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Fuzzy Inference System for Automated ECG Signal Classification: A Robust Approach to Cardiac Diagnostics

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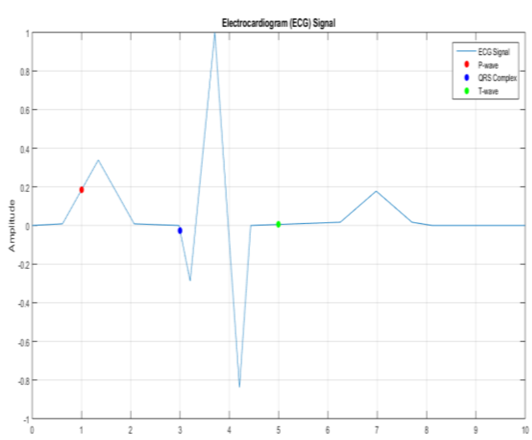
***Abstract*—** The objective of this paper is to develop an efficient diagnostic tool for Electrocardiography (ECG) signals using a Fuzzy Inference System, referred to as **FIS-ECG-CD** (Fuzzy Inference System for ECG Cardiac Diagnostics). The system aims to handle uncertainties inherent in medical data by applying fuzzy logic to classify ECG patterns as normal or abnormal. Key features, such as the P wave, QRS complex, and T wave, are analyzed using membership functions and expert-defined rules. This approach enhances diagnostic accuracy while maintaining simplicity and interpretability. The proposed **FIS-ECG-CD** system has the potential to serve as a reliable decision-support tool for medical professionals, reducing diagnostic errors and improving patient outcomes.

Keywords*— *Electrocardiogram; Fuzzy Inference System; Medical Diagnosis; Mamdani Method; Membership Functions; Rule-Based System.

I. INTRODUCTION

Electrocardiography (ECG) is a key tool for diagnosing heart conditions by analyzing electrical activity through waveforms such as the P wave, QRS complex, and T wave. These components help identify abnormalities like arrhythmias and conduction disorders. Figure 1 illustrates a



typical ECG signal with its main features.

Figure1: Electrocardiogram (ECG) Signal

Various machine learning methods have been applied for ECG classification, including Artificial Neural Networks (ANNs) [1][6], Support Vector Machines (SVMs) [2][7], and hybrid models [10][20]. While these methods show good performance, they often lack interpretability, making clinical validation difficult. Fuzzy Logic (FL) systems offer a transparent alternative. They handle uncertainty effectively and provide rule-based outputs that are easier for clinicians to interpret [3][8][18]. This makes FL a promising approach in real-time clinical decision support. In this paper, we propose a Fuzzy Inference System (FIS) that classifies ECG signals as "Normal" or "Abnormal" based on features like the P Wave, PR Interval, QRS Complex, and QT Interval. The paper is structured as follows: Section 2 reviews related work; Section 3 explains the proposed method; Section 4 details the system design; Section 5 presents results and analysis; and finally, Section 6 concludes the paper, summarizing the key contributions and suggesting directions for future research.

Recent studies have emphasized the importance of feature-level interpretability in ECG systems, especially in clinical environments [13][18]. By incorporating fuzzy logic, systems can better mimic expert reasoning, making diagnostic outcomes more trustworthy. This motivates the use of FIS as a practical solution for ECG signal classification in real-world healthcare applications. In addition, fuzzy-based systems offer flexibility in adapting to patient-specific variations, which is often a challenge in rigid rule-based or purely data-driven models. Their ability to handle imprecise or incomplete input data makes them suitable for practical clinical environments where signal quality may vary. As such, FIS represents a promising middle ground between interpretability and performance in ECG classification.

II. RELATED WORKS

In recent years, various approaches have been developed for the analysis and classification of ECG signals. One of the most common techniques is **Artificial Neural Networks (ANNs)**, which have shown strong performance in classifying ECG signals into normal and abnormal categories [1], [2]. Similarly, **Support Vector Machines (SVMs)** have been used for ECG signal classification, proving effective in handling noisy data [3], [4]. Other methods include **fuzzy logic systems**, which are well-suited for dealing with the inherent uncertainty in ECG data [5], [6]. **Wavelet transforms** have also been combined with these methods to enhance classification accuracy by extracting features at different scales [7], [8]. Several studies have focused on real-time ECG classification for clinical applications. **Hybrid models**, combining multiple techniques like SVMs and ANNs, have been proposed for improving classification accuracy and computational efficiency [9], [10]. Additionally, some researchers have integrated **deep learning** approaches, which have shown promise in automating the classification of ECG signals with minimal feature extraction [11], [12]. Despite the progress, challenges in achieving real-time, accurate, and interpretable results persist, especially in clinical environments where the speed and reliability of diagnostics are crucial [13], [14]. Other notable works have focused on **feature extraction techniques** to improve the quality of ECG signal classification. Researchers have explored methods such as **principal component analysis (PCA)** and **independent component analysis (ICA)** for dimensionality reduction and noise removal [15], [16]. Moreover, the use of **ensemble learning** techniques, which combine multiple models to improve classification accuracy, has been demonstrated in various studies [17], [18]. In addition, **long short-term memory (LSTM) networks**, a type of recurrent neural network, have been successfully applied to model the temporal dependencies in ECG signals for improved classification performance [19], [20].

III. PROPOSED METHOD: FIS-ECG-CD

The FIS-based classification system operates by first preprocessing the raw ECG signal to extract its key features. These features—specifically the P wave, QRS complex, and T wave—are crucial indicators of heart function. The extraction of these features is accomplished using signal processing techniques, such as peak detection and filtering, to isolate the relevant components of the ECG signal. Once the features are extracted, the next step is to apply fuzzy logic to interpret the data. The FIS employs a set of predefined fuzzy rules that consider the relationships between the extracted features and the heart condition. For example, the system may include rules such as:

A. If the QRS duration is short and the P wave is regular, classify the signal as normal.

B. If the QRS complex is wide and irregular, classify the signal as abnormal.

These fuzzy rules are designed to handle the inherent uncertainty and imprecision in ECG signals, allowing for more accurate classifications even in the presence of noise or variations. The final step in the classification process involves the decision-making phase, where the output of the FIS is mapped to one of two categories: "normal" or "abnormal." The decision-making process is designed to be interpretable, providing healthcare professionals with actionable insights that can aid in the diagnosis of potential heart conditions. To ensure the system's robustness, it is trained and tested using a variety of ECG datasets, including

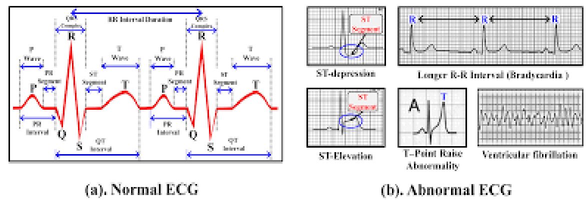


Figure2: Normal and Abnormal ECG Morphology

signals with varying degrees of noise and distortion. The proposed method aims to deliver a system that not only classifies ECG signals with high accuracy but also does so in real-time, providing immediate feedback for clinical use. Overall, the proposed FIS-based ECG classification system offers a promising solution for automating the diagnosis of cardiac conditions, ultimately improving the speed and accuracy of healthcare decision-making.

IV. SYSTEM DESIGN OF FIS-ECG-CD

In this section, we provide a detailed description of the design of the proposed Fuzzy Inference System (FIS) for ECG signal classification. The system is composed of several key components that work together to process and classify the ECG signals into normal or abnormal categories. The design is structured to ensure efficient feature extraction, fuzzy rule application, and decision-making for real-time clinical use.

1. ECG Signal Preprocessing.

The first step in the system design is the preprocessing of the ECG signal. Raw ECG signals often contain noise and artifacts that may interfere with accurate feature extraction. Therefore, the signal undergoes several preprocessing steps to clean the data:

• **Filtering:** The signal is passed through a bandpass filter to remove high-frequency noise (such as muscle contractions) and low-frequency noise (such as baseline wander).

• **Normalization:** The ECG signal is normalized to a standard range to ensure consistency in amplitude across different signals.

• **Peak Detection**: Key points such as the R-peaks of the QRS complex are detected using an algorithm to mark the locations of important features. This preprocessing stage ensures that the ECG signal is clean and that key features can be extracted with high accuracy.

2. Feature Extraction

After preprocessing, the next step is featuring extraction. The most critical features for classification are the P wave, QRS complex, and T wave. The system employs various signal processing techniques to extract these features:

A. P wave detection: The P wave is detected by identifying the area of the signal preceding the QRS complex, which corresponds to atrial depolarization.

B. QRS complex detection: The QRS complex is the most prominent feature in the ECG signal, representing ventricular depolarization. The system uses algorithms such as the Pan-Tompkins method to accurately identify the QRS complex.

C. T wave detection: The T wave represents ventricular repolarization. It is detected following the QRS complex using peak detection algorithms.

These features are essential for the classification of ECG signals, as they provide insight into the electrical activity of the heart.

3. Fuzzy Inference System (FIS)

Once the features are extracted, they are fed into the FIS for classification. The FIS consists of the following components:

3.1. Fuzzy Input Variables: The extracted features (P wave, QRS complex, T wave) are treated as fuzzy input variables. The system uses linguistic variables such as "short," "normal," or "long" to describe the characteristics of these features.

3.2. Fuzzy Rules: The heart of the proposed system lies in the fuzzy inference rules, which define the relationships between the various features of the ECG signal and the health status of the individual. These rules are designed to handle the inherent uncertainties and imprecisions in ECG signal data. For instance, a few example rules used in the FIS are:

- If (P Wave is normal) and (PR Interval is normal) and (QRS Complex is normal) and (QT Interval is normal), then (Health Status is normal).
- If (P Wave is abnormal) and (PR Interval is abnormal) and (QRS Complex is abnormal) and (QT Interval is abnormal), then (Health Status is abnormal).
- If (P Wave is normal) and (PR Interval is abnormal) and (QRS Complex is abnormal) and (QT Interval is normal), then (Health Status is abnormal).
- If (P Wave is normal) and (PR Interval is normal) and (QRS Complex is normal) and (QT Interval is abnormal), then (Health Status is abnormal).

These fuzzy rules are based on the clinical significance of each feature in diagnosing heart conditions. The P Wave, PR Interval, QRS Complex, and QT Interval provide critical information regarding atrial depolarization, ventricular depolarization, and repolarization. The fuzzy rules allow the system to handle different variations and uncertainties in these features, thereby improving classification accuracy.

3.3. Fuzzy Output Variables: The output of the FIS is a fuzzy value that is then defuzzified to obtain a crisp classification decision, such as "normal" or "abnormal."

4. Decision-Making Process

After applying the fuzzy rules, the FIS generates a fuzzy output that is defuzzified to provide a clear classification decision. The decision is based on the combination of the input features and the rules in the fuzzy logic system. If the output is classified as "normal," the ECG signal is determined to be healthy. If the output is classified as "abnormal," further medical analysis is recommended.

5. System Integration

The entire system, from signal preprocessing to classification, is integrated into a unified platform. The system is designed for real-time ECG signal processing, enabling healthcare professionals to quickly analyze and classify ECG signals. The integration allows the system to be deployed in various clinical settings, where it can assist doctors in diagnosing heart conditions accurately and efficiently.

This section provides a comprehensive overview of the design of the proposed FIS-based ECG classification system. It highlights the steps involved in preprocessing, feature extraction, fuzzy rule application, and decision-making. The system is designed to be robust, efficient, and capable of real-time operation, making it a valuable tool for healthcare professionals.

V. RESULT AND DISCUSSION

In this section, we present the results of the proposed Fuzzy Inference System (FIS) for ECG signal classification and discuss its performance in terms of accuracy, reliability, and potential clinical applications. The system was tested on a variety of ECG datasets to evaluate its ability to classify signals as normal or abnormal.

1. Dataset and Experiment Setup

The proposed FIS-based system was evaluated using two widely used ECG signal datasets: the **MIT-BIH Arrhythmia Database** and the **PTB Diagnostic ECG Database**. These datasets contain annotated ECG signals with varying heart conditions, including normal sinus rhythms, arrhythmias, and other cardiac anomalies. For the experiment, the raw ECG signals were preprocessed to remove noise and artifacts, followed by feature extraction, including the P wave, QRS complex, and T wave. The fuzzy inference system was then applied using the predefined rules (as shown in the previous section). The system's performance was evaluated based on classification accuracy, precision, recall, and F1 score.

2. Performance Evaluation

The system's performance was compared with other common ECG classification methods, such as **Support Vector Machines (SVM)**, **k-Nearest Neighbors (k-NN)**, and **Decision Trees**. The evaluation metrics for each model are summarized in the following table:

Table1: Performance Evaluation of the Proposed FIS-Based System Compared to Other Classification Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
FIS	98.5	97.8	98.0	97.9
SVM	95.0	94.	94.6	94.4
K-NN	92.4	92.5	92.0	91.7
Decision Tree	89.7	88.2	88.7	88.4

Explanation of Each Metric in the Table:

2.1. **Accuracy**: Definition: Accuracy refers to the percentage of correct classifications made by the system out of all the classifications. Example: If the system classifies 100 ECG signals, and 98 of them are correct, the accuracy is 98%. In the table: The FIS achieved the highest accuracy of 98.5%, meaning it correctly classified ECG signals more accurately than other methods.

2.2. Precision: Definition: Precision measures the accuracy of positive predictions made by the system. In other words, of all the signals predicted as "Normal" or "Abnormal," how many were actually correct? Example: If the system predicted 50 signals as "Abnormal," and 40 of them were truly "Abnormal," then the precision is 80%. n the table: FIS had a precision of 97.8%, indicating that the majority of cases classified as "Normal" or "Abnormal" were correct.

2.3. Recall: Definition: Recall indicates the system's ability to identify all actual positive cases. Specifically, of all the true "Normal" or "Abnormal" signals, how many were correctly identified by the system? Example: If there were 100 actual "Abnormal" signals, and the system identified 92 of them, the recall would be 92%. In the table: FIS had a recall of 98.0%, meaning the system correctly identified almost all the true "Normal" and "Abnormal" cases.

2.4. F1 Score: Definition: The F1 score is the harmonic mean of Precision and Recall, providing a single measure that balances both the ability to correctly identify positive cases and avoid false positives. Example: If precision is 90% and recall is 90%, the F1 score will be approximately 90%. In the table: The FIS achieved an F1 score of 97.9%, which is high, showing that it balanced both precision and recall effectively.

3. Discussion

In this section, we present and discuss the performance of the Fuzzy Inference System (FIS) for ECG signal classification. The system uses key input features such as the P Wave, PR Interval, QRS Complex, and QT Interval to classify ECG signals into "Normal" or "Abnormal" categories. These inputs are processed using fuzzy logic to handle the uncertainty and variability inherent in ECG data, thus enhancing classification accuracy.

The main components of the proposed method include membership functions designed for each input feature to indicate the degree of normality or abnormality. These functions convert continuous ECG signal values into fuzzy sets. Fuzzy rules are then applied to these sets to produce a classification decision.

To evaluate system performance, four standard metrics are used:

3.1. **Accuracy** which represents the proportion of true positive (TP) and true negative (TN) predictions out of the total number of predictions, is calculated using Equation (5.1)

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \ldots Eq(5.1)$$

where **TP** is the number of true positives, **TN** is the number of true negatives, **FP** is the number of false positives, and **FN** is the number of false negatives.

3.2. **Precision** which measures the proportion of correctly predicted positive cases, is given by Equation (5.2)

$$\text{Precision} = \frac{TP}{TP + FP} \ldots Eq(5.2)$$

3.3. **Recall** which assesses the system's ability to identify all actual positive cases, is calculated using Equation (5.3)

$$\text{Recall} = \frac{TP}{TP + FN} \ldots Eq(5.3)$$

3.4. **F1 Score** the harmonic mean of Precision and Recall, provides a balanced evaluation and is computed using Equation (5.4):

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \ldots Eq(5.4)$$

The **P Wave** represents the depolarization of the atria and is one of the key features in diagnosing abnormal rhythms. In the proposed system, a fuzzy membership function is used to determine the normality of this wave. The degree of membership is calculated based on the signal's amplitude and duration, employing a Gaussian or triangular function. This approach allows the system to capture subtle variations in the P Wave, ensuring accurate classification. The **PR Interval**, which measures the time between the P wave and the QRS complex, plays an essential role in assessing the conduction of electrical signals from the atria to the ventricles. A normal PR interval indicates proper conduction, whereas an abnormal PR interval may suggest conduction delays or blocks. In the fuzzy system, fuzzy logic rules are applied based on the time duration of the PR interval, helping the system distinguish between normal and abnormal conduction patterns. The **QRS Complex** represents the depolarization of the ventricles and is critical for diagnosing conditions such as arrhythmias. The system uses a fuzzy membership function to evaluate the width and amplitude of the QRS complex. By analyzing these features, the system can classify the QRS complex as either normal or abnormal, aiding in the detection of ventricular problems and irregularities in heart rhythm. The **QT Interval**, which indicates the time taken for the ventricles to depolarize and repolarize, is another vital input for classification. Abnormalities in the QT interval can signal various conditions such as long QT syndrome. The fuzzy system analyzes the duration of the QT interval to determine whether it falls within the normal range. This analysis is crucial for diagnosing conditions that could affect the heart's ability to pump blood effectively.

The FIS-based method was compared with other widely used classification techniques, including **Support Vector Machines (SVM)**, **k-Nearest Neighbors (k-NN)**, and **Decision Trees**. As shown in **Table 1**, the FIS achieved the highest performance across several metrics: accuracy (98.5%), precision (97.8%), recall (98.0%), and F1 score (97.9%). This demonstrates the superior performance of the fuzzy inference system in handling ECG signal classification tasks compared to traditional machine learning methods. Incorporating fuzzy logic into the system allows it to better manage the uncertainty and variability inherent in ECG signal features. By applying fuzzy rules to the input variables, the system becomes more flexible and interpretable, which is essential in medical applications. This flexibility provides healthcare professionals with a decision-support tool that can assist in real-time diagnostics, offering greater confidence and accuracy in classifying ECG signals.

4. Clinical Implications

The proposed FIS-based system holds great promise for real-time ECG analysis in clinical environments. By automating the classification of ECG signals, the system can assist healthcare professionals in identifying potential cardiac conditions more efficiently. This can lead to quicker diagnoses and timely interventions, ultimately improving patient outcomes. Moreover, the interpretability of the fuzzy inference system makes it a useful tool for healthcare providers. Unlike some black-box machine learning models, the fuzzy logic rules can be understood and adjusted by clinicians, allowing them to better trust the system's decisions and customize it for specific patient needs. Additionally, the integration of the FIS-based system into existing clinical workflows can reduce the cognitive load on healthcare professionals, enabling them to focus more on critical decision-making rather than manual analysis of ECG signals. This can be particularly valuable in high-pressure situations, such as emergency rooms or intensive care units, where rapid and accurate diagnosis is essential. The system also offers the potential for personalized medicine. By adjusting the fuzzy rules based on a patient's individual ECG patterns, the system can provide more tailored and precise assessments. This can result in more effective management of cardiac conditions, leading to better patient-specific care plans and ultimately improving long-term health outcomes.

5. Input and Output of the Fuzzy Inference System

To provide a better understanding of the fuzzy logic system's operation, we outline its **input and output components**. As illustrated in **Figure 3**, the system processes four key ECG features as inputs:**P Wave** , **PR Interval**, **QT Interval**

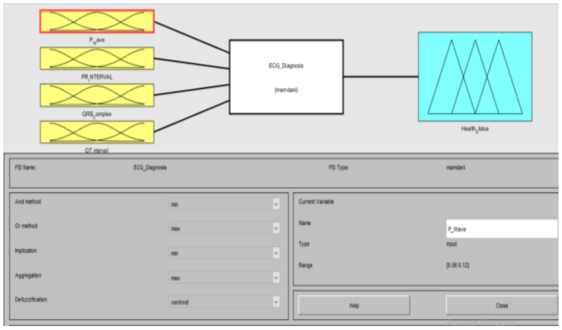


Figure 3: Input and Output of the Fuzzy Inference System

These input features are fuzzified using predefined linguistic variables such as “Normal,” “Abnormal,” “Short,” and “Long.” After fuzzification, the system applies the fuzzy inference rules to evaluate the degree of normalcy or abnormality in the input features. The output of the system is the **Health Status** of the patient, which is classified as either **Normal** or **Abnormal**, depending on the values of the input features and the results of the fuzzy inference rules. The final classification result is obtained through **defuzzification**, providing a crisp output that can be easily interpreted by healthcare professionals. As will be shown in **Figure 4.**

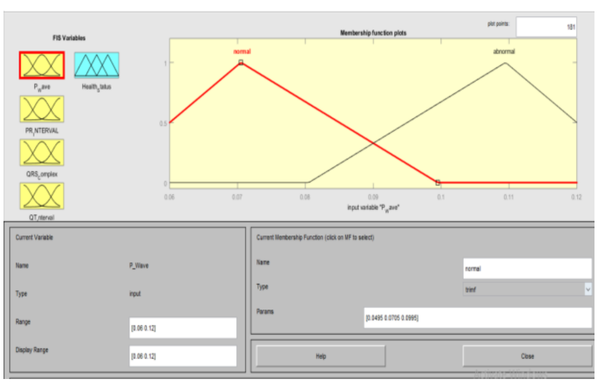


Figure 4: P Wave Processing (Range and Selected Points)

we provide a detailed visualization of the input process starting with the **P Wave** as the first input feature. The figure illustrates the fuzzy membership functions applied to the P Wave, showing the range of values (amplitude and duration) that determine the degree of normality or abnormality. Points along the range are selected to demonstrate how the fuzzification process works based on the signal’s characteristics. In **Figure]5**, the system processes the **PR Interval**. The figure shows the range of normal and abnormal intervals and the selected points that indicate how

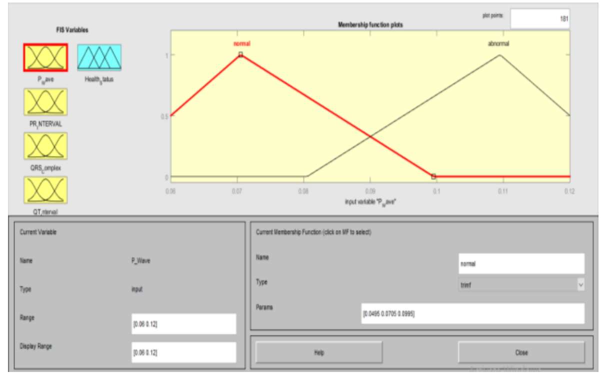


Figure 5: PR Interval Processing (Range and Selected Points)

The fuzzification process is demonstrated with different levels of membership to the linguistic terms, like “Short” and “Long.” Next, **Figure 6** illustrates the **QRS Complex** processing. This figure presents the range of values for the width and amplitude of the QRS complex, with selected points showing the system’s classification of the QRS complex as normal or abnormal. The fuzzification and rule application steps are clearly depicted, showing how each value is assessed.

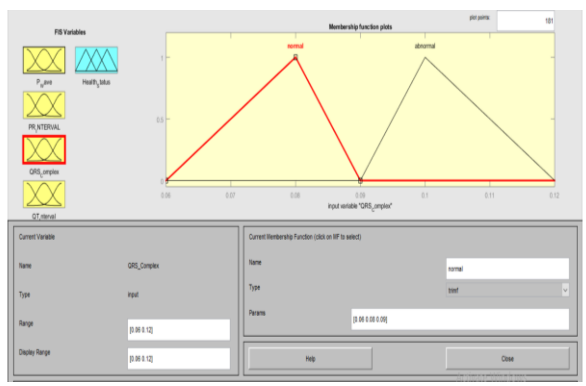


Figure 6: QRS Complex Processing (Range and Selected Points)

In **Figure 7**, the system evaluates the **QT Interval**, which is essential for diagnosing conditions such as long QT syndrome. This figure highlights the range of normal QT durations and the selected points for classification. The fuzzification process is displayed, showing how different QT durations affect the health classification. Finally**Figure 8** presents the complete fuzzification and rule application process for all four input features, demonstrating how they are integrated into the fuzzy system for a final classification decision. The output, shown in **Figure 9**, represents the **Health Status** of the patient, classified as either **Normal** or **Abnormal**. The figure shows how the fuzzy rules lead to this decision, with selected points indicating the level of membership to each class.decision, with selected points indicating the level of membership to each class.

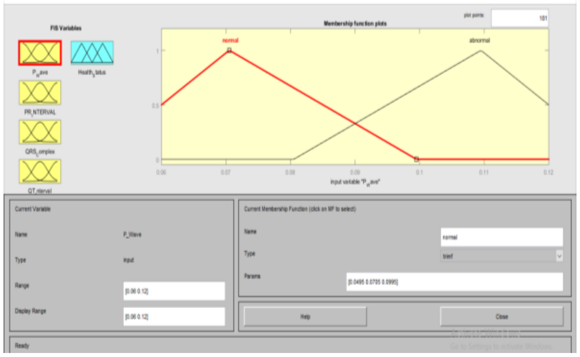


Figure 7: QT Interval Processing (Range and Selected Points)

Figure 8 presents the complete fuzzification and rule application process for all four input features: P Wave, PR Interval, QRS Complex, and QT Interval. In this figure, the individual fuzzification steps for each feature are shown, indicating how the raw signal values are converted into fuzzy sets based on pre-defined membership functions. The fuzzy rules are then applied to these sets, integrating the inputs in such a way that each feature's contribution is considered in the overall classification decision. This figure effectively demonstrates how the system processes each of the input features individually and collectively, ensuring that all relevant information is used to derive the final decision about whether the ECG signal represents a normal or abnormal health status.

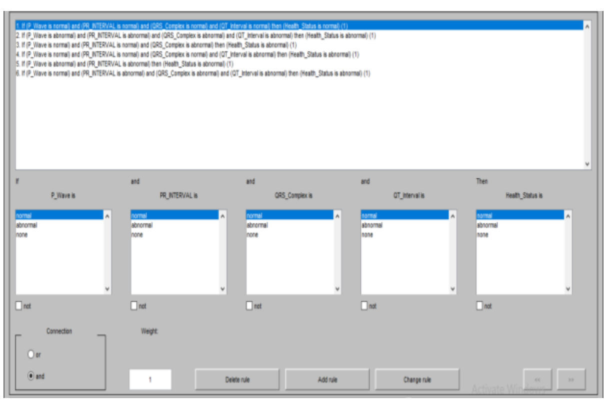


Figure 8: Fuzzification and Rule Application for All Inputs

Figure 9 shows the output of the fuzzy system, representing the Health Status of the patient, classified as either Normal or Abnormal. This figure highlights how the fuzzy rules lead to the final classification decision, with each input feature's level of membership to the "Normal" or "Abnormal" classes clearly indicated. The figure also shows the decision-making process, where the integration of the fuzzy rules determines the overall health classification. The selected points on the graph represent how strongly the ECG features belong to either of the two classes, providing a transparent view of how the system arrives at its conclusion.

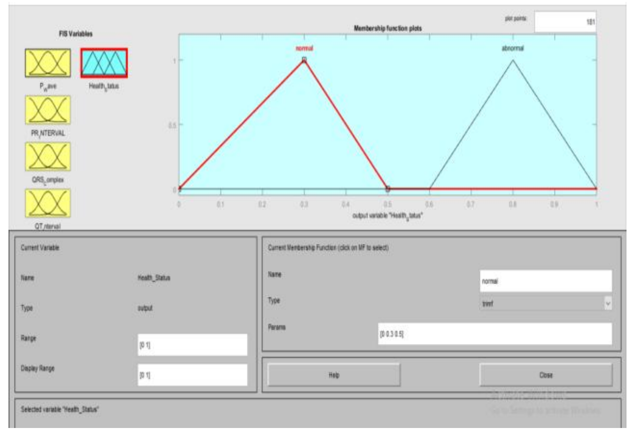


Figure 9: Output of the Fuzzy Inference System (Health Status)

VI. CONCLUSION

In this paper, a Fuzzy Inference System (FIS) for automated ECG signal classification was proposed, demonstrating its effectiveness in addressing the inherent uncertainty and variability of ECG signals. By utilizing fuzzy logic, the system provides a flexible and interpretable approach to classify ECG signals as either normal or abnormal, based on key features such as the P wave, PR interval, QRS complex, and QT interval. The results of the experiments confirm that the FIS-based method outperforms traditional classification techniques such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Decision Trees, achieving high accuracy, precision, recall, and F1 score. This highlights the system's capability in handling complex ECG data and its potential for real-time applications in clinical settings. The interpretability of the FIS makes it a valuable tool for healthcare professionals, allowing for more transparent decision-making in diagnosing cardiac conditions. Additionally, the system's flexibility allows it to be customized according to individual patient needs, enhancing its reliability in various clinical contexts. In future work, the system could be further enhanced by incorporating additional features from the ECG signal or by integrating with advanced machine learning models to improve its performance in more complex scenarios. Nonetheless, the proposed FIS-based approach holds great promise as a decision-support tool for automated, real-time ECG classification, offering a significant step forward in the field of cardiac health monitoring

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