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Research Article

A Comparative Study of ANFIS and TANFIS Hybrid Techniques for Prediction of Heart Disease

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Abstract
Smart clinical decision support (SCDS) system enhances the accuracy and reduces the error in the diagnosis of a disease. But it requires huge clinical datasets and smart algorithms for taking better decision. In last few decades many smart hybrid algorithms have been evolved for the prediction of heart diseases. Adaptive Neuro Fuzzy Inference System (ANFIS) and Internet of Things (IoT) based Tuned Adaptive Neuro Fuzzy Inference System (TANFIS) are two smart hybrid algorithms have shown good accuracy in prediction. This study utilizes the Cleveland heart disease dataset for a comparative study about the accuracy of these two methods in the prediction of heart diseases. We also evaluate the accuracy of TANFIS as a remote SCDS system, when clinical data is fused with online data gathered through IoT.

Keywords: Smart clinical decision support (SCDS), Adaptive Neuro Fuzzy Inference System (ANFIS), Tuned Adaptive Neuro Fuzzy Inference System (TANFIS), heart disease.

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1. Introduction

Heart disease continues to be a major cause of illness and death globally, highlighting the need for improved predictive tools to support early diagnosis and timely intervention. The advent of intelligent systems has significantly revolutionized healthcare, particularly in the realm of Clinical Decision Support Systems (CDSS). Among these, Adaptive Neuro-Fuzzy Inference System (ANFIS) and its variant, Type-2 [1] Adaptive Neuro-Fuzzy Inference System (TANFIS) [2], have emerged as powerful tools in predicting heart disease.

ANFIS integrates the learning capabilities of neural networks with the human-like reasoning style of fuzzy logic, creating a hybrid system that can handle the uncertainties and nonlinearities inherent in medical data. On the other hand, TANFIS extends this approach by incorporating interval type-2 fuzzy logic [3], which provides an additional layer of robustness against uncertainties and variations in the input data, thereby potentially enhancing predictive accuracy [4]. Heart disease is a dangerous condition that damages heart function and can central to stern problems like coronary vein impurity and compact blood pitcher hole, excessive blood pressure, diabetes, an irregular heartbeat, and excessive cholesterol are among the concomitant risk factors linked to heart disease [5]. The integration of sensors with the human body has led to a rapid development in the use of IoT for healthcare data in recent years. With the use of cardiac echo pictures from an echocardiography, heart disease can be estimated. Predicting cardiac illness is a very difficult task, which makes it a time-consuming process for the physicians [6].

This comparative study aims to evaluate the effectiveness of ANFIS and TANFIS in predicting heart disease, focusing on their accuracy, computational efficiency, and ability to manage uncertainty in clinical data [7]. By leveraging a dataset comprising various risk factors for heart disease, we aim to provide a comprehensive analysis of these two intelligent systems, highlighting their strengths and identifying areas for improvement. This research not only contributes to the academic discourse on intelligent systems in healthcare but also holds practical implications for the development of more reliable and efficient CDSS, ultimately aiding clinicians in making informed decisions for better patient outcomes. ANFIS-PSO is a model designed to analyze positron emission tomography pictures of squamous cell carcinoma. The efficacy of this approach in identifying laryngeal cancers from clinical datasets was validated. The ANFIS-PSO model is contrasted with self-organizing map classifier, fuzzy C-means, ANN, and KNN. This paradigm causes an algorithm's temporal complexity because the input data varies [8]. Many researchers also employed FIS techniques to solve real-world challenges [9-23]. 3. ANFIS modeling technology has been used for heart diseases, health care industries and other medical purpose in previous studies [24-37].

In the following sections, we will delve into the theoretical foundations of ANFIS and TANFIS, review related works, describe the methodology adopted for this study, present and discuss the findings, and conclude with insights and recommendations for future research.

2. Data & Methodology

2.1 A suggested smart IoT-based system for predicting heart disease

Three layers make up the framework: the cloud layer, the fog layer, and the Internet of Things layer. Fig.1 illustrates the general paradigm for the suggested heart disease prediction.

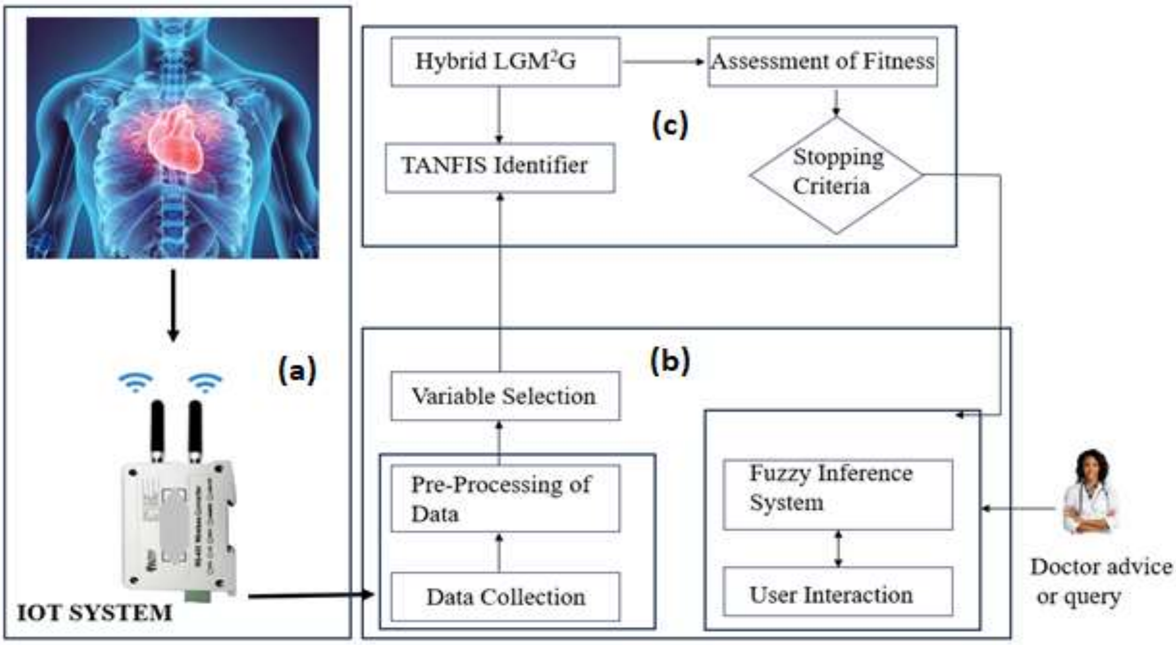

Fig. 1: Flow Chart of heart disease prediction of patient, (a) IOT system Layer, (b) Fog Layer, (c) Cloud Layer

(a) Internet of Things layer: The first layer initiates the data collection process, typically obtaining information from sensors. The primary function of this layer is to manage environmental data in real-time. It compiles data on the patient, including parameters linked to their health that can remain tracked at all besides sent to a cloud stage. This opens the door near improving the healthcare system's affordability and accessibility. Furthermore, the IoT layer will create enormous amounts of data faster. The collected data has been used to forecast a range of illnesses, enabling patients to receive treatment sooner.

(b) The Fog layer: Wearable sensor data collecting can be used to complete the data acquisition process. For a computer to process the data, this attempts to convert the samples of a patient's physical health status in the actual world into statistical numbers. The smart healthcare devices in an IoT healthcare environment enabled by fog encompass the collection and real-time monitoring of data. The collected data is stored in a fog layer to prepare it for pre-processing. The processed data is then subjected to clinical illness detection at the cloud layer.

(c) The Cloud layer: The distributed computing proficiency in data processing and storage allows it to perform a variety of tasks. As a matter of fact, the cloud layer maintains data storage and its operations for an extended period, whereas the vapor coating provides limited loading size. The patient, a knowledgeable physician, a reserve structure, household followers, before all prompt interposition can all function as the user interaction engine.

2.2 The TANFIS

The TSK-type Adaptive Network-based Fuzzy Inference System (TANFIS) classifier is a hybrid model that integrates fuzzy logic with neural networks to provide robust classification capabilities. This methodology leverages the strengths of both fuzzy systems, which handle uncertainty and imprecision, and neural networks, which learn from data to create a powerful classification tool. The TANFIS classifier combines the TSK-type FIS with the adaptive capabilities of neural networks, creating a system that can learn from data while handling imprecision and uncertainty.

2.2.1 Architecture framework

a) Input Layer: Receives the input features.
b) Fuzzification Layer: Transforms the inputs into fuzzy sets using membership functions.
c) Rule Layer: Represents the fuzzy rules. Each node corresponds to a fuzzy rule.
d) Normalization Layer: Normalizes the output of each rule to ensure they sum to one.
e) Consequent Layer: Implements the linear functions that form the consequents of the fuzzy rules.
f) Output Layer: Aggregates the consequents to produce the final output.

2.2.2 Detailed Steps

Initialization

- **Membership Functions**: Define the initial membership functions for the fuzzy sets.
- **Fuzzy Rules**: Initialize the fuzzy rule base. Typically, the rules are set based on expert knowledge or clustering techniques.

Training

1. **Data Collection**: Gather and preprocess the training data.
2. **Forward Pass**: Pass the inputs through the network:
   - o Fuzzify the inputs using the membership functions.
   - o Apply the fuzzy rules to generate rule outputs.
   - o Normalize the rule outputs.
   - o Compute the weighted sum of the normalized outputs using the linear consequents.
3. **Error Calculation**: Compare the network output with the desired output to compute the error.
4. **Backward Pass**: Adjust the parameters:
   - o **Membership Functions**: Update using gradient descent to minimize error.
   - o **Rule Parameters**: Adjust the parameters of the linear consequents using learning algorithms such as least squares estimation.
5. **Iteration**: Repeat the forward and backward passes until the error converges to an acceptable level or a predefined number of epochs is reached.

Inference

Once trained, the TANFIS classifier can classify new inputs:

1. **Fuzzification**: Convert the new input into fuzzy sets.
2. **Rule Evaluation**: Implement the fuzzy rules on the input after it has been fuzzified.
3. **Normalization**: Normalize the rule outputs.
4. **Aggregation**: Compute the final output by aggregating the normalized rule outputs.

Advantages and Applications of TANFIS

- **Adaptability**: Learns from data, improving its performance over time.
- **Robustness**: Handles noisy and imprecise data effectively.
- **Interpretability**: The fuzzy rules provide an interpretable framework for decision-making.
- **Nonlinearity**: Capable of modeling complex nonlinear relationships between inputs and outputs.

The TANFIS classifier is suitable for various applications, including:

- **Pattern Recognition**: Identifying patterns in data such as recognition of images or speech.
- **Medical Diagnosis**: Classifying medical conditions based on patient data.
- **Financial Forecasting**: Predicting market trends and stock prices.
- **Control Systems**: Implementing adaptive control strategies in engineering systems.

The TANFIS classifier merges the strengths of fuzzy systems and neural networks to create a versatile and powerful classification tool. Its ability to learn from data while managing uncertainty makes it ideal for complex and real-world applications. Through a structured approach to initialization, training, and inference, the TANFIS classifier offers an effective solution for a variety of classification challenges.

2.3 Methodology of Hybrid LGM^{2}G

Hybrid optimization methods are designed to leverage the strengths of multiple optimization techniques to solve complex problems more efficiently. The Hybrid Local Gradient Method with Genetic Algorithm (LGM2G) combines the deterministic local search capabilities of the Local Gradient Method (LGM) with the global search abilities of the Genetic Algorithm (GA). This synergy aims to provide a robust approach for finding high-quality solutions in complex, multi-modal optimization landscapes.

2.3.1 Local Gradient Method (LGM)

Concept

The Local Gradient Method (LGM) is a gradient-based optimization technique that uses the gradient of the objective function to guide the search for an optimum. It is effective for fine-tuning solutions in the vicinity of local optima due to its fast convergence properties.

Steps

1. **Initialization**: Begin with an initial guess X_0.
2. **Gradient Computation**: Calculate the gradient $\nabla F(X_k)$ of the objective function F at the current point X_k
3. **Step Size Determination**: Choose an appropriate step size α using methods such as line search.
4. **Update Rule**: Update the current solution as $X_{k+1}=X_k-\alpha\nabla F(X_k)$
5. **Convergence Check**: Continue the process until the norm of the gradient $\|\nabla F(X_k)\|$ falls below a pre-set threshold ϵ.

2.3.2 Genetic Algorithm (GA)

Concept

GA are evolutionary algorithms encouraged through the ideologies of ordinary variety and genetics. They are adept at exploring a wide search space and avoiding local optima, making them suitable for global optimization problems.

Steps

1. Initialization of the Population: Construct a starting population of possible answers.
2. Selection: Determine each person's level of health and choose parents for reproduction based on that evaluation.
3. Crossover: Using crossover operations, combine parent pairs to create offspring.
4. Mutation: To preserve genetic diversity, give some offspring random mutations.
5. Replacement: Provide infants to replace the population's least suitable members.
6. Convergence Check: Keep going until a stopping criterion meets the criteria, either by setting a maximum number of generations or achieving a target level of fitness.

2.3.3 Hybrid LGM^{2}G Optimization

The Hybrid LGM2G optimization method aims to combine the local refinement capabilities of LGM with the global search strength of GA to improve convergence speed and solution quality.

Framework

1. **Initialization**:
   - Generate an initial population for the GA.
   - Apply LGM to each individual in the population to refine them locally.
2. **Genetic Algorithm Phase**:
   - **Selection**: Evaluate and select the best individuals for reproduction.
   - **Crossover and Mutation**: Generate offspring using crossover and mutation operations.
   - **Local Refinement**: Refine each offspring using LGM.
   - **Replacement**: Update the population with the refined offspring.
3. **Iteration**: Continue the GA phase, incorporating local refinement, for a set number of generations or until convergence criteria are met.
4. **Convergence**: The process terminates when the convergence criteria are satisfied, yielding the final optimized solution.

2.3.4 Detailed Procedure

Initialization

- **Population Generation**: Randomly create an initial population $P=\{X_1, X_2,\ldots X_N\}$
- **Local Refinement**: For each individual X_i in P, refine using LGM:

1. Compute the gradient $\nabla f(X_i)$
2. Determine the step size α.
3. Update X_i using $X_i = X_i - \alpha\nabla f(X_i)$
4. Continue iterating until convergence is reached or the maximum number of iterations is achieved.

Selection

- **Fitness Evaluation**: Evaluate the fitness of each refined individual.
- **Selection Method**: Utilize a selection technique, such as roulette wheel or tournament selection, to pick individuals for reproduction.

Crossover and Mutation

- **Crossover**: Combine selected pairs to produce offspring using methods such as single-point, multi-point, or uniform crossover.
- **Mutation**: Introduce mutations in the offspring at a predefined rate to ensure diversity.

Local Refinement

- **Gradient-Based Refinement**: Apply LGM to each offspring:

1. Compute the gradient ∇F
2. Determine step size α
3. Update the solution using gradient descent.
4. Continue iterating until convergence is reached or the maximum number of iterations is achieved.

Replacement

- **Fitness Evaluation**: Assess the fitness of the refined offspring.
- **Population Update**: Replace the least fit individuals in the population with the refined offspring.

2.3.5 Convergence Criteria

- **Generations**: Terminate after a fixed number of generations.
- **Fitness Threshold**: Stop when the objective function value reaches a predefined threshold.
- **Improvement Plateau**: End if there is no significant perfection in the best result over several generations.

The Advantages and Applications of Hybrid LGM^{2}G method offers multiple benefits such as Efficiency: Rapid local search combined with broad global exploration, Robustness: Effective in avoiding local optima in complex landscapes and Versatility: Applicable to diverse optimization problems in fields such as engineering, economics, and machine learning. The Hybrid LGM2G optimization technique effectively combines the strengths of both the Local Gradient Method and Genetic Algorithm. By integrating local and global search strategies, it achieves superior performance in solving complex optimization problems, making it a valuable tool for a wide range of applications.

2.4 Hybrid LGM2G adaptation using with the TANFIS classifier

Primary goal of using the mix technique LGM^2G algorithm is to move ideal weights into levels 4 and 5, hence optimizing the TANFIS classifier parameters. The information can be divided into two categories: datasets for training and testing, along with their respective parameter values. and the LGM^2G method is primarily responsible for retrieving the predicators. The membership function has subsequently been assessed using a fuzzy C-means method. Thus, it is possible to optimize and modify the TANFIS classifier weighted values using the hybrid LGM^2G algorithm. It explores whole regions that make it easier to reach the ideal parameter in order to find the best-weighted value. The fitness values are then determined using this equation after the TANFIS classifier has been trained with the ideal parameters.

$$Mean\ Square\ error = \sum_{i=1}^{n} \frac{(x_i - y_i)^2}{n} \quad \ldots\ldots\ldots\ldots\ldots. \quad Eq. 1$$

where n is the number of input sample sizes, y_i is the target output value, and x_i is the actual value. Typically, the fitness matrix is assessed using the error of mean square parameter. It is used to estimate regression performance outcomes without affecting the algorithm's computing cost. The least amount of error between the expected and actual output values can be used to determine which option is best. Lastly, the optimal solution is fed to classify the data, and Fig. 2 shows an illustration of the suggested TANFIS- LGM^2G approach.

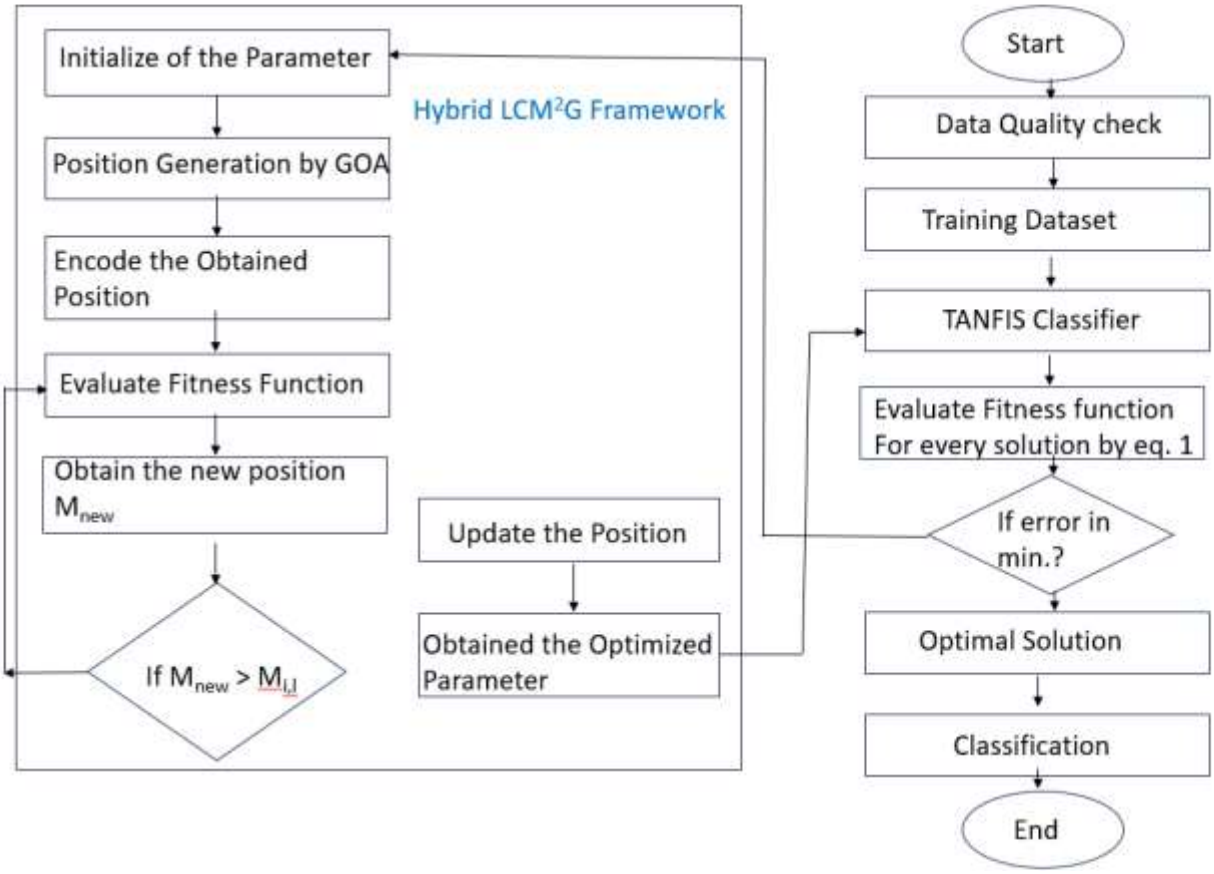

Fig. 2: Flowchart TANFIS- LGM^2G Coupled technique

3. Results and Discussion

Classification of heart disease

Heart disease is a significant clinical analysis difficulty and contributes significantly to global mortality rates. It multiplies the effects of other illnesses such as arrhythmia, hypertension, and stroke. Clinical examination used to be able to predict the disease. However, because it requires professionals, specialized care facilities, and well-equipped laboratories, clinical utilization has been restricted. Approximately 60% of individuals with heart disease nowadays died suddenly from their hearts. Therefore, it is necessary to provide an effective IoT model for real-time monitoring in order to diagnose heart illness in emergency situations.

The suggested algorithm is used in this article to forecast heart disease, and cloud along with haze layers are used to investigate the condition. Fig. 3 shows the proposed classification model's sequential process. Preprocessing of that information may be correct done in the haze layer, which helps with managing the fog layer's data storage and real-time environmental monitoring. The Cleveland database was used in the suggested strategy to identify the patient's cardiac condition. There are 250 patient details in the database, but six of those details are lacking data. The remaining 235 patient details are used for the preprocessing phase after the missing information is segregated. Out of these, 102 patient details indicate that heart disease is present, and the remaining 140 data show that heart disease is absent. Table 1 shows that out of the 56 traits that the dataset imputes, only 12 are changed in this simulation.

Fig. 3: Proposed model for heart disease arrangement

Preprocessing of the data: The UCI repository dataset is known to be used as input statistics for the prediction of the heart disease. During the stage that involves information preliminary processing noise is eliminated and absent statistics values are replaced. The relationship between feature selection application will be utilized to ascertain which features are most effective in identifying heart disease. The TANFIS classifier is equipped with the reduced features from the original dataset after feature selection for classification.

Categorization of data: Heart disease can be predicted by data analysis and categorization. The TANFIS classifier with underlying LGM^{2}G parameters is used in the suggested method.

The 13 characteristics are used as the last feature to indicate that a patient has cardiac disease during the diagnosis process. The property #58 num is a predictor of heart disease, with values ranging from 0 to 4. A severe severity of heart disease will be represented by a value of 4. Table 2 shows the selected features for 10 cardiac patients.

The Weka Explorer tool can be castoff to choose the correlation structures. The 62 features were included in the dataset on heart disease have been decreased to 11 features. The suggested model is trained and tested using the acquired features. To ensure data stability, data normalization is formulated with an interval of [0,1] for both input and output.

Table 1: Features that describe the UCI dataset

Attributes	Characterization	Datatype
#1 Age	Age in number of years	Numeric
#2 Sex	Gender (male is represented as 1 and female is represented as 0)	Nominal
#3 Chol	Serum Cholesterol Level (in mm/dl)	Numeric
#4 Trestbps	Blood pressure level at resting mode (in mm/Hg)	Numeric
#5 Restecg	Electrocardiographic results are depicted as: 0 for normal; 1 for abnormality, 2 Left ventricular hepertrophy	Nominal
#6 Exang	Exercise impelled angina Yes-1; No-0;	Nominal
#7Slope	• Slope of the peak exercise • Upsloping • Flat • Downsloping	Nominal
#8 FBS	Blood sugar level (fasting) is 120 mg/dl modeled as 1 =true and 0 = false.	Nominal
#9Thali	Attainment of maximum heart rate	Numeric
#10 Cp	Chest pain classified as: • Typical angina • Atypical angina • Nonanginal pain • Asymptotic	Nominal
#11 Oldpeak	Depression incepted through exercise with respect to rest.	Numeric
#12 Thal	Condition of the heart is categorized as: Normal-3 Fixed defect-6 Reversible defect-7	Nominal
#12Ca	Major vessels (0–3)	Numeric
#14 Num (target)	Prediction of heart disease Indicates the absence of heart disease Illustrates the presence of heart disease	Nominal

The TANFIS classifier was trained using the training dataset, and the performance of the TANFIS classifier parameters obtained by utilizing the LGM^{2}G optimization technique will be verified using the testing dataset. One possible way to divide the dataset is to use 70% of the samples for training and 30% for testing. For each dataset, there are 30 simulation runs and 100 iterations as the terminating criterion. Table 3 shows the outcome that the suggested TANFIS-LGM^{2}G approach produced for the training and testing dataset.

Comparing the exactness of the advised technique by various heart disease forecast methodologies is another significant addition of the current research, as indicated in Table 4. Since accuracy represents the percentage of heart disease cases correctly classified, it is often regarded as a key evaluation metric for classifiers. To replicate these tests, the identical dataset sample, training process, training methodology, and performance evaluation were all employed.

Table 2: Characteristics containing ten patients (Cleveland database)

Age	Cp	Trestbps	Thalach	Old peak	Restecg	Num (target)	Slope
45	2	120	182	0.6	0	1	1
60	1	145	162	1	1	1	1
57	3	120	170	2.2	0	1	2
43	2	130	150	3.4	0	0	2
34	3	110	158	3.1	1	0	0
39	2	135	152	2.8	1	0	1
20	2	140	176	0.8	0	0	1
65	o	130	172	1	1	0	1
25	o	120	165	3.2	0	1	0
62	1	120	159	2.7	1	1	0

As per the accuracy analysis, the suggested TANFIS-LGM^{2}G method achieves superior accuracy in comparison to the current cutting-edge methods. The suggested LGM2G algorithm's use of the Operator for Gaussian transformation, which balances the exploitation and exploration processes, is primarily responsible for this improved accuracy. with use the feature based on correlation selection methods, it also provides a greater classification rate, resulting in a higher accuracy of 99.44%.

Table 3: Heart disease data performance metrics

Performance Parameters	Training	Testing
Average error	.26342	.28654
Average fitness	.09321	.13254
Best fitness	.19342	.21341
Standard deviation	.23137	.36987
Worst fitness	.29878	.37321
Accuracy	99.44%	

As an alternative, the current algorithms require certain modifications to attain improved accuracy, which results in a number of constant parameters. Specifically, the MDCNN and HOBDBNN approach combines multiple hidden layers to execute convolution and apply the subsampling technique to extract attributes ranging from levels to lowest to higher. These two approaches addressed the identification of heart illness by utilizing the cuttlefish optimization algorithm based on mapping and morphological analysis. Nevertheless, the use of several shrouded layers increased computing complexity, resulting in an average accuracy of 99.03% and 98.2%, respectively.

Table 4: Comparison with proposed with existing methodology

Year	Methodology	Feature Selection	Environment	Accuracy (%)
2019	HOBDBNN [24]	IoT based wearable medical device	Median studentized residual approach	99.03
2020	MDCNN [25]	IoT	Mapping-based cuttlefish optimization algorithm	98.20
2024	Proposed TANFIS-LGM^{2}G	IoT+Fog+Cloud	Correlation approach	99.44

Based on the analysis above, the following conclusions can be drawn: The proposed TANFIS-LGM2G method demonstrates superior performance in heart disease classification. It effectively combines the strengths of the LGM2G algorithm, striking a balance between exploration and exploitation. This approach enhances convergence and reduces diversity loss, thereby lowering computational complexity. Additionally, the method is optimized to achieve the global optimum while avoiding local optima, all with minimal iterations.

Conclusion

The Internet of Things (IoT) framework provides numerous advantages for smart healthcare applications. This study introduces an advanced IoT-based system that efficiently detects and categorizes heart disease by utilizing smart sensors to collect patient healthcare data. The LGM2G algorithm improves the equilibrium between exploration and exploitation within the search space, helping the optimization process identify optimal parameters for the TANFIS classifier during its training phase. Performance was assessed in MATLAB through multiple simulation scenarios across diverse datasets, allowing a comparative evaluation of the proposed TANFIS-LGM2G method against other optimization techniques, the TANFIS-LGM^{2}G method demonstrated superior performance with an accuracy of 99.44%, a best fitness score of 0.22125, and an average fitness score of 0.09234. These accuracy results highlight the reliability and resilience of the proposed approach TANFIS-LGM^{2}G technique, indicating its potential to significantly enhance a clinical decision-making system designed to provide precise heart disease diagnoses.

Currently, the framework's secure access to healthcare data is not addressed by the suggested method. Subsequent research endeavors ought to concentrate on using blockchain technology to guarantee safe data transfer, employing inventive security algorithms to augment data confidentiality in the Internet of Things environment.

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