

Optimized Adaptive Neuro-Fuzzy Inference Model for Early Identification of Premature Heart Attacks

S. E. Dogo¹, E. J. Garba², Y. M. Malgwi³, Abraham Danlami⁴

^{1, 2, 3}*Department of Computer Science, Faculty of Computing & Artificial Intelligence, Modibbo Adama University Adamawa State, Adamawa State, Nigeria*

⁴*Department of Computer Science, Faculty of Computing & Artificial Intelligence, Federal University Wukari, Taraba State, Nigeria*

Abstract- Cardiovascular diseases (CVDs), particularly premature heart attacks, remain a leading cause of mortality worldwide, with increasing prevalence in developing countries such as Nigeria. Early detection is critical for effective prevention and clinical intervention. This study proposes an Ensemble Adaptive Neuro-Fuzzy Inference System (ANFIS) for the early diagnosis of premature heart attacks using clinically relevant patient data. The dataset was obtained from the Federal Medical Centre (FMC), Jalingo, Taraba State, and supplemented with benchmark datasets, comprising 918 patient records with 12 attributes related to cardiovascular health. Data preprocessing, feature encoding, and model training were conducted using Python-based machine learning and fuzzy logic libraries. The proposed ANFIS model was trained and evaluated using standard performance metrics. Experimental results demonstrate that the model achieved an overall accuracy of 92%, with high precision, recall, and F1-scores across both classes. The findings indicate that the ensemble ANFIS model is effective, robust, and suitable as an intelligent decision-support tool for early detection of premature heart attacks.

Key Words: Fuzzy Logic, Adaptive Neuro-Fuzzy Inference System, Cardiovascular Diseases

I. INTRODUCTION

Heart disease remains the world's biggest cause of mortality, according to the World Health Organization. These days, heart disease is on the rise due to poor diet, stressful lifestyles, and dietary modifications. Heart disease-related mortality has risen by more than 2 million since 2000, reaching about 9 million in 2019 (WHO, 2020). Electrocardiography (ECG) is not able to identify abnormalities in the majority of heart disease cases when there is no heart attack, which makes early diagnosis extremely challenging. Investigating heart

illnesses involves applying a variety of artificial intelligence techniques, including machine learning, deep learning, fuzzy logic, neural networks, genetic algorithms, probabilistic reasoning, and image processing, in order to acquire more accurate medical diagnoses (Adler *et al.*, 2020).

Cardiovascular diseases are among the most significant global health challenges, accounting for millions of deaths annually. Premature heart attacks, which occur in individuals below the expected age threshold, pose an even greater concern due to their socioeconomic and health implications. In many developing regions, including Nigeria, late diagnosis, inadequate screening tools, and limited access to advanced healthcare technologies contribute to high mortality rates (Akalya *et al.*, 2024).

Traditional diagnostic methods often rely on static statistical models and clinician judgment, which may fail to adequately capture the nonlinear and uncertain nature of medical data. Consequently, intelligent computational approaches such as machine learning, fuzzy logic, and hybrid systems have gained attention for medical decision support. Among these approaches, the Adaptive Neuro-Fuzzy Inference System (ANFIS) combines the learning capability of neural networks with the interpretability of fuzzy logic, making it well-suited for healthcare applications (Ali *et al.*, 2024).

Cardiovascular disease remains a major global cause of death, largely due to the limitations of conventional diagnostic methods such as ECG, which are often static and ineffective at detecting early-stage abnormalities. Although advanced computational techniques—including neural networks, genetic

algorithms, and deep learning models—have improved prediction accuracy, their clinical adoption is limited by poor adaptability, high data requirements, lack of real-time learning, and low interpretability (Amar 2024 and Azad *et al.*, 2021).

While Adaptive Neuro-Fuzzy Inference Systems (ANFIS) offer better interpretability and flexibility, existing models typically rely on limited clinical parameters and fail to integrate genetic, demographic, and lifestyle factors or adapt dynamically to new patient data. Consequently, there is a critical need for an intelligent, adaptive, and transparent diagnostic framework (Balamurugan *et al.*, 2022).

This research focuses on the development of an ensemble ANFIS-based model for the early detection of premature heart attacks. By integrating multiple intelligent techniques and clinically relevant features, the study aims to improve diagnostic accuracy, reduce uncertainty, and support healthcare professionals in making informed clinical decisions.

This study addresses this gap by proposing an Ensemble Adaptive Neuro-Fuzzy Inference System (ANFIS) that integrates heterogeneous patient data and employs ensemble and hybrid optimization techniques to improve accuracy, adaptability, and early detection of premature heart attacks.

II. FUZZY INFERENCE SYSTEM (FIS)

The obstruction of blood flow in the heart limits oxygen supply to the cardiac muscle, potentially resulting in irreversible injury (Ali & Goni, 2024). Adler *et al.* (2020) classify heart attacks clinically as ST-segment Elevation Myocardial Infarction (STEMI) or Non-ST-segment Elevation Myocardial Infarction (NSTEMI), both of which provide considerable health hazards.

A Fuzzy Inference System use fuzzy set theory to correlate inputs with outputs through a series of rules

(Stéfano, 2020). The FIS utilizes membership functions and fuzzy operators to understand fuzzy values, enabling it to manage intricate decision-making processes characterized by uncertainty and imprecision (Vidhya & Shanmugalakshmi, 2020). Sarabjeet and Vijay (2019) assert that a fuzzy inference system in healthcare diagnostics can quantify ambiguous symptoms and clinical characteristics, yielding a more refined diagnosis.

III. FUZZY LOGIC

Fuzzy logic makes use of fuzzy set theory and membership functions to enable the expression of common knowledge, mostly of the qualitative linguistic kind, in the setting of mathematical language. Fuzzy logic, also known as non-crisp logic, is a type of multivalued logic where probability is used to translate the true values of language variables into any real number between zero and one (Chee, and Ramli 2022).

Consequently, it is employed to handle the concept of partial truth, where the truth value may vary from being totally true to being totally false. The only possible truth values for variables in Boolean (classical or crisp) logic, on the other hand, are zero and one. As seen in figure 1, fuzzy logic presupposes that people develop opinions based on vague and non-numerical data. For the purpose of identifying coronary heart disease, fuzzy logic is a very successful artificial intelligence technique (Dipti, 2022).

By merging linguistic traits with a membership function, it is utilized to predict the occurrence of sickness. Fuzzy logic makes use of language variables, which frequently let us gauge things with precise numerical values. The next step in figuring out the relevant factors is called fuzziness. Fuzzy inference systems, a fuzzy model, are built on the rules that are created using linguistic variables and term sets (Migliaccio *et al.*, 2024).

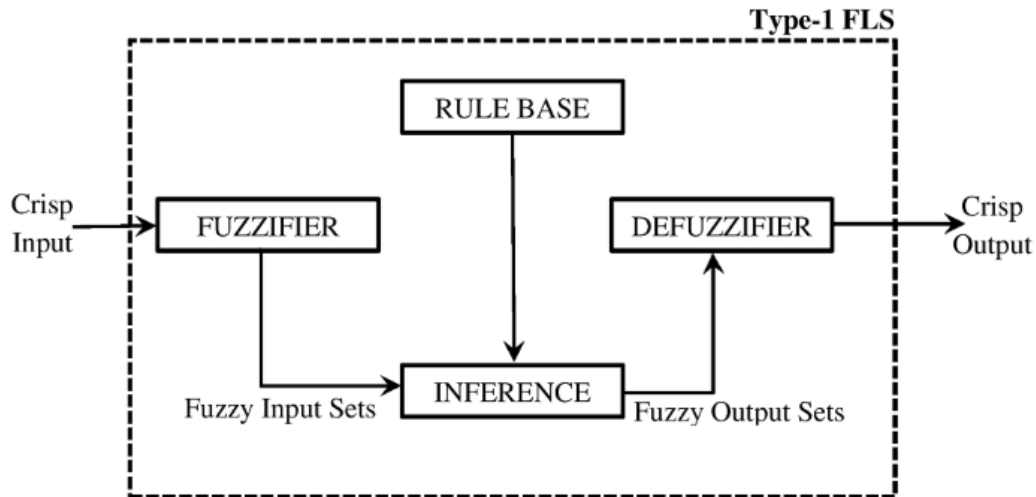


Figure 1: Fuzzy System (Sarabjeet *et al.*, 2019).

As seen in figure 1, a fuzzy model often uses membership functions (MFs) to identify the number of MFs that affect the model's optimality and accuracy. An adaptive Neuro-fuzzy inference system (ANFIS) model's performance is influenced by the kind of training that artificial neural networks (ANNs) give, the system parameters' complexity, and how well they are chosen. Seven parameters and the K-Fold cross-validation method were used to build an ANFIS strategy for categorizing cardiovascular illnesses degree, and the patient's heart disease degree was diagnosed with 92.3% accuracy. Electrocardiogram (ECG) feedback was compared using ANFIS controllers to create a control system for people with CVDs (Srivastava & Kumar, 2022).

5. Adaptive Neuro-Fuzzy Inference System (ANFIS)
The Adaptive Neuro-Fuzzy Inference System is a hybrid intelligent framework that integrates neural networks and fuzzy logic principles to develop a model proficient in learning from data and reasoning

under ambiguity (Srivastava & Kumar, 2022). Pekaslan *et al.*, (2020) states that ANFIS is extensively utilized in domains necessitating adaptive decision-making, such as medical diagnostics, where it analyzes medical data inside an adaptive framework to forecast outcomes based on acquired patterns and rules.

IV. ENSEMBLE MODEL

An ensemble model consolidates predictions from various models to yield a more precise and resilient output (Bamanga *et al.*, 2021). Spotintelligence (2023) states that by integrating many learning algorithms, ensemble models mitigate the effects of individual biases and errors, hence improving overall predictive performance. This research employs an ensemble methodology on ANFIS models, each trained on distinct data subsets (e.g., genetic, clinical, lifestyle), to enhance the precision and thoroughness of heart attack predictions

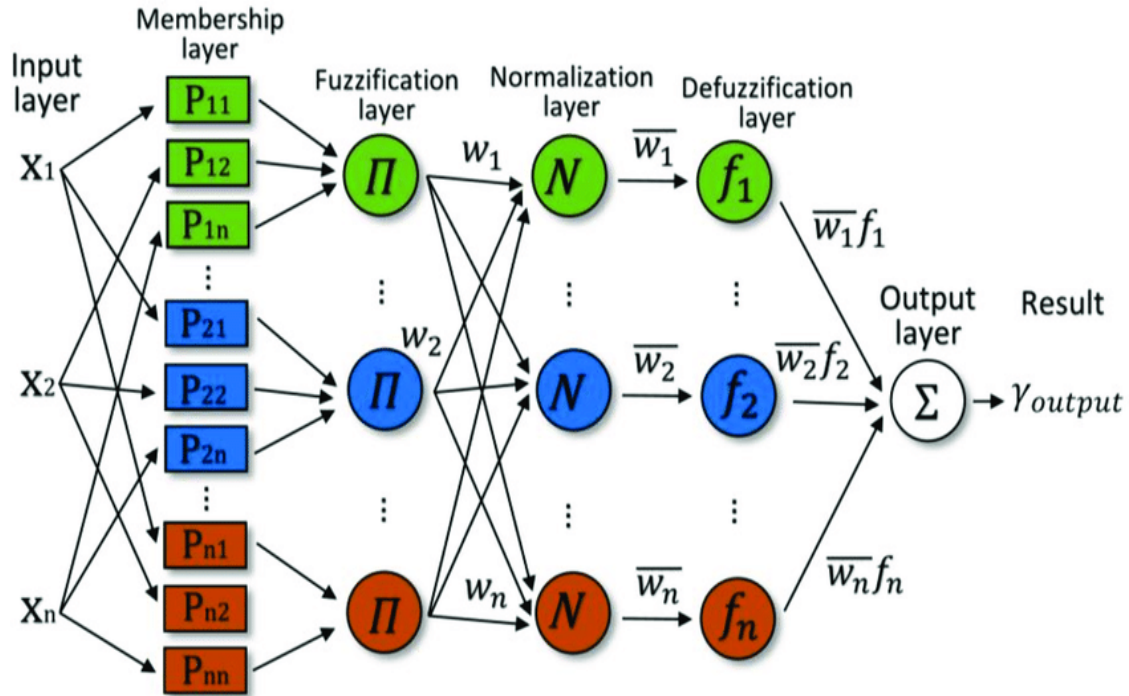


Figure 2: Adaptive Neuro-fuzzy system Architecture (Stéfano *et al.*, 2020)

V. AIM AND OBJECTIVES OF THE STUDY

This research aims to design and evaluate an ensemble adaptive neuro-fuzzy inference system for early detection of premature Heart attacks, and the objectives are to:

- i. Collect a diverse patient medical dataset with demographic, clinical, and lifestyle data, including age, cholesterol, blood pressure, ECG, and family history of heart disease.
- ii. Utilize the dataset to train the ANFIS model to identify patterns and associations indicating early heart attacks.

- iii. Develop the ANFIS model by combining neural network learning and fuzzy logic principles.
- iv. Evaluate the efficacy of the ANFIS model with relevant performance measures

Compare the performance of the proposed model with other ensemble models

VI. LITERATURES REVIEWED

Table 1: Summary of literatures reviewed

Table 1 below showed the literatures reviewed of the study.

Year / Authors	Methods Used	Key Findings	Weaknesses	Identified Research Gap
Zheng et al. (2015)	SVM on heart sounds and ECG data	Achieved >97% accuracy in murmur detection	Limited dataset; focused on signal data only	No integration of lifestyle or clinical risk factors
Benjamin et al. (2018)	RNN, CNN, NB, SVM	RNN outperformed other models in prediction accuracy	Poor interpretability; black-box nature	Lack of explainable and adaptive models
Jan et al. (2018)	Ensemble (RF, NB, SVM, ANN)	Ensemble outperformed	Relied only on UCI datasets	No real-time or adaptive learning

		individual classifiers (98.12%)		
Zabbah et al. (2018)	ANN + Neuro-fuzzy system	Hybrid model improved diagnostic accuracy	Small sample size	Limited scalability and feature diversity
Ansari et al. (2019)	SNP-based genetic analysis	Genetic markers influence CVD phenotype	Genetic data analyzed in isolation	No fusion with clinical or lifestyle data
Shah et al. (2020)	NB, DT, RF, KNN	RF showed good predictive performance	Limited to 14 attributes	Neglect of genetic and behavioral factors
Du et al. (2020)	SVM, KNN, ANN	SVM achieved 85.18% accuracy	Moderate accuracy; static models	No adaptability to evolving patient data
Pires et al. (2020)	NN, DT, KNN, SVM, SGD	Achieved up to 87.69% accuracy	Small validation set	Limited generalization
Vidhya & Shanmugalakshmi (2020)	ANFIS (lifestyle-based)	Effective risk-level classification	Excluded genetic and clinical markers	Incomplete risk assessment
Jawalkar et al. (2023)	Genetic Algorithm + NN	Improved prediction; high-risk age group identified	Offline training	No real-time adaptability
Dubey et al. (2022)	PSO + Feedforward NN	Optimized feature selection	High computational cost	Scalability and real-time issues
Balamurugan et al. (2022)	AHHO + Deep Evolutionary Algorithm	Achieved 97.3% accuracy	MATLAB-based; image-centric	Limited clinical interpretability
Manimurugan et al. (2022)	Hybrid HLDA-MALO + R-CNN	High accuracy (up to 99.15%)	Complex architecture	High computational overhead
Peng, Hou & Cheng (2023)	LR, RF, GB, NN on EMR	Demonstrated ML effectiveness on EMR	Interpretability issues	No fuzzy or hybrid reasoning
Sagias et al. (2024)	ANFIS-based classification	Accurate and interpretable predictions	Limited input parameters	Lack of ensemble learning
Migliaccio et al. (2024)	Dual ANFIS classifiers	ANFIS outperformed traditional models	Static rule base	No real-time optimization
Amar (2024)	FCM + SEM	Improved interpretability	Static weight matrix	No adaptive learning mechanism
Akayla & Swedha (2024)	Big data + data mining	Improved early detection	Prototype-level system	No neuro-fuzzy integration

VII. METHODOLOGY

a) Data Collection and Preprocessing

The dataset used in this study was retrospectively collected from patients aged 25 years and above who attended the cardiology department of the Federal Medical Centre (FMC), Jalingo, Taraba State. The dataset consisted of 918 records with 12 attributes,

including age, gender, chest pain type, resting blood pressure, cholesterol level, fasting blood sugar, ECG results, maximum heart rate, exercise-induced angina, ST depression, ST slope, and heart disease status. Patient anonymity was ensured by excluding personal identifiers.

Data preprocessing involved cleaning, handling missing values, converting categorical variables to numerical form, and normalizing continuous attributes to ensure compatibility with the ANFIS model.

b) Model Development

The proposed system employed Python as the programming language due to its extensive machine learning and fuzzy logic libraries. An ANFIS model was designed using fuzzy membership functions and rule-based inference. Clinically significant input variables were selected and represented using linguistic terms such as low, medium, and high.

An ensemble learning approach was adopted by integrating ANFIS with boosting and bagging techniques to enhance prediction robustness and generalization. The dataset was split into training and testing subsets, and a 10-fold cross-validation technique was applied to validate model performance.

c) Model Evaluation

The model was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. These metrics provided a comprehensive

assessment of the model’s predictive capability across both classes (presence and absence of heart disease).

VIII. RESULTS

a) ANFIS Model Evaluation

The classification report in table 1 showcases a high-performing model that effectively distinguishes between two classes (0 and 1). For class 0, the model achieves a precision of 0.95 and a recall of 0.92, indicating that when it predicts an instance as class 0, it is correct 95% of the time, and it successfully identifies 92% of all actual class 0 instances. Similarly, for class 1, the model demonstrates strong performance with a precision of 0.90 and a recall of 0.93, signifying that 90% of its class 1 predictions are accurate, and it captures 93% of all true class 1 instances. This balanced and high performance across both classes is further reflected in the overall accuracy of 0.92 and the high F1-scores for both classes (0.93 for class 0 and 0.91 for class 1), as well as the consistently high macro and weighted averages. This report signifies a robust and reliable classification model capable of accurately predicting the class membership of instances in this dataset

Table 2: Classification Performance of the Proposed Ensemble ANFIS Model Results

Class	Precision	Recall	F1-Score	Support
0 (No Heart Disease)	0.95	0.92	0.93	79
1 (Heart Disease)	0.90	0.93	0.91	100
Accuracy	—	—	0.92	179
Macro Average	0.93	0.93	0.92	179
Weighted Average	0.92	0.92	0.92	179

b) Mathematical Formulations

i. Precision (for class 0):

$$Precision_0 = TP_0 / (TP_0 + FP_0) \quad 1$$

Where TP₀ is the number of instances correctly classified as 0, and FP₀ is the number of instances incorrectly classified as 0 (they actually belong to class 1).

ii. Recall (for class 0):

$$Recall_0 = TP_0 / (TP_0 + FN_0) \quad 2$$

Where FN₀ is the number of instances of class 0 that were incorrectly classified as 1.

iii. F1-score (for class 0):

$$F1 - score_0 = 2 * (Precision_0 * Recall_0) / (Precision_0 + Recall_0) \quad 3$$

iv. Precision (for class 1):

$$Precision_1 = TP_1 / (TP_1 + FP_1) \quad 4$$

Where TP₁ is the number of instances correctly classified as 1, and FP₁ is the number of instances incorrectly classified as 1 (they actually belong to class 0).

v. Recall (for class 1):

$$Recall_1 = TP_1 / (TP_1 + FN_1) \quad 5$$

Where FN_1 is the number of instances of class 1 that were incorrectly classified as 0.

vi. F1-score (for class 1):

$$F1 - score_1 = \frac{2 * (Precision_1 * Recall_1)}{Precision_1 + Recall_1} \quad 6$$

vii. Accuracy: This is the total number of correctly classified instances divided by the total number of instances.

$$Accuracy = \frac{TP_0 + TP_1}{TP_0 + FP_0 + TP_1 + FN_1} \quad 7$$

The experimental evaluation of the proposed ensemble ANFIS model demonstrated strong predictive performance. The model achieved an overall accuracy of 92%, indicating a high level of correct classification.

For Class 0 (absence of heart disease), the model recorded a precision of 95%, recall of 92%, and F1-score of 0.93. For Class 1 (presence of heart disease), the precision was 90%, recall 93%, and F1-score 0.91. The macro and weighted average metrics further confirmed the consistency and balance of the model across both classes.

These results indicate that the proposed system effectively minimizes both false positives and false negatives, making it reliable for early heart attack risk detection.

IX. RESULT DISCUSSION

The proposed Ensemble Adaptive Neuro-Fuzzy Inference System (ANFIS) was evaluated using the cleaned and preprocessed dataset obtained from the Federal Medical Centre (FMC), Jalingo, and benchmark datasets. The dataset comprised clinically relevant attributes including age, blood pressure, cholesterol level, fasting blood sugar, ECG results, maximum heart rate, exercise-induced angina, and ST depression. The model was trained and validated using a 10-fold cross-validation technique to ensure robustness and minimize overfitting.

The experimental results indicate that the proposed model achieved an overall classification accuracy of 92%, demonstrating a high level of predictive

reliability. For Class 0 (absence of heart disease), the model recorded a precision of 95%, recall of 92%, and an F1-score of 0.93. Similarly, for Class 1 (presence of heart disease), the model achieved a precision of 90%, recall of 93%, and an F1-score of 0.91. These results reflect the model's balanced performance across both classes, with minimal bias toward either outcome.

The macro and weighted average metrics further confirm the consistency of the model's predictions. Both macro and weighted F1-scores were approximately 0.92, indicating that the ensemble ANFIS model maintained stable performance despite slight variations in class distribution. The high recall value for Class 1 is particularly significant in a medical context, as it implies that the model successfully identified most patients at risk of heart disease, thereby reducing the likelihood of false negatives.

The findings of this study demonstrate that the proposed Ensemble ANFIS model is effective for the early detection of premature heart attacks. The achieved accuracy of 92% compares favorably with many existing machine learning and neuro-fuzzy models reported in the literature, such as standalone neural networks, support vector machines, and conventional ANFIS implementations. The improved performance can be attributed to the integration of ensemble learning, which reduces variance and enhances generalization by combining the strengths of multiple learners.

The high precision and recall values indicate that the model is capable of making reliable predictions while minimizing misclassification. In particular, the strong recall for the positive class (heart disease presence) is critical for clinical applications, as early identification of at-risk patients can facilitate timely intervention and reduce mortality. This aligns with findings by Sagias, Zacharia, and Tempeloudis (2024), who emphasized the effectiveness of neuro-fuzzy systems in handling uncertainty in cardiovascular diagnosis.

Unlike deep learning models that often operate as black boxes, the ANFIS-based framework provides interpretability through fuzzy rules, allowing clinicians to understand how input factors such as

cholesterol, blood pressure, and age contribute to the final prediction. This transparency enhances trust and usability in real-world clinical environments. Furthermore, the adaptive learning capability of ANFIS enables continuous improvement of the model as new patient data becomes available, addressing a major limitation of static diagnostic systems highlighted in earlier studies.

The ensemble approach further strengthens the system by mitigating the weaknesses of individual models and improving robustness against noisy or incomplete data, which are common challenges in healthcare datasets. These results confirm that combining fuzzy logic, neural learning, and ensemble techniques offers a powerful and practical solution for early heart attack prediction.

X. FINDINGS

- The proposed Ensemble ANFIS model achieved a high prediction accuracy of 92%, indicating strong diagnostic capability.
- Balanced precision and recall values across both classes demonstrate reliable and unbiased classification performance.
- The model effectively reduces false negatives, which is crucial for early detection of heart attack risks.
- The integration of ensemble learning and ANFIS enhances robustness, adaptability, and interpretability compared to standalone models.
- The proposed system shows strong potential as an intelligent clinical decision-support tool for early diagnosis of premature heart attacks.

XI. CONCLUSION

This study successfully developed and evaluated an Ensemble Adaptive Neuro-Fuzzy Inference System for the early detection of premature heart attacks. By combining the learning capability of neural networks, the reasoning strength of fuzzy logic, and the robustness of ensemble learning, the proposed model effectively addressed the limitations of traditional and standalone machine learning diagnostic approaches. The experimental results, with an overall accuracy of 92% and high precision and recall values, confirm the

reliability and effectiveness of the model in identifying patients at risk of premature heart attacks. The interpretability of fuzzy rules further enhances clinical trust and usability, making the system suitable for real-world healthcare environments. Overall, the study demonstrates that ensemble ANFIS models can significantly support early diagnosis, timely intervention, and improved cardiovascular healthcare outcomes.

The high classification accuracy and balanced performance metrics demonstrate that the ensemble ANFIS model outperforms traditional diagnostic approaches and offers a reliable clinical decision-support tool. The system has the potential to assist healthcare professionals in early diagnosis, improve patient outcomes, and reduce mortality associated with cardiovascular diseases.

a) Recommendations

Based on the findings of this study, the following recommendations are made:

- **Clinical Adoption:** Healthcare institutions should consider integrating ensemble ANFIS-based decision-support systems to assist clinicians in early heart attack risk assessment.
- **Data Expansion:** Hospitals and medical centers should encourage systematic collection of comprehensive and high-quality cardiovascular data to further improve model performance.
- **Training and Awareness:** Medical personnel should be trained on the use and interpretation of intelligent diagnostic systems to enhance acceptance and effective utilization.
- **Policy Support:** Government and health policymakers should support the deployment of intelligent health monitoring systems, particularly in resource-limited settings, to reduce cardiovascular mortality.

b) Further Studies

- Future research may explore the following directions:
- Incorporation of genetic, behavioral, and lifestyle data to enhance personalized heart attack risk prediction.

- Development of real-time and IoT-based ANFIS systems using wearable sensors for continuous cardiovascular monitoring.
- Comparative evaluation of the proposed model with deep learning and explainable AI (XAI) frameworks.
- Optimization of ANFIS parameters using advanced metaheuristic algorithms to further improve accuracy and computational efficiency.
- Deployment and validation of the model in large-scale, multi-center clinical environments to assess scalability and generalizability

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