower blood pressure and help prevent strokes (33,34).

Logistic regression identified diabetes mellitus, hypertension, RA, physical activity, family history, blood sugar, uric acid, and salt intake as significant stroke predictors. Among these, diabetes is a major risk factor, as elevated blood sugar damages vessels and accelerates atherosclerosis, increasing ischemic

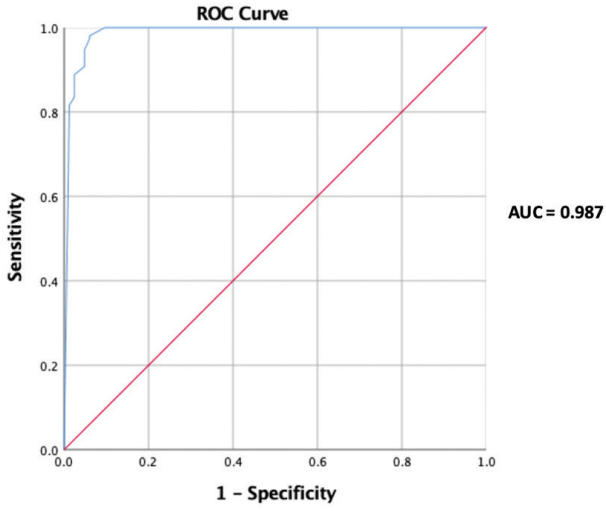

Figure 3. ROC curve
Area under the curve 98.7% this indicates a very strong interpretation. The Hosmer and Lemeshow test yielded a p-value of 0.493, indicating that the p-value >0.05 means the model has a good fit or is suitable for the data. A p-value greater than 0.05 indicates that there is no significant difference between the values predicted by the model and the observed values, which means the model has a good fit, as shown in Figure 3.
ROC: Receiver operating characteristic, AUC: Area under the curve

stroke risk (11,18). Hypertension is the most dominant risk factor for stroke. High blood pressure can cause damage to the brain's blood vessels and increase the likelihood of haemorrhagic and ischemic strokes. Research results show that a history of hypertension has an elevated OR in predicting the occurrence of stroke.

RA can increase the risk of stroke through prolonged systemic inflammation. This inflammation can affect cardiovascular health and increase the risk of blood clots, which can ultimately lead to a stroke (35,36). Low physical activity is directly related to an increased risk of stroke. Lack of physical activity can lead to obesity, hypertension, and diabetes, all of which are risk factors for stroke (37,38). Individuals with an active lifestyle have a lower risk of stroke, while a positive family history significantly increases susceptibility due to genetic and environmental influences on cardiovascular health (39). RA also emerged as a significant predictor of stroke. RA is a chronic autoimmune disease characterized by persistent systemic inflammation, which has been increasingly recognized as a risk factor for cardiovascular events, including stroke (36). High random blood sugar levels also contribute to the risk of stroke, especially in individuals with diabetes. Uncontrolled blood sugar can cause damage to blood vessels and increase the incidence of ischemic stroke (40). High uric acid levels contribute to inflammation and vascular damage, which increase stroke risk, while excessive salt intake raises blood pressure and worsens cardiovascular health, thus making both important modifiable risk factors (41,42).

This model achieved high accuracy with a sensitivity of 92.1% and specificity of 94.6%, surpassing many existing models. Its enhanced performance is likely due to the inclusion of diverse risk factors and the use of easily accessible clinical and behavioral variables, making it practical for populations with high comorbidity burdens.

This study has several limitations that should be considered when interpreting the findings. First, the research was conducted at a single-center hospital, which may limit the generalizability of the results to other populations or healthcare settings. Second, although the predictive model demonstrated a high AUC, we acknowledge the lack of external validation with an independent dataset. Internal validation using cross-validation was conducted, but further multi-center studies are needed to confirm model stability and reproducibility. Third, the study did not incorporate comprehensive socio-economic or dietary variables (e.g., income level, education, dietary habits beyond salt intake), which are known to influence stroke risk. Finally, some of the data, particularly regarding physical activity, stress, and medical history, were collected through self-reported questionnaires, which are subject to recall and reporting bias. Addressing these limitations in future studies will help strengthen and refine the predictive model.

Conclusion

This study identified eight key predictors of stroke—diabetes mellitus, hypertension, RA, low physical activity, family health history, elevated random blood sugar, high uric acid, and excessive salt intake—using a predictive model with strong discriminative ability (AUC 98.7%). The model offers potential to enhance early stroke detection in high-risk patients, but its single-center design and lack of external validation warrant caution. Future multi-center studies are recommended to confirm generalizability and strengthen their clinical applicability.

Ethics

Ethics Committee Approval: The research protocol was approved by the Komisi Etik Penelitian Kesehatan Health Research Ethics Committee (decision no.: 003.6/II.3.AU/F/KEPK/I/2025, date: 07.01.2025).

Informed Consent: This research has obtained written consent from the patients involved in the study.

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Footnotes

Authorship Contributions

Concept: P.A.W.S., B.W., E.E., E.S., Design: P.A.W.S., B.W., E.E., Data Collection or Processing: P.A.W.S., B.W., E.S., Analysis or Interpretation: P.A.W.S., E.E., Literature Search: P.A.W.S., B.W., E.E., E.S., Writing: P.A.W.S.

Conflict of Interest: The author declared no conflict of interest.

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