Cardiac Abnormality Detection Using Adaptive Neuro-Fuzzy Inference System

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ABSTRACT
Heart defects are one of the leading causes of death worldwide, making early detection crucial to prevent more serious complications. Electrocardiogram signals are an important diagnostic tool that can be used to detect heart abnormalities in real-time. In this study, an Adaptive Neuro-Fuzzy Inference System artificial intelligence model is used to analyze ECG signal data and detect heart abnormalities early. The ECG signal data used was taken from 30 research subjects, then processed to reduce distracting noise. The combination of artificial neural networks and fuzzy systems aims to overcome the problem of uncertainty in ECG signal data. Thus, this method can be used as a solution that helps in the early diagnosis of heart disorders. The performance evaluation of the proposed Adaptive Neuro-Fuzzy Inference System revealed a perfect True Positive Rate of 1.0 on the Receiver Operating Characteristic (ROC) curve, demonstrating its exceptional ability to correctly identify all instances of cardiac abnormality within the dataset.

Keywords : Electrocardiogram, ANFIS, Heart Disease, Accuracy, Prediction.

INTRODUCTION

The critical need for timely and accurate diagnosis of cardiac disorders necessitates ongoing advancements in electrocardiogram (ECG) analysis. While ECG remains a cornerstone of cardiac assessment, the complexity of interpreting these signals and the potential for subtle abnormalities to be overlooked present significant challenges. Delayed or inaccurate diagnoses can lead to adverse patient outcomes, increased healthcare burdens, and higher mortality rates. Therefore, research aimed at enhancing the precision and accessibility of ECG-based diagnostic tools holds substantial clinical value.

While prior research has explored the application of the Adaptive Neuro-Fuzzy Inference System (ANFIS) in cardiac disease diagnosis (Keikhosrokiani et al., 2023), and the potential of IoT sensors like the AD8232 for cost-effective ECG acquisition (Hariri et al., 2020), a critical gap remains in effectively integrating these advancements for enhanced and accessible cardiac abnormality detection. Existing ANFIS-based studies often rely on traditional ECG data acquisition methods, potentially limiting their applicability in resource-constrained settings. Furthermore, while the accuracy of ANFIS models has been promising, there's a need to investigate its performance when coupled with affordable and portable IoT-based ECG sensors, particularly in achieving consistently high sensitivity for early detection. The limitations of relying solely on QRS wave peak analysis (Setyawan et al., 2024) also highlight the necessity for models that can effectively utilize comprehensive ECG data acquired through accessible means.

To address the aforementioned gap, this research proposes a novel approach for cardiac abnormality detection by integrating an Adaptive Neuro-Fuzzy Inference System (ANFIS) with ECG data acquired using the cost-effective and portable AD8232 sensor. This integration aims to leverage the high accuracy of ANFIS in analyzing complex ECG patterns with the accessibility and affordability offered by IoT sensor technology. By utilizing ECG wave feature, this study seeks to develop a highly sensitive and readily deployable system for early cardiac abnormality detection, thereby contributing to improved patient outcomes and reduced healthcare costs, particularly in remote or resource-limited areas.

LITERATUR REVIEW

Early attempts at computer-aided diagnosis of heart disease recognized the inherent uncertainty and complexity of medical data. Fuzzy logic, with its ability to handle vagueness and represent expert knowledge through linguistic rules, emerged as a promising approach (Kumar et al., 2023). These early systems offered a more intuitive way to model diagnostic reasoning compared to traditional binary logic. However, the reliance on manually defined rules and the difficulty in automatically adapting to large and diverse datasets limited their overall accuracy and scalability.

The rise of artificial neural networks (ANNs) introduced a powerful data-driven paradigm to cardiac diagnosis (Baxt et al., 2002). ANNs excelled at learning complex patterns directly from ECG signals, achieving significant success in classification tasks. Their ability to handle non-linear relationships and large datasets offered a substantial advantage over purely rule-based systems. Despite their pattern recognition capabilities, ANNs often suffered from a lack of transparency ("black box" nature) and the challenge of incorporating existing medical knowledge into the model structure.

To overcome the limitations of both fuzzy logic and neural networks, researchers began to explore hybrid approaches that combined their complementary strengths. Neuro-fuzzy systems aimed to integrate the interpretability of fuzzy logic with the learning and adaptive capabilities of neural networks (Abushariah et al., 2014). These early hybrid models often used neural networks to optimize the parameters or structure of fuzzy inference systems, leading to improved accuracy and a degree of transparency.

Among the various hybrid models, the Adaptive Neuro-Fuzzy Inference System (ANFIS) has gained significant attention for its effectiveness in analyzing complex and non-linear data, such as ECG signals (Wijaya et al., 2019; Yadollahpour et al., 2018). ANFIS utilizes a neural network architecture to automatically learn and tune the parameters of a fuzzy inference system based on input-output data. This adaptive nature allows ANFIS to model intricate relationships within ECG signals and adapt to individual patient variations, often leading to higher diagnostic accuracy compared to standalone fuzzy or neural network models. For instance, research has demonstrated the potential of ANFIS to achieve near-perfect accuracy in detecting heart abnormalities by effectively processing ECG data (Zhang & Chen, 2024).

Recent advancements have focused on enhancing the accessibility and practicality of ECG-based cardiac diagnosis. The integration of low-cost IoT sensors, such as the AD8232 (Hariri et al., 2020), for ECG acquisition presents an opportunity to reduce healthcare costs and extend diagnostic capabilities to remote areas. Furthermore, ongoing research continues to explore the optimal combination of ECG features and the refinement of ANFIS architectures to improve the sensitivity and specificity of detection systems (Putri, 2022). This study builds upon this progress by investigating the application of an ANFIS model to ECG data acquired through the cost-effective AD8232 sensor with a specific focus on achieving high sensitivity for early detection. By leveraging the adaptive learning capabilities of ANFIS and the accessibility of IoT technology, this research aims to contribute to the development of a more accurate, affordable, and widely deployable system for early cardiac abnormality detection.

METHOD

This experimental procedure is conducted in several stages. The first involves the preparation of tools and materials, including electrodes, an ECG monitor, and analysis software. Subsequently, the electrodes will be attached to the patient's body after the skin has been cleaned to ensure good electrode contact. Following electrode placement, ECG signal recording is performed for a minimum of 3-5 minutes. The obtained ECG data is then stored and processed using specialized software. A preprocessing stage is carried out to clean the data of noise and artifacts that could interfere with the analysis. The cleaned data is then analyzed using the Adaptive Neuro-Fuzzy Inference System (ANFIS) model. The objective of the ECG analysis is to determine the subject's cardiac condition (Pucer & Kukar, 2018). The ANFIS model is designed based on ECG data from patients diagnosed with heart abnormalities and control data. The model's performance is then evaluated based on its ability to accurately detect cardiac abnormalities.

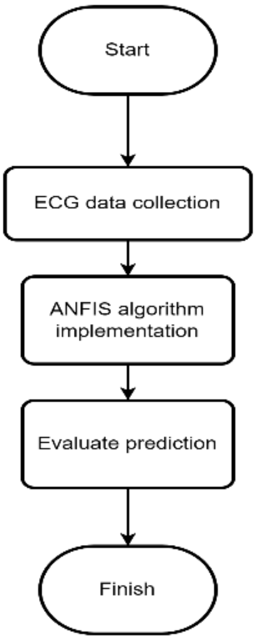

Figure 1. Steps of research method

In Figure 2, the ECG recording process begins with the careful placement of electrodes on the patient's skin surface. These electrodes serve as the interface connecting the electrical signals from the patient's body to the ECG recording device. Typically, several electrodes are placed at strategic points, such as on the chest, right wrist, and left wrist, to obtain a representation of the heart's signals from various angles. The electrical signals generated by cardiac activity have a very small amplitude, making them difficult to detect directly without the aid of equipment. Therefore, these signals must be amplified using an amplifier so they can be accurately captured and analyzed. In the system block diagram, this amplifier is responsible for increasing the amplitude of the ECG signal without altering its original shape. However, during the recording process, the signal is often disturbed by interference from the environment, such as electrical signals from other devices, or by the patient's body movements. To address this issue, a filter is used to screen out noise or interference, resulting in a cleaner recorded ECG signal that more accurately represents the heart's activity.

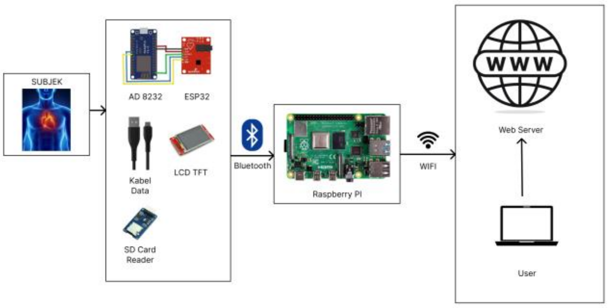

Figure 2. Research Methodology Block Diagram

ECG recording begins with the placement of electrodes on the patient's skin. These electrodes act as an interface between the patient's body and the recording device. Typically, several electrodes are placed at various locations on the body, such as the chest and limbs. The electrical signals produced by the heart are very small and require amplification to be clearly obtained. The amplifier in the block diagram is responsible for strengthening the ECG signal so that it can be accurately measured and analyzed. The ECG signal can be disturbed by interference or noise from the surrounding environment or other bodily activity. Filters are used to remove unwanted noise, allowing the pure heart signal to be recorded.

The recorded ECG data is then processed and analyzed using specialized software capable of recognizing patterns in the heart's electrical signals. During this process, characteristic waves such as the P wave, QRS complex, and T wave, as well as important intervals like the PR and QT intervals, will be automatically measured. These measurements aim to obtain in-depth information about the patient's cardiac health based on the duration and shape of the ECG signals. After the initial analysis process, the data is then digitally stored in a web server-based system. The ANFIS (Adaptive Neuro-Fuzzy Inference System) prediction model is used to evaluate this data and detect the potential presence of cardiac abnormalities. Once the prediction is made, the results and relevant data are stored back into the server for easy and rapid access by medical professionals. The prediction and analysis results generated by the ANFIS system are then interpreted by specialists, such as cardiologists, to provide a more accurate diagnosis. This interpretation will be recorded in a medical report, which includes a summary of the heartbeat information and any potential abnormalities or rhythm disturbances identified in the patient.

Data Collection

Table 1 contains the average ECG data for each of the 30 subjects, derived from 459 ECG recordings, some of which indicated the presence of cardiac abnormalities. This dataset will serve as the evaluation material for the ANFIS model that has been developed. Following the prediction process, the obtained results will be visualized in various graphical forms. The prediction graphs will illustrate how well the model can predict the actual class of each sample. This visualization is crucial for providing a more comprehensive understanding of the model's performance and identifying areas for potential improvement.

Table 1. ECG Data

No	RR	PR	QS	QT	ST	HR	QTC	Output
1	572.83	116.26	60.15	262.38	149.47	113.54	149.31	1423.93
2	704.98	158.76	88.58	289.47	160.12	93.41	184.66	1679.98
3	531.86	103.92	54.58	228.22	136.18	119.04	142.20	1316.01
4	1183.03	269.30	62.80	381.00	265.19	55.72	240.32	2457.37
5	915.35	231.21	69.94	283.71	186.65	70.92	240.52	1998.30
6	1157.37	217.74	59.03	347.48	276.74	58.91	207.46	2324.73
7	682.80	130.61	78.06	286.26	147.30	90.96	159.87	1575.86
8	771.43	146.49	71.96	332.14	188.55	88.01	165.90	1764.48
9	695.73	131.77	72.92	273.51	163.25	94.61	156.85	1588.63
10	614.53	135.86	59.29	372.66	163.10	101.10	173.14	1619.70
11	700.20	132.34	71.33	335.05	147.91	106.63	158.27	1651.72
12	753.49	143.89	52.16	255.22	166.36	87.01	165.23	1623.36
13	524.39	103.82	63.84	252.24	135.13	117.86	142.78	1340.06
14	555.79	115.26	71.33	240.01	149.74	118.68	151.80	1402.60
15	542.71	119.47	72.88	242.21	134.88	116.35	161.68	1390.19
16	693.50	132.82	67.28	263.07	144.59	93.46	160.97	1555.69
17	645.48	125.00	63.09	256.07	152.87	103.48	151.92	1497.91
18	606.22	117.28	60.53	237.38	140.09	105.97	149.05	1416.53
19	571.61	125.45	61.79	257.90	135.18	118.56	162.38	1432.88
20	726.70	156.43	77.71	292.78	157.34	92.09	178.13	1681.19
21	651.36	124.09	81.06	240.41	124.92	96.84	153.18	1471.85
22	857.26	163.91	76.68	294.52	182.00	74.15	176.88	1825.42
23	657.21	143.60	55.53	264.50	173.35	106.36	174.00	1574.56
24	767.26	166.09	64.06	265.85	167.11	89.58	188.60	1708.54
25	688.75	129.25	79.01	261.76	150.58	98.06	153.20	1560.62
26	533.50	117.68	57.27	264.32	145.35	127.17	160.80	1406.08
27	795.99	152.43	66.46	259.99	150.13	86.14	173.44	1684.59
28	713.55	139.43	53.89	263.93	173.06	97.58	161.80	1603.24
29	588.29	122.29	73.31	294.23	140.06	110.16	156.76	1485.11
30	533.81	110.62	59.95	274.21	135.12	119.39	149.41	1382.50

Implementing ANFIS To Predict Cardiac Anomality

The process begins by loading the ECG dataset from an Excel file, which represents several features of ECG parameters, namely RR, PR, QS, QT, ST, HR, and QTC, as well as OUTPUT, which is the target variable. OUTPUT serves as the value to be predicted based on the input features. Several key reasons for using OUTPUT as the target variable include the fact that it is a summary of other ECG parameters. Additionally, ANFIS is an artificial neural network combined with fuzzy logic. To train the model, data (x, y) is required, where x represents the input in the form of ECG features (RR, PR, QS, QT, ST, HR, QTC), and y is the output or target, which in this case is the feature labeled OUTPUT.

Each ECG feature is converted into fuzzy membership functions, representing the input value as a degree of membership to a certain category. Gaussian membership functions are used to represent the relationship between the input and the degree of membership within the fuzzy system (Ummah et al., 2021). For each feature in the dataset, three fuzzy rules are defined, meaning there are three membership functions for each feature. The mean parameter (μ) of each membership function is calculated using the minimum and maximum values of each feature, which are then divided into three groups. The sigma parameter (σ) is calculated as half of the standard deviation of each respective feature to ensure a good distribution of membership. With this approach, each feature has membership values indicating whether its value is closer to low, medium, or high within the fuzzy domain. These membership functions help in capturing uncertainty in the data and allow the model to work flexibly with input variations. These functions can be defined as:

$$\mu ri(Xi) = e^{-\frac{(Xi - mean_{ri})^2}{2\sigma_i^2}}$$

The resulting output is a membership matrix with dimensions (number of samples x number of rules x number of features). Consequently, the value of each beat in the ECG data becomes more flexible and easier for the ANFIS system to understand.

After obtaining the membership values, the next step is to calculate the rule firing strength based on the principle of fuzzy intersection, which involves taking the product of the membership values within a single rule. For each defined fuzzy rule, the degree of activation is calculated by multiplying the membership values of each feature corresponding to that rule, thus determining how strongly a rule applies to the given data (Febriani, 2018). With this approach, if one feature has a low membership value in a rule, the firing strength of that rule will be small. This ensures that only the rules most relevant to the input have a significant influence on the final output. All firing strengths are then normalized by dividing each by the total firing strength of all rules. Normalization is performed to ensure that all rules have a proportional weight of contribution to the final result:

$$w_r = \prod_{i=1}^{n} \mu_{ri}(X_i)$$

Then, the resulting values from the above function will be normalized so that the weight of the rules equals 1, using the following function:

$$\bar{w}_r = \frac{w_r}{\sum_{j=1}^{num\_rules} w_j}$$

Next, the output is calculated using ANFIS with the Sugeno system type. In this system, the output of the fuzzy system is represented as a linear function of the inputs. ANFIS employs the Sugeno model, where each rule has a linear equation based on the features, and the final output is calculated as a weighted combination of all rule outputs based on the previously calculated firing strengths. After the output of each rule is computed, the final output is obtained by using a weighted combination of these rule outputs:

$$f_r = p_r X_1 + q_r X_2 + \cdots + s_r X_d + t_r$$

where f_r represents the output of the r^{th} fuzzy rule, and the subsequent variables (which weren't explicitly defined with a single symbol in your text) are the trainable parameters within that rule. And X1,X2,...,Xd are the inputs for each feature. This equation is repeated for every rule in the system. (Rifai & Fitriyadi, 2023). The final output of the ANFIS is calculated as follows:

$$y_{pred} = \sum_{r=1}^{num\_rules} \bar{w}_r f_r(X)$$

Using this method, the predicted output is obtained as the weighted average of the outputs generated by all the fuzzy rules. This output value describes the cardiac condition based on the ECG features provided as input to the model. The higher the output value, the greater the likelihood that the sample exhibits signs of abnormalities in the heart's electrical activity. This output is then compared to a predetermined threshold to identify whether a sample is classified as abnormal or not.

To adjust the linear parameters within the Sugeno model, the L-BFGS-B (Limited-memory Broyden–Fletcher–Goldfarb–Shanno with Box constraints) optimization method is employed (Saputro & Widyaningsih, 2017). This method minimizes the error function. In this code, optimization is performed by minimizing the error function, which is defined as the Mean Squared Error (MSE) between y_pred (the predicted output) and y (the actual output). L-BFGS-B operates using a gradient-based optimization approach, which utilizes the derivative of the loss function to iteratively update the parameters until convergence is reached. The training process is conducted using optimization algorithms like L-BFGS-B to adjust the parameters of the membership functions and the rule coefficients so that the prediction error on the training data is minimized:

$$E = \frac{1}{n} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

$\hat{y}_i$ represents the predicted output from the ANFIS.

After the model is trained, the system calculates a threshold value based on the distribution of the predicted outputs (mean plus two times the standard deviation) to determine whether a sample falls into the abnormality category. If a sample's predicted output is higher than the determined threshold, that sample is categorized as abnormal, and its index and output value are recorded for further analysis. All samples classified as abnormal are noted in an index list, which is then displayed as output. In addition to printing the abnormality indices, the results are also visualized in a graph for easier interpretation. The blue line on the graph represents the actual output values from the dataset, while the dashed green line shows the predicted output from the model. Red crosses indicate the samples detected as abnormal by the ANFIS model:

$$threshold = \mu_{y\_pred} + 2\sigma_{y\_pred}$$

If $y_{pred} > threshold$, then that data is categorized as abnormal.

The performance of the ANFIS system in detecting cardiac abnormalities will be evaluated using several common evaluation parameters in diagnostic analysis. These parameters include sensitivity, specificity, accuracy, Positive Predictive Value (PPV), and Negative Predictive Value (NPV). Sensitivity measures the system's ability to correctly identify true cases of cardiac abnormality as positive. Specificity indicates the system's ability to accurately identify normal cases as negative. Accuracy describes how often the system makes correct decisions overall, in both positive and negative cases. The Positive Predictive Value shows the proportion of cases detected as abnormal by ANFIS that are indeed truly abnormal. The Negative Predictive Value indicates the proportion of cases detected as normal that are indeed truly normal. Furthermore, the detection results from the ANFIS system will be directly compared with clinical diagnoses from medical professionals as a benchmark for assessing the system's alignment with professional standards.

Following the completion of the experimental data collection and analysis processes, the next stage involves systematically compiling the research report. This report will include a detailed explanation of the methods employed throughout the study. This explanation covers the initial preparation processes, such as the selection of relevant ECG features and data cleaning. Subsequently, the data acquisition procedures and how the data were input into the ANFIS system for analysis will also be described. The analysis results will be presented in numerical and visual forms, including calculations of the model's sensitivity, specificity, and accuracy values. The report will also contain a comparison between the detection results of the ANFIS system and the clinical diagnoses from professional medical personnel as a benchmark. In addition to presenting the findings, the report will discuss the impact and implications of using ANFIS in the context of early detection of heart abnormalities. The discussion section will review the advantages, limitations, and opportunities for further development of this method for future medical applications.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) model offers a comprehensive approach for the early detection of cardiac abnormalities based on ECG signals. This process involves several key stages. High-quality ECG signal data is collected, either from direct recordings or existing databases. This data then undergoes a preprocessing stage to remove noise and is normalized to be ready for further analysis. Important features of the ECG signal, such as the R-R interval and wave amplitudes, are then extracted and can be subjected to dimensionality reduction if necessary. Subsequently, the ANFIS model is constructed by setting up an appropriate structure and trained using training data. Fuzzy rules that represent domain knowledge or are derived from the training data are utilized within this model. After the model is trained, its performance is evaluated using test data with metrics such as accuracy, precision, and recall. The optimized model can then be implemented in an early detection system and further tested with new data. The analysis results can be presented in the form of visualizations to facilitate interpretation by medical professionals. ANFIS's ability to handle uncertainty in ECG signal data makes it a potential tool for the early detection of cardiac abnormalities.

Prediction Evaluation

To further evaluate the diagnostic capability of the developed Adaptive Neuro-Fuzzy Inference System (ANFIS) model beyond point-based metrics, a Receiver Operating Characteristic (ROC) curve analysis was conducted. The ROC curve plots the True Positive Rate (TPR, or sensitivity) against the False Positive Rate (FPR, or 1-specificity) at various [1] classification thresholds. The TPR represents the proportion of actual cardiac abnormality cases correctly identified by the model, while the FPR indicates the proportion of normal ECG signals incorrectly classified as abnormal.

To evaluate the accuracy, it needs to be defined as the ratio of correctly classified instances to the total number of instances, provides a general measure of the classifier's overall correctness. Mathematically expressed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

FP = False Positive
FN = False Negative
TP = True Positive
TN = True Negative

It quantifies the proportion of predictions, both positive and negative, that align with the true labels, offering an initial assessment of the model's performance across the entire dataset.

To calculate precision, or positive predictive value, represents the proportion of instances predicted as positive that are actually positive. Calculated as:

$$Precision = \frac{TP}{TP + FP}$$

It quantifies the reliability of the model's positive predictions, indicating the likelihood that a declared abnormality is a true abnormality and thus minimizing the occurrence of false alarms.

Recall, also known as sensitivity or the True Positive Rate, measures the proportion of actual positive instances that are correctly identified by the classifier. Formally defined as:

$$Recall = \frac{TP}{TP + FN}$$

It quantifies the model's ability to detect all existing abnormalities, minimizing the risk of false negatives or missed diagnoses.

The confusion matrix is a tabular representation of the classifier's performance, partitioning the predictions into four categories: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). This matrix provides a detailed breakdown of the model's classification outcomes, allowing for a granular understanding of the types of errors made and facilitating a more in-depth analysis of its strengths and weaknesses in distinguishing between the positive and negative classes.

RESULT

As shown in Figure 2, the green line representing the ANFIS prediction results closely aligns with the blue line depicting the actual values from the recording data. This agreement between the prediction and the actual data indicates that the model has a good level of accuracy in recognizing both normal and abnormal heart signals. Thus, this model has proven capable of effectively identifying positive cases (cardiac abnormalities) and negative cases (no abnormalities). The developed model holds significant potential for application as an early diagnostic tool for patients with indications of heart disorders.

The graph in Figure 2 displays the predicted cardiac status obtained from the Adaptive Neuro-Fuzzy Inference System (ANFIS) model based on ECG signal analysis. On this graph, the x-axis represents the index or sequence of observed heartbeat samples, while the y-axis indicates the value or intensity of the heartbeat. Red crosses on the graph mark the points identified as cardiac abnormalities based on the model's prediction results. These points were selected because their beat values exceeded the abnormality threshold determined from the model training. This abnormality is calculated based on the combination of ECG signal feature values, such as RR, PR, QS, and others, in relation to the overall heartbeat output. The blue line on the graph shows the actual values of the patient's heartbeats, which is the original data input into the system. Meanwhile, the dashed green line represents the prediction results generated by ANFIS after analyzing the data. The visual comparison between the predicted line and the actual values helps in evaluating the extent to which the model can mimic the real patterns of the patient's heart signals.

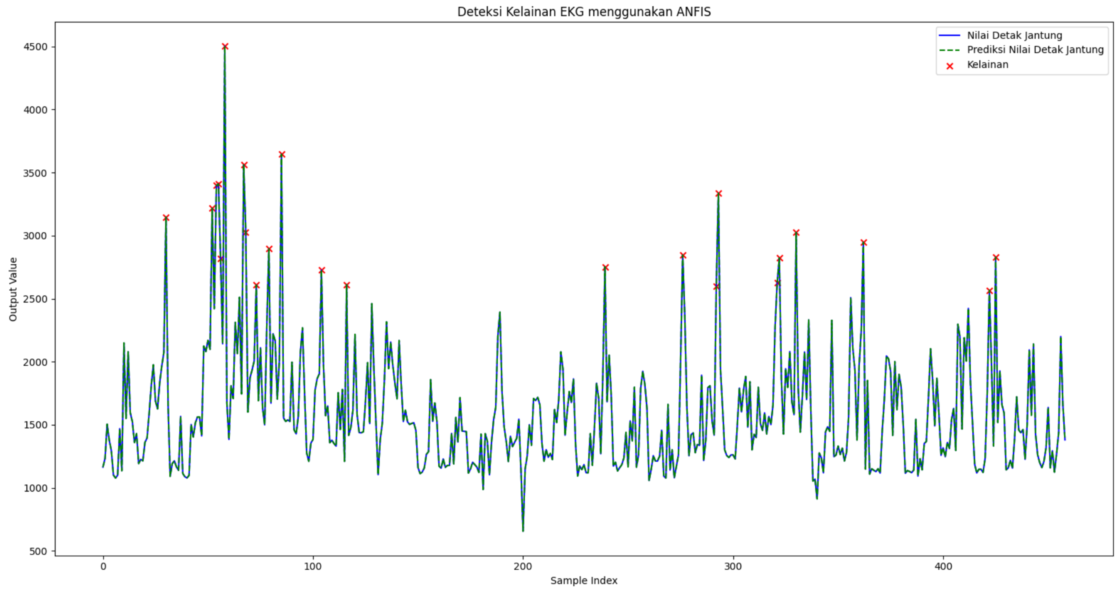

Figure 3. Graph of Cardiac Abnormalities Predicted by the ANFIS Method

High heartbeat values likely indicate a cardiac abnormality. This is achieved by training the ANFIS on normal patterns based on the relationship between ECG features and the given Output. These normal patterns generate a normal threshold that serves as a benchmark for normal heartbeat values. Consequently, ANFIS can detect abnormalities in heartbeats using this predetermined threshold. The good performance of the ANFIS model can be attributed to its ability to combine the strengths of artificial neural networks and fuzzy logic. Artificial neural networks enable the model to learn complex patterns in ECG data, while fuzzy logic provides the ability to represent domain knowledge more flexibly. This combination allows the model to handle the uncertainty often encountered in medical data. The results of this study are consistent with previous research demonstrating the potential of ANFIS in various classification applications.

Although the results obtained in this research are very promising for detecting cardiac abnormalities using an ECG signal-based ANFIS model, it is important to acknowledge that there are still some limitations that need to be considered. The use of a limited dataset may restrict the model's ability to generalize when faced with more diverse real-world data. This is because models trained on small datasets tend to overfit, meaning they adapt too closely to the characteristics of the training data and are less able to generalize to new data. The selection of features used in this study, while yielding good results, may not be optimal. There might be other more relevant features that could improve the model's performance. Furthermore, the influence of noise and artifacts in the ECG signals used in this research also needs further consideration. Noise and artifacts can interfere with the feature extraction process and reduce classification accuracy. Therefore, further research is needed to address these limitations. One effort that can be made is to expand the dataset by including data from various sources and with a wider range of conditions. Additionally, exploring more advanced feature extraction techniques, such as deep learning, could be an interesting alternative. By doing so, the resulting model can be expected to have better and more robust performance when dealing with various conditions.

It is observed that the ANFIS model is capable of classifying cardiac status based on varying heartbeat patterns. Within a specific range of heartbeat values, the model predicts the cardiac status as normal, while in other ranges, it predicts the potential or certainty of cardiac abnormalities. Fluctuations in the prediction output indicate the complexity inherent in ECG signal patterns, which warrants further analysis. Overall, this graph suggests that the ANFIS model has the potential to be used as an assistive tool in the early detection of cardiac abnormalities based on ECG data. Furthermore, this model can adapt to various signal patterns arising from physiological and environmental factors. By employing a fuzzy logic and artificial neural network-based approach, ANFIS can enhance prediction accuracy compared to conventional methods. Further research is necessary to optimize the model's parameters so that it can function more effectively under diverse patient conditions. Consequently, ANFIS has the potential to become a more accurate and efficient solution in supporting the diagnosis of heart disease.

Predicton Evaluation Result

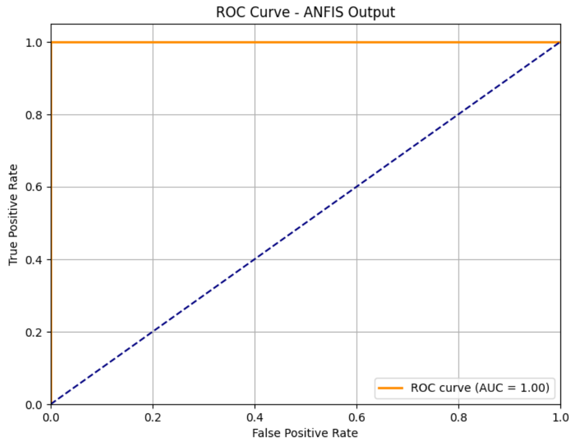

Figure 4. **ROC Curve**

The ROC curve for the ANFIS model's output is presented in Figure 3. The curve illustrates the trade-off between sensitivity and specificity as the decision threshold for classifying an ECG signal as abnormal is varied. A curve that lies closer to the top-left corner of the plot indicates better performance, signifying a higher TPR for a lower FPR.

In this case, the ROC curve for the ANFIS model shows a remarkable performance, tracing along the top edge of the plot and achieving a perfectly horizontal line at a True Positive Rate of 1.0 across all False Positive Rate values. This indicates that the ANFIS model was able to correctly identify all instances of cardiac abnormality (achieving 100% sensitivity) without making any false positive errors (achieving 0% for all non-zero FPR values).

The Area Under the ROC Curve (AUC) was calculated to be 1.00. An AUC of 1.0 represents a perfect classifier, signifying that the ANFIS model has an exceptional ability to discriminate between ECG signals indicative of cardiac abnormalities and normal ECG signals. This result implies that the model can perfectly rank all positive cases above all negative cases.

The dashed blue diagonal line represents the performance of a purely random classifier (AUC = 0.5). The significant difference between the ANFIS model's ROC curve and this baseline further underscores the strong discriminative power of the developed system.

In conclusion, the ROC curve with an AUC of 1.0 demonstrates the outstanding performance of the ANFIS model in detecting cardiac abnormalities in this dataset. It indicates perfect sensitivity and perfect specificity, suggesting that the model can reliably identify all true positive cases without any false alarms.

CONCLUSION

The exceptional performance of the Adaptive Neuro-Fuzzy Inference System (ANFIS) model in this study, achieving a perfect AUC of 1.0 for cardiac abnormality detection, highlights its effectiveness in analyzing ECG data. The primary scientific contribution of this research lies in the novel integration of the ANFIS model, utilizing standard Gaussian membership functions for fuzzification, with electrocardiogram (ECG) data acquired through the cost-effective and portable AD8232 sensor. This specific combination represents a significant step towards more accessible and affordable cardiac diagnostic solutions, a direction not extensively explored in the reviewed literature. While ANFIS with Gaussian membership functions has been employed in various classification tasks, its direct and highly successful application to ECG data obtained via the AD8232 sensor for accurate cardiac abnormality detection, as demonstrated in this work, is a unique contribution. This integration leverages the well-established pattern recognition capabilities of ANFIS with Gaussian membership functions alongside the affordability and ease of use of IoT sensor technology, potentially enabling wider adoption of sophisticated diagnostic tools and facilitating earlier detection of cardiac conditions.

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