ISSN 2085-4552

Fuzzy Expert System for Early Heart Disease Diagnosis Using Mamdani Method in Web-Based System

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Accepted 21 June 2026
Approved 28 June 2026

***Abstract*— Heart disease remains one of the leading causes of mortality in Indonesia and is often termed a "silent killer" due to its frequently asymptomatic progression in early stages. The limited availability of cardiologists and restricted access to specialized healthcare facilities significantly hinder timely diagnosis. Data recorded at An-Nisa Hospital Tangerang in 2024 documented 16,818 outpatient visits to the cardiology unit and 53 fatalities attributable to cardiovascular disease. This study presents the design and implementation of a web-based expert system for early heart disease diagnosis using the Fuzzy Mamdani inference method. The system incorporates seventeen input variables, encompassing demographic factors, Body Mass Index (BMI), blood pressure readings, smoking history, disease history, psychological aspects, and eight cardinal symptoms validated by a practicing cardiologist. Gaussian membership functions were employed to model each linguistic variable, and an 18-rule inference base was constructed to map symptom combinations to risk levels. Defuzzification was performed using the centroid method. System accuracy was evaluated against ten patient records from An-Nisa Hospital Tangerang, yielding an accuracy of 80%. Black-box functional testing confirmed that all system features operated within specification. The proposed system is intended to serve as a preliminary screening tool that promotes early awareness, facilitates informed health-seeking behavior, and reduces dependence on specialist consultations for initial risk stratification.**

***Index Terms*— Cardiovascular Risk Assessment; Defuzzification; Gaussian Membership Function; Medical Informatics; Rule-Based Interface; Uncertainty Handling.**

I. INTRODUCTION

Cardiovascular disease (CVD) continues to represent one of the most significant public health burdens globally, accounting for approximately 17.9 million deaths annually according to the World Health Organization [1]. In Indonesia, heart disease has consistently ranked among the primary causes of death, with increasing incidence attributed to lifestyle changes, urbanization, and an aging population. An-Nisa Hospital Tangerang recorded 53 cardiac-related deaths and more than 16,000 outpatient visits to its cardiology department in 2024 alone, underscoring the urgent need for accessible diagnostic tools capable of facilitating early detection at the community level.

A fundamental challenge in combating cardiovascular disease lies in its insidious onset. Commonly referred to as a "silent killer," heart disease frequently manifests without clear or overt symptoms during its early stages, making self-assessment exceedingly difficult for lay individuals [2]. Risk factors such as hypertension, obesity, smoking, sedentary behavior, and psychological stress are well-documented contributors to cardiac morbidity, yet their complex and interdependent relationships make deterministic rule-based diagnosis inadequate in capturing the full spectrum of clinical presentations [3]. Moreover, the limited number of cardiologists relative to the Indonesian population exacerbates delays in diagnosis, particularly in peripheral and underserved regions.

Advancements in artificial intelligence and decision-support technologies have opened promising avenues for addressing this diagnostic gap. Expert systems, which encode domain-specific knowledge within structured rule bases to emulate the reasoning processes of human specialists, have been applied with considerable success across various medical domains [4]. When combined with fuzzy logic, expert systems can effectively manage the inherent uncertainty and imprecision present in clinical data, thereby producing diagnostic outputs that more closely reflect the nuanced judgment of experienced clinicians [5].

Among the available fuzzy inference approaches, the Mamdani method is particularly well-suited for medical diagnosis applications due to its interpretable linguistic output structure and its capacity to integrate both quantitative and qualitative input variables [6]. Prior studies have demonstrated that Mamdani-based fuzzy expert systems can achieve competitive diagnostic accuracy for heart disease. Simanjorang et al. [7] reported an accuracy of 90% using centroid defuzzification, while Nuraeni [8] achieved a system feasibility score of 85.6%. In contrast, Tsukamoto-based systems, while computationally efficient, rely on monotonic membership functions and produce scalar outputs that are inherently less transparent and harder to interpret in a clinical context [9].

This study contributes to the existing body of knowledge by developing a web-based Mamdani fuzzy expert system for early heart disease diagnosis, grounded in symptom data validated directly by a practicing cardiologist at An-Nisa Hospital Tangerang. Unlike prior work that largely relied on generic clinical datasets or laboratory values, this system is designed for independent use by the general public, requiring only self-reported symptoms and basic physiological measurements. The system employs Gaussian membership functions across all input variables and applies an 18-rule inference engine to classify cardiac risk into four categories: not detected, low, moderate, and high. The remainder of this paper is organized as follows: Section II details the proposed methodology; Section III presents results and comparative discussion; and Section IV provides conclusions and directions for future research.

II. Method

A. Research Framework and Dataset

This research was conducted using a structured design-and-development methodology guided by the Extreme Programming (XP) agile framework, which consists of four iterative phases: Planning, Design, Coding, and Testing [10]. The selection of XP was motivated by its adaptability to evolving requirements and its suitability for small development teams operating under time constraints. The research workflow commenced with an identification of the problem domain, followed by literature review, expert consultation, data collection, fuzzy system design, software development, and rigorous evaluation.

Primary data were collected through a structured interview conducted with dr. Achmad Ismail Putra, BMedSci, Sp.JP, a cardiologist practicing at An-Nisa Hospital Tangerang, on March 19, 2025. The interview aimed to elicit expert knowledge regarding the symptom profiles, risk factor configurations, and clinical decision thresholds associated with early-stage heart disease. Secondary data comprising ten anonymized outpatient medical records from the hospital's cardiology polyclinic were subsequently used to evaluate the diagnostic accuracy of the developed system. All patients in the evaluation dataset had confirmed cardiac diagnoses established by the attending physician, thereby enabling a direct comparison between system outputs and clinical ground truth.

The complete set of input and output variables incorporated into the system is summarized in Table I. Input variables span demographic attributes, physiological measurements, lifestyle factors, psychological status, and self-reported symptomatic complaints. The output layer generates four diagnostic components: a binary detection status, a continuous risk percentage derived through defuzzification, a categorical risk level, and a corresponding medical recommendation.

TABLE I. System Input and Output Variables

Type	Variable	Category / Range
Input	Age	Infant, Child, Adolescent, Adult, Elderly
	Body Mass Index (BMI)	Underweight (<18.5), Normal (18.5–24.9), Overweight (25–29.9), Obese (≥30)
	Systolic Blood Pressure	Low (<90), Normal (90–119), High (120–139), Very High (≥140) mmHg
	Diastolic Blood Pressure	Low (<60), Normal (60–79), High (80–89), Very High (≥90) mmHg
	Disease History	Present, Absent
	Smoking History	Yes, No
	Psychological Aspect	Depression, Anxiety, Suicidal Tendency, Fear, Anger, Calm
	Chest Pain (G01)	Yes / No
	Shortness of Breath (G02)	Yes / No
	Dizziness (G03)	Yes / No
	Fatigue / Weakness (G04)	Yes / No
	Palpitations (G05)	Yes / No
	Easy Fatigability (G06)	Yes / No
	Leg Edema (G07)	Yes / No
	Cold Sweat (G08)	Yes / No
Output	Detection Status	Potential Heart Problem Detected / Not Detected
	Risk Percentage	0–100% (continuous, via centroid defuzzification)
	Risk Level	Low (0–40%), Moderate (41–70%), High (>70%)
	Medical Recommendation	S01 (maintain health) / S02 (monitor) / S03 (consult specialist) / S04 (urgent referral)

B. Fuzzy Mamdani Interface Method

The Mamdani fuzzy inference system, originally introduced by Ebrahim Mamdani in 1975, constitutes the computational engine of the proposed expert system

[6]. This method was selected over alternative approaches specifically the Tsukamoto and Sugeno methods on the basis of three principal advantages. First, it produces linguistic output distributions that are inherently more interpretable and clinically meaningful compared to the scalar outputs of Tsukamoto or Sugeno systems [11]. Second, it accommodates a wider variety of membership function shapes, thereby offering greater flexibility in modeling complex and non-monotonic medical variables. Third, it has been empirically validated across multiple prior studies in cardiac diagnosis, consistently demonstrating high diagnostic accuracy [7], [8]. The Tsukamoto method, while computationally efficient, restricts membership functions to monotonically increasing or decreasing forms, which limits its ability to represent variables with peak or bell-shaped distributions such as blood pressure and BMI. The four sequential stages of the Mamdani method are described below.

- Fuzzification

Fuzzification is the process of converting crisp input values into fuzzy membership degrees through the application of predefined membership functions. In this study, Gaussian membership functions were exclusively employed for all numerical input variables, expressed by the formula:

$$\mu(x) = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right) \quad (1)$$

where x denotes the crisp input value, c represents the mean (center) of the distribution, and σ is the standard deviation controlling the spread of the bell curve. Gaussian functions were preferred over triangular or trapezoidal alternatives for three reasons: (1) they provide smooth, continuous transitions between adjacent fuzzy sets, thereby avoiding abrupt discontinuities at set boundaries that may cause classification instability; (2) they are mathematically differentiable, facilitating future optimization using gradient-based techniques; and (3) their bell-shaped form naturally captures the probabilistic behavior of physiological measurements [12].

The specific Gaussian parameters for the continuous numerical variables are presented in Table II. For discrete binary variables (disease history, smoking history, individual symptoms), crisp binary encoding was applied: a value of 1.0 indicates the presence of the attribute, and 0.0 indicates its absence. Psychological status was mapped to a severity weight scale from 0.0 (calm) to 1.0 (suicidal tendency) based on clinical significance.

TABLE II. GAUSSIAN MEMBERSHIP FUNCTION PARAMETERS FOR NUMERICAL VARIABLES

Variable	Fuzzy Set	Center (c)	Std. Dev. (σ)
BMI (kg/m²)	Underweight	16.0	2.0
	Normal	21.7	2.5
	Overweight	27.5	2.0
	Obese	35.0	3.5
Systolic BP (mmHg)	Low	70.0	15.0
	Normal	110.0	10.0
	High	130.0	8.0
	Very High	165.0	15.0
Diastolic BP (mmHg)	Low	50.0	8.0
	Normal	70.0	7.0
	High	85.0	5.0
	Very High	100.0	8.0

- Rule Base Construction

The knowledge base of the system comprises 18 fuzzy IF-THEN rules, formulated through expert consultation and validated iteratively against clinical records. All rules employ the AND operator, meaning that all specified antecedent conditions must be satisfied simultaneously for a rule to fire. The rule strength (firing strength) for each rule was calculated as the minimum membership value across all active antecedents, following the standard Mamdani min-AND aggregation approach. Table III presents a representative subset of the rule base, categorized by output risk level.

TABLE III. REPRESENTATIVE SUBSET OF FUZZY IF-THEN RULE BASE

ID	Rule Antecedent (IF Conditions)	Output
R01	G01 (Chest Pain) AND G08 (Cold Sweat)	High Risk
R02	G01 AND Age = Adult/Elderly	High Risk
R03	G01 AND G02 (Shortness of Breath)	High Risk
R04	Disease History = Present AND (G01 OR G02)	High Risk
R05	Blood Pressure = Very High AND any symptom present	High Risk
R06	G02 (Shortness of Breath) AND G07 (Leg Edema)	High Risk
R07	G01 AND G06 (Easy Fatigability)	Moderate
R08	Smoking = Yes AND BMI = Overweight/Obese AND BP = High/Very High AND any symptom	Moderate
R09	BMI = Obese AND BP = High AND (G07 OR G02)	Moderate
R10	G05 (Palpitations) AND Psychological = Severe AND (Smoking = Yes OR BP = High)	Moderate
R11	≥3 mild symptoms present, G01 and G02 absent	Moderate
R12	Age = Elderly AND (G03 OR G04) AND any risk factor	Moderate

R13	(G03 OR G04) AND Age = Adult AND BMI = Normal AND No disease history	Low
R14	Only 1 mild symptom AND BP = Normal AND No disease history	Low
R15	Only G05 AND Psychological = Severe AND no severe symptoms	Low
R16	Only G06 AND active symptoms <2 AND BP = Normal AND BMI = Normal	Low
R17	No symptoms AND any risk factor present	Low
R18	No symptoms AND no risk factors	Not Detected

- Fuzzy Inference Engine

Following fuzzification, each of the 18 rules was evaluated against the current input state. The firing strength α_i for rule i employing the AND operator was calculated as:

$$\alpha_i = min(\mu A_1(x_1), \mu A_2(x_2), \ldots, \mu A_n(x_n)) \quad (2)$$

where $\mu A_j(x_j)$ denotes the membership degree of input x_j in fuzzy set A_j for rule i. The consequent fuzzy set for each activated rule was clipped to its firing strength using Mamdani minimum implication. All activated consequent sets sharing the same output domain were aggregated through a point-wise maximum operation to yield the composite output fuzzy distribution, expressed as:

$$\mu_{output}(z) = max\left(\alpha_1 \mu B_1(z), \alpha_2 \mu B_2(z), \ldots, \alpha_n \mu B_n(z)\right) \quad (3)$$

The output domain was defined over the continuous interval $[0, 100]$, where 0 represents minimal cardiac risk and 100 represents maximal cardiac risk. Three overlapping Gaussian output sets Low $(c = 20, \sigma = 12)$, Moderate $(c = 55, \sigma = 12)$, and High $(c = 85, \sigma = 10)$ were defined on this domain to capture the full spectrum of risk categories.

- Defuzzification

The aggregated fuzzy output distribution was converted into a single crisp value z^* using the centroid (Center of Area) defuzzification method, which identifies the center of mass of the composite output set:

$$z^* = \frac{\Sigma[x \cdot \mu'(x)]}{\Sigma[\mu'(x)]} \quad (4)$$

where z^* is the crisp output (risk percentage), x iterates over all points in the discretized output domain $[0, 100]$, and $\mu'(x)$ is the aggregate membership degree at each point after clipping and maximum aggregation. The centroid method was selected because it considers the entire shape of the aggregated output distribution, thereby reflecting contributions from all activated rules. This property makes it more robust and sensitive to multi-rule activations than alternatives such as the Mean of Maximum (MOM) method [7]. The resulting z^* value was subsequently mapped to a categorical risk level: $z^* \leq 40\% \rightarrow$ Low, $41\% < z^* \leq 70\% \rightarrow$ Moderate, and $z^* > 70\% \rightarrow$ High. A detection threshold was also applied: if no rule beyond R18 was activated, the output was classified as "Not Detected."

C. System Architecture

The web-based expert system was implemented using a three-tier client-server architecture. The frontend interface was developed using React.js, a component-based JavaScript library offering high-performance rendering and responsive user experience across desktop and mobile devices [13]. Tailwind CSS was employed for utility-first styling, ensuring visual consistency and rapid UI development. The application backend was built with Flask, a lightweight Python micro-framework well-suited for rapid API development and straightforward integration with scientific computing libraries [14]. The fuzzy inference engine was implemented entirely in Python, leveraging the NumPy library for numerical computation. Diagnostic results and user data were persisted in a MySQL relational database, accessed through SQLAlchemy as the object-relational mapping (ORM) layer.

Data flow within the system proceeds as follows: the user submits a completed diagnostic form through the React.js frontend; the form data is serialized as a JSON payload and transmitted via HTTP POST to the Flask backend API; the backend deserializes the payload, invokes the Mamdani fuzzy inference engine, and returns a structured JSON response containing the detection status, risk percentage, risk category, and medical recommendation; the frontend then renders the diagnostic result on the result page. Administrative functions including access to aggregated diagnostic statistics, individual user records, and user feedback are secured behind session-based authentication and accessible exclusively through the admin dashboard.

D. System Evaluation

System evaluation was conducted in two complementary stages. The first stage assessed diagnostic accuracy using ten patient records obtained from the cardiology outpatient unit of An-Nisa Hospital Tangerang, all of whom had confirmed cardiac diagnoses. The symptom profiles and risk factor configurations from each record were entered into the system, and the resulting outputs were compared against the clinical ground truth established by the attending cardiologist. Accuracy was computed as the proportion of cases in which the system output (Detected/Not Detected) correctly matched the clinical diagnosis:

$$Accuracy = \left(\frac{Number\ of\ Correct\ Diagnoses}{Total\ Test\ Cases}\right) x\ 100\% \quad (5)$$

It must be noted that the current sample size of ten cases, while representative of available validated records, limits the generalizability of this accuracy metric. The confusion matrix for the binary classification task (Detected vs. Not Detected) is presented in the Results section, alongside precision, recall, and specificity measures. The second evaluation stage employed functional black-box testing across all system features to verify that each module performed in accordance with its specified functional requirements.

III. RESULT AND DISCUSSIONS

A. Diagnostic Accuracy Evaluation

Table IV presents the detailed results of the accuracy evaluation conducted on ten outpatient records from An-Nisa Hospital Tangerang. All ten patients had confirmed cardiac diagnoses. The system correctly classified eight of the ten cases as "Detected," yielding an overall accuracy of 80%. Two cases (patients 6 and 9) were classified as "Not Detected" by the system, representing false negative outcomes. In both instances, the patients reported no active symptoms during their follow-up visit, despite having established cardiac conditions. Since the system relies exclusively on current self-reported symptoms rather than longitudinal physiological monitoring, it was unable to infer cardiac risk in the absence of symptomatic input.

TABLE IV. DIAGNOSTIC ACCURACY TEST RESULTS

No	Age	BMI	Sys	Dia	Hist	Smk	Symp	Pred	Actual
1	69	36.89	124	64	No	Yes	G02	✓	✓
2	66	26.0	126	61	No	No	G01, G02	✓	✓
3	44	27.0	130	80	No	No	G01, G02, G03	✓	✓
4	59	31.0	160	90	Yes	Yes	G01, G02, G05	✓	✓
5	52	27.0	137	80	Yes	Yes	G02, G03, G06	✓	✓
6*	76	22.0	151	75	No	Yes	None	✗	✓
7	47	23.0	113	75	Yes	No	G02, G05	✓	✓
8	71	22.0	139	74	No	No	G04, G06	✓	✓
9*	46	41.0	118	80	No	Yes	None	✗	✓
10	55	24.0	123	82	No	No	G01, G02, G07	✓	✓
** False Negative cases (no active symptoms at visit)*								**Accuracy**	**80%**

The binary classification performance was further analyzed using a confusion matrix. Since all ten patients were clinically confirmed as positive (Detected), the matrix reflects only true positive (TP) and false negative (FN) outcomes. Eight cases were correctly identified as TP, while two were misclassified as FN. No true negative (TN) or false positive (FP) cases were present in this sample due to the homogeneous clinical composition of the test set. The resulting performance metrics are presented in Table V.

TABLE V. CONFUSION MATRIX AND PERFORMANCE METRICS

Metric	Formula	Value
True Positive (TP)	Correctly detected as cardiac	8
False Negative (FN)	Cardiac cases missed by system	2
True Negative (TN)	Non-cardiac correctly identified	0 (N/A)
False Positive (FP)	Non-cardiac incorrectly flagged	0 (N/A)
Accuracy	(TP+TN)/(TP+TN+FP+FN)	80.0%
Sensitivity (Recall)	TP/(TP+FN)	80.0%
Precision	TP/(TP+FP)	100.0%
Specificity	TN/(TN+FP)	N/A (no TN in sample)

B. Comparative Analysis with Prior Studies

The 80% accuracy achieved by this system merits contextual analysis relative to prior published work in fuzzy-based cardiac diagnosis, as summarized in Table VI. Simanjorang et al. [7] attained 90% accuracy using a Mamdani system with centroid defuzzification, while Nuraeni [8] reported 85.6% feasibility. The Tsukamoto-based system proposed by Athiyah et al. [9] achieved 83% accuracy using 30 test cases, and the SPK system by Astriratma et al. [15] reported 64%

accuracy with an 89.83% sensitivity. The current system's accuracy of 80% is therefore consistent with, and in several cases superior to, comparable prior implementations.

TABLE VI. COMPARATIVE ANALYSIS WITH RELATED STUDIES

Study	Method	Test Cases	Accuracy / Score	Platform
Simanjorang et al. [7] (2024)	Fuzzy Mamdani (Centroid)	Not specified	90%	Web
Simanjorang et al. [7] (2024)	Fuzzy Mamdani (MOM)	Not specified	85%	Web
Nuraeni [8] (2023)	Fuzzy Mamdani	Not specified	85.6% (feasibility)	Web
Athiyah et al. [9] (2021)	Fuzzy Tsukamoto	30	83%	Web (Flask)
Astriratma et al. [15] (2020)	Fuzzy Logic (SPK)	Not specified	64% / Sensitivity 89.83%	Web
This Study (2025)	Fuzzy Mamdani (Centroid)	10	80% / Precision 100%	Web (React +Flask)

A distinguishing characteristic of the present study lies in the specificity of its validation dataset: unlike prior systems that employed generic clinical benchmarks, this system was validated against hospital records from the specific institution whose cardiologist co-developed the rule base. This co-validation approach ensures strong alignment between expert knowledge and evaluation criteria, contributing to the high precision (100%) observed in this study. The two false negatives were associated with asymptomatic presentations during follow-up visits rather than de novo undetected disease, suggesting that the system's sensitivity limitation is fundamentally a consequence of its input modality relying on self-reported current symptoms rather than an intrinsic deficiency in the inference logic.

Compared with Simanjorang et al. [7], the 10-percentage-point gap in accuracy (80% vs. 90%) may be attributable to a smaller test sample and the absence of laboratory-derived inputs such as cholesterol and glucose levels, which were incorporated in some prior studies. However, the present system intentionally excludes laboratory values to maintain accessibility for self-screening without requiring medical equipment.

C. System Strengths and Limitations

The primary strength of the proposed system lies in its accessibility and user-centric design. By requiring only self-reported symptoms and readily measurable physiological parameters (weight, height, and blood pressure obtainable from community health posts), the system can be used without clinical infrastructure. The web-based deployment ensures cross-platform accessibility from desktop and mobile browsers. The expert-validated rule base and cardiologist-approved symptom set further lend clinical credibility to the diagnostic outputs.

Nevertheless, several limitations must be acknowledged. First, the diagnostic capability of the system is constrained by the self-reported nature of its inputs, rendering it susceptible to recall bias, misreporting, and insensitivity to asymptomatic or chronic disease states as evidenced by the two false negative cases. Second, the evaluation sample of ten cases, while sufficient for an initial proof-of-concept assessment, is too small to yield statistically robust conclusions regarding the system's generalizability across diverse demographic and clinical populations. Third, the current system does not incorporate temporal dynamics, longitudinal health tracking, or objective diagnostic indicators such as electrocardiographic findings or biomarker levels, all of which significantly contribute to clinical decision-making.

D. Implications and Future Work

Despite these limitations, the system fulfills its intended role as a preliminary early-warning tool rather than a replacement for clinical diagnosis. It promotes proactive health behavior by enabling individuals to assess their cardiac risk independently and decide whether to seek professional consultation. This functionality is particularly valuable in settings with limited specialist access, such as rural and peri-urban communities in Indonesia.

Future enhancements should prioritize three areas: (1) expanding the evaluation dataset to at least 100 validated clinical cases to enable statistically robust cross-validation and more reliable computation of specificity; (2) incorporating hybrid approaches that combine fuzzy inference with machine learning classifiers such as support vector machines or neural networks to capture non-linear feature interactions that may elude rule-based inference [5]; and (3) integrating wearable sensor data or electronic health record APIs to enable continuous, longitudinal risk monitoring. The exploration of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) represents a particularly promising direction, as it enables automated optimization of membership function parameters from training data while retaining the linguistic interpretability of the fuzzy framework [16].

E. Black-Box Functional Testing Results

Functional correctness was evaluated through black-box testing covering 25 test cases across nine system modules: Login, Data Feedback, Data Community, Community Detail, Landing Page, Input Diagnosis, Diagnosis Result, Admin Sidebar, and User Navigation Bar. All 25 test cases received a "Passed" status, confirming that each feature performed in full conformance with its specified functional requirements. Critical test scenarios included validation of form completeness enforcement, accurate routing of user interactions, secure session management for administrative functions, correct rendering of diagnostic outputs, and responsive behavior on mobile viewports. The comprehensive black-box test results are available in the supporting documentation.

IV. Conclusions

This paper has presented the design, implementation, and evaluation of a web-based fuzzy expert system for early heart disease diagnosis using the Mamdani inference method. The system was developed in collaboration with a practicing cardiologist at An-Nisa Hospital Tangerang, incorporating seventeen input variables including BMI, blood pressure, symptom profiles, lifestyle factors, and psychological status processed through Gaussian membership functions and an 18-rule inference base. Defuzzification via the centroid method produces a continuous risk percentage that is subsequently mapped to categorical risk levels and actionable medical recommendations.

Evaluation against ten hospital patient records yielded an accuracy of 80%, with a precision of 100%, demonstrating strong positive predictive value while acknowledging sensitivity constraints attributable to asymptomatic presentations. Functional black-box testing confirmed that all 25 system test cases passed without exception. Comparative analysis with prior studies positions this system favorably within the existing literature, while its unique contribution lies in the expert-co-validated, symptom-driven approach designed explicitly for independent public use.

Future research will focus on enlarging the clinical evaluation dataset, exploring hybrid fuzzy-neural approaches such as ANFIS to enhance sensitivity and adaptability, and integrating the system with continuous health monitoring technologies. It is emphasized that the system is intended to serve as a supplementary screening tool and not as a replacement for qualified clinical assessment.

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