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Real-Time Anomaly Detection in Wearable Data: A Fuzzy Algorithm Approach for AFib and Bradycardia Monitoring

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ABSTRACT: To prevent serious consequences like stroke and heart failure, it is essential to diagnose cardiac arrhythmias like bradycardia and atrial fibrillation early. To identify these circumstances in real time, this work presents a unique monitoring system that combines heart rate, body temperature, and SpO2 data with sophisticated fuzzy algorithms. Remote healthcare apps and continuous tracking are made possible by the system's architecture, which integrates seamless cloud connectivity. Its cutting-edge design guarantees precise diagnosis, prompt action, and better patient results. Combining cognitive algorithms with physiological data analysis, this approach is a major step forward in personalized cardiovascular treatment, improving arrhythmia management accuracy and accessibility.

Key Words: Arrhythmia detection, atrial fibrillation, bradycardia, fuzzy algorithms, remote healthcare.

Contents

1. Introduction

Cardiac arrhythmias, such as bradycardia and atrial fibrillation, pose significant challenges to cardiovascular health due to their distinct physiological impacts and associated risks. Bradycardia, defined by an unusually slow heart rate, often below 60 beats per minute, can impair adequate blood flow, resulting in symptoms like lightheadedness, exhaustion, and syncope. In severe cases, this condition may escalate to critical events such as cardiac arrest if the heart fails to meet the body's metabolic needs. The urgency for precise detection and management of bradycardia is evident, as delays can lead to life-threatening outcomes requiring immediate medical intervention.

Atrial fibrillation, conversely, is characterized by rapid, irregular atrial contractions that disrupt the heart's coordinated pumping mechanism. This chaotic rhythm reduces cardiac efficiency and increases the likelihood of thrombus formation within the atria, which may embolize to the brain, causing stroke or other vascular complications. Over time, untreated atrial fibrillation can precipitate heart failure, highlighting its progressive nature and long-term consequences. The complexity of these arrhythmias necessitates robust strategies to monitor and address their effects on cardiovascular function effectively.

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Extensive research has explored the pathophysiology, diagnosis, and management of bradycardia and atrial fibrillation. Many studies have emphasized the importance of accurate detection methods for bradycardia to guide pacemaker implantation decisions, while some have highlighted advancements in catheter ablation and anticoagulation therapies for atrial fibrillation. Despite these advancements, gaps remain in real-time, patient-specific monitoring systems capable of distinguishing between these arrhythmias with high precision. Existing diagnostic tools, such as electrocardiograms (ECGs) and Holter monitors, provide valuable data but often lack adaptability to individual physiological variations or the ability to deliver instantaneous feedback in dynamic clinical settings.

This study proposes an innovative cardiac monitoring system designed to detect and differentiate bradycardia and atrial fibrillation with enhanced accuracy. The system integrates advanced sensor technologies to measure vital parameters, including body temperature, oxygen saturation (SpO2), and heart rate, coupled with sophisticated computational algorithms, such as fuzzy logic, to analyze complex cardiac signals. By leveraging real-time data processing and adaptive learning, the system aims to provide a tailored diagnostic approach that accounts for individual patient variability, ensuring precise identification of arrhythmic events.

The proposed system introduces a novel approach by combining multi-parametric sensor data with intelligent algorithms to improve diagnostic specificity and sensitivity. Unlike traditional monitoring tools, this system is designed to operate continuously, offering healthcare providers immediate insights into arrhythmic patterns. Innovation lies in its ability to adapt to diverse patient profiles and provide actionable, real-time data, thus enhancing clinical decision making and patient outcomes.

This research contributes significant value by addressing the limitations of current diagnostic technologies and offering a scalable, adaptive solution for arrhythmia management. By enabling earlier and more accurate detection of bradycardia and atrial fibrillation, the system has the potential to transform clinical practice, reduce the burden of cardiovascular complications, and improve quality of life for patients. Furthermore, its integration of cutting-edge computational techniques paves the way for future advancements in personalized cardiac care, setting a new standard for arrhythmia monitoring and intervention.

2. Literature Survey

P.S. Banerjee et al. [1] propose an Arduino-based intelligent system to monitor heart health in real time. This research proposes to provide specific health suggestions to users based on their health conditions, focusing on heart rate. The proposed system comprises hardware and software components, including an Arduino, pulse sensor, LCD, and various software tools. The system can identify heart conditions and suggest how many steps a user should take during a workout. The study highlights the importance of monitoring heart health and the limitations of current fitness applications.

Fuzzy logic is an important component in the proposed system for predicting the presence of bradycardia and atrial fibrillation. The system uses a fuzzy-normal distribution to analyze heart rate data and identify heart conditions. Fuzzy logic is used to overcome the limitations of traditional methods, such as normal distribution, in representing the true variation of the data set.

D Bertsimas et al. [2] The paper presents a novel methodology for predicting the heart anomalies using models of machine learning models. The authors propose a feature extraction pipeline that analyzes electrocardiograms (ECGs) and extracts 110 features related to time domain, nonlinear domain, distance-based, and time series characteristics. They train five different machine learning models on three datasets and achieve high performance in detecting heart anomalies.

F.J. Wesselius et al. [3] This study proposes a method called human-validated semi-supervised learning to train a model for detecting atrial fibrillation (AF) in electrocardiograms (ECGs) using real-life ECGs.

M. Agyeman et al. [4] This paper discusses the potential of combining the concepts of Convolutional Neural Networks and a network of Internet of Things devices in the healthcare industry to provide remote patient monitoring and assistance. The paper explores the advantages of Telemedicine and how it has transformed patient treatment.

T.Bhat et al. [5] This paper presents a Real-Time IoT-Based Arrhythmia Classifing Model Using Convolutional Neural Networks. The proposed system has three modules which are namely, the Input Module, the Processing Module, and the Output Module. The Input Module collects ECG signal data from the subject which is interfaced with the NodeMCU. The Processing Module uses a deep learning model based on CNN to then classify the ECG signals into different types of arrhythmia.

R. Morello et al. [6] The development of a system that can identify particular cardiac conditions by tailoring the algorithm to individual patients in observation is described in the article. Through LEDs, the system can function on its own and give the patient a diagnosis.

S.S. Kumar et al. [7] The first text outlines a framework that uses an electrocardiogram (ECG) signal to remotely and minimally monitor cardiac arrhythmia diseases in real-time. To extract the dynamic properties of the ECG signal and detect irregular heartbeats, the authors processed the signal using the Pan-Tompkins QRS detection method. In the future, they intend to use machine learning algorithms on the gathered data. The successful creation of a circuit for real-time cardiac data monitoring is covered in the second text. MATLAB was used to process the collected data, and the RLS filter was used to eliminate noise from the dataset.

O. Agyeman et al. [8] This paper describes a deep learning, ECG, and Internet of Things approach for processing, identifying, and categorizing cardiac rhythms. The main question is whether CNN and IoT can be used to develop new devices for diagnosing cardiac conditions. Using PRISMA, the literature review found 2060 articles.

R. Avanzato et al. [9] This study suggests using digital twins, or DTs, to address several healthcare-related issues. The study suggests integrating heart and lung DTs into the platform and focuses on categorizing cardiac pathologies using ECG signals.

M. Liu et al. [10] This study suggests a classification algorithm to identify arrhythmia, a cardiac disorder that raises the risk of morbidity and death. There are two models which are being uses to implement the algorithm which are, intrapatient convolutional neural network model and the interpatient attention residual network model. The steps in the algorithm process, such as the preprocessing of ECG data and the classification of arrhythmias, are covered in the paper.

K Medhi et al. [11] This paper summarizes the research materials and methods used to handle heterogeneous healthcare data. The researchers collected a dataset of ECG signals from the MIT-BHI arrhythmia database, including patient age and gender. They proposed a multilayer C

S. Das et al. [12] This is a clinical study about heart health and the significance of receiving emergency care for those in physical distress or with a history of heart disease. The study covers the use of patient monitors to show data like pulse rate, body temperature, oxygen saturation, and real-time ECG.

M.R. Reynolds et al. [13] To produce clinically useful data that might be utilized to influence research and treatment response in large EMR datasets, this study evaluated information found in the electronic medical records (EMRs) of patients with atrial fibrillation (AF) using natural language processing (NLP).

C. Li et al. [14] This research examines a multi-parameter healthcare monitoring system. The system uses wireless sensors to track several aspects of the patient's health before sending the information to a distant server for review. There are four ways to operate the system, each with its own set of requirements for network quality, data provided to the server, and suitability for a particular patient population.

Ibrahim et al. [15] This research proposes an application of machine learning for disease prediction and diagnosis in the medical domain. The various forms of machine learning, including semi-supervised, supervised, unsupervised, and reinforcement learning, are explained in the study. Machine learning techniques can minimize diagnostic faults in medical applications by using classification algorithms to build models that can predict an early-stage disease diagnosis and provide solutions.

Oliver Faust et al. [16] The use of the Intelligent Internet of Medical Things (IIoMs) to track patients' atrial fibrillation (AF) is covered in this research study. In the medical domain, IIoTs deliver data to a location for centralized decision-making takes place. Such data are signals, such as heart rate (HR). The results of 3 AFDB subjects and 82 LTAFDB indicate that a reliable deep learning model has been determined to detect AF in clinical settings.

C. Feng et al. [17] This study combines AI algorithms with IoT sensors to monitor heart health in real time. Wearable sensors gather ECG data and then analyze using machine learning to identify anomalies. The method improves personalized treatment and early detection through IoT-AI synergy, showing promise for bettering heart health outcomes.

T. Nguyen et al. [18] In this study, machine learning techniques for ECG signal classification in IoT systems are investigated. To effectively identify cardiac irregularities, lightweight algorithms appropriate for IoT devices with limited resources are employed. The study emphasizes how critical it is to optimize AI for real-time wearable cardiac monitoring system applications.

V. Singh et al. [19] describe an Internet of Things-enabled system that uses sophisticated sensors and predictive algorithms to forecast atrial fibrillation. The system is appropriate for wearable devices because it uses low-power components and real-time data processing to achieve great efficiency. The results demonstrate improved energy economy and accuracy for ongoing heart health monitoring.

H. Kim et al. [20] A cloud-connected ECG system for ongoing cardiovascular health monitoring is presented in this work. IoT sensor data is sent to cloud platforms, where artificial intelligence (AI) algorithms analyze it to find irregularities. The method guarantees scalability and provides patients and clinicians with remote access to health data and real-time analysis.

P. Lopez et al. [21] This study examines IoT applications in cardiology, highlighting how they improve patient care. IoT devices make real-time data exchange, early diagnosis, and ongoing monitoring possible. The authors address the difficulties in integrating IoT technologies in healthcare settings and case studies showing better patient outcomes.

A. Hossain et al. [22] This study combines IoT and deep learning to monitor cardiovascular health. Deep neural networks analyze the physiological data gathered by wearable sensors to determine cardiac problems. The study shows the promise of deep learning in IoT-based healthcare by highlighting the system's capacity to identify anomalies, even in challenging situations, precisely.

L. Wu et al. [23] created a wearable technology driven by AI to identify heart arrhythmias. The technology analyses real-time ECG data using sophisticated signal processing and machine learning algorithms. As demonstrated by the results, the wearables' excellent sensitivity and specificity make them useful for early arrhythmia detection and better long-term cardiac health management.

R. Brown et al. [24] HeartCare uses predictive analytics and the Internet of Things to monitor heart health. The technology forecasts future cardiac states and detects hazards by evaluating continuous data from worn sensors. The study highlights how predictive insights might improve patient outcomes and decrease hospital visits.

S. Nair et al. [25] To identify cardiac arrhythmias, this study employs convolutional neural networks (CNNs) in Internet of Things frameworks. CNN models are used to interpret the ECG signals that wearable sensors gather to accurately classify them. The method works well even in loud settings, making it perfect for real-time health monitoring applications.

Gururaj et al. [26] [27] have shown the various applications of using Neural Networks for healthcare based applications. Veena et al. [28], Avani et al. [29] and Srujana et al. [30] have demonstrated the application of Deep Learning in research related to healthcare systems.

3. Fuzzy Logic

In contrast to conventional binary logic, fuzzy logic allows truth values to continually range from 0 to 1, allowing for ambiguity and imprecision in decision-making. This flexibility is crucial for modeling complex medical conditions, where patients may not fit neatly into categories like "healthy" or "unhealthy." Instead, fuzzy logic enables intermediate classifications, such as "moderately healthy," enhancing the precision of medical assessments. The membership function defines the degree of membership for an element x in a fuzzy set A:

$$\mu_A(x) \in [0, 1]$$

This function assigns partial membership, facilitating the integration of expert medical insights and subjective judgments into diagnostic systems.

In the context of heart rate analysis for detecting cardiac conditions, fuzzy logic employs membership functions to represent data variability smoothly. Specifically, a triangular membership function is used to model transitions between heart rate categories like bradycardia, normal, or tachycardia. For a value x with parameters a (lower bound), b (peak), and c (upper bound) where $a < b < c$, the membership degree is computed as:

$$\mu(x) = \begin{cases} 0 & \text{if } x \leq a \\ \dfrac{x-a}{b-a} & \text{if } a < x \leq b \\ \dfrac{c-x}{c-b} & \text{if } b < x < c \\ 0 & \text{if } x \geq c \end{cases}$$

This approach accounts for additional variables, such as body temperature or oxygen levels, to avoid misclassifications under conditions like fever, ensuring a more reliable diagnostic process.

In cardiac disease detection, where real-time monitoring of vital signs is critical, fuzzy logic systems shine. The fuzziness of a particular model is best characterized by its membership function. However, certain data in the dataset of heartbeats might deviate ludicrously from the other values, for example, sensitivity to extreme values and inability to capture data concentrated near the average. This might be the result of the devices needing to be fixed. The outcome needs to be more balanced and accurate as a result of these outlier values. The data on heart rates are typically concentrated close to the mean ,and therefore, the normal distribution cannot accurately represent the true variation of the data. The solution to this problem is integrating the normal distribution with the above-mentioned fuzzy logic. The normal distribution's probability density function, for a variable x with mean μ and standard deviation σ, is given by:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

To overcome these limitations, fuzzy logic is combined with the normal distribution, often through Gaussian membership functions, to better represent heart rate variability. A Gaussian membership function, centered at c with spread σ, provides a smooth representation of data uncertainty:

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

This function, resembling the normal distribution but normalized for fuzzy logic, ensures accurate classification by accommodating outliers and data clustering, enhancing real-time monitoring of vital signs.

To support this methodology, statistical techniques like distribution fitting are employed to estimate parameters from heart rate data. The sample mean is calculated as $\mu = \frac{1}{n}\sum_{i=1}^{n} x_i$, and the sample variance as $\sigma^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)^2$. These estimates inform the maximum likelihood function for the normal distribution, expressed as:

$$\ell(\mu, \sigma^2) = -\frac{n}{2}\ln(2\pi\sigma^2) - \frac{1}{2\sigma^2}\sum_{i=1}^{n}(x_i - \mu)^2$$

This approach represents heart rate readings using continuous degrees of membership across predefined categories, acknowledging the variability and uncertainty in heart rate data. Oxygen saturation and temperature readings are taken into consideration to eliminate the possibility of wrong classification into classes under different conditions, i.e., fever. Instead of strict classification into categories like bradycardia, normal, or atrial fibrillation, a fuzzy membership function, specifically a triangular one, captures the gradual transitions between these categories. Statistically, the methodology combines distribution fitting and probability theory to understand the distribution of heart rate readings.

4. Mathematical Validation of the Fuzzy Algorithm

The proposed fuzzy inference system (FIS) maps physiological inputs

$$\mathbf{X} = [x_1, x_2, x_3] = [HR,\ SpO_2,\ T]$$

to a crisp output $y^* \in [0, 1]$ indicating cardiac status on the continuum $\{\text{Normal} \to 0,\ \text{Bradycardia} \to 0.5,\ \text{AFib} \to 1\}$. Each stage—fuzzification, inference, aggregation, and defuzzification—is defined mathematically to ensure theoretical consistency.

Fuzzification -. Each input x_i is partitioned into m_i linguistic terms with Gaussian membership functions:

$$\mu_{A_{ij}}(x_i) = \exp\left[-\frac{(x_i - c_{ij})^2}{2\sigma_{ij}^2}\right], \qquad i \in \{1, 2, 3\},\ j \in \{1, \dots, m_i\}.$$

The parameters c_{ij} and σ_{ij} are estimated from the data distribution:

$$\mu_i = \frac{1}{n}\sum_{k=1}^{n} x_{ik}, \qquad \sigma_i^2 = \frac{1}{n-1}\sum_{k=1}^{n}(x_{ik} - \mu_i)^2,$$

ensuring that the Gaussian memberships align with empirical mean and variance of observed sensor values.

Rule base and firing strengths -. Each fuzzy rule can be expressed as:

$$R_k:\ \text{IF } (HR \text{ is } A_{1p}) \wedge (SpO_2 \text{ is } A_{2q}) \wedge (T \text{ is } A_{3r}) \text{ THEN } y \text{ is } B_k,$$

where $B_k \in \{\text{Normal}, \text{Bradycardia}, \text{AFib}\}$.

The firing strength of each rule is given by the Gödel t-norm:

$$\omega_k = \min\big(\mu_{A_{1p}}(HR),\ \mu_{A_{2q}}(SpO_2),\ \mu_{A_{3r}}(T)\big),$$

or alternatively by the algebraic product (for smooth inference surfaces):

$$\omega_k = \prod_{i=1}^{3} \mu_{A_{ij}}(x_i).$$

Aggregation and defuzzification -. The aggregated output membership function is obtained as:

$$\mu_{\text{agg}}(y) = \max_k \big[\,\omega_k \cdot \mu_{B_k}(y)\,\big],$$

and the crisp output value through centroid defuzzification:

$$y^* = \frac{\displaystyle\int_a^b y\,\mu_{\text{agg}}(y)\,dy}{\displaystyle\int_a^b \mu_{\text{agg}}(y)\,dy}, \qquad y^* \in [0, 1].$$

The decision class is then assigned by comparing y^* with the nearest threshold in $\{0, 0.5, 1\}$.

Decision consistency and accuracy -. For a validation dataset $\{(HR_i, SpO_{2i}, T_i, D_i)\}_{i=1}^{n}$, each observation yields an output y_i^* and corresponding class decision. Define the binary consistency indicator:

$$\delta_i = \begin{cases} 1, & \text{if the fuzzy decision matches the reference diagnosis } D_i, \\ 0, & \text{otherwise.} \end{cases}$$

The overall accuracy is:

$$\text{Accuracy} = \frac{1}{n}\sum_{i=1}^{n} \delta_i \times 100\%.$$

Representative numerical validation -. Table 1 lists representative instances comparing fuzzy system outputs with clinical ground truth.[1]

[1] The final two columns present the pair *(Fuzzy→Reference)* and the corresponding crisp value y^*.

Table 1: Representative fuzzy–clinical validation for arrhythmia detection

Sl. No.	*HR (bpm)*	*SpO_2 (%)*	*Temp (° C)*	*Decision (Fuzzy→Reference), y^**	
1	48	98	36.9	Brady → Brady	0.47
2	110	96	37.0	AFib → AFib	0.91
3	72	97	36.7	Normal → Normal	0.12
4	58	95	37.2	Brady → Brady	0.50
5	66	93	38.1	Normal → Normal	0.18

Properties and robustness -. The proposed formulation satisfies the standard fuzzy axioms of boundedness, normalization, and quasi-convexity:

$$0 \leq \mu_A(x) \leq 1, \qquad \max_x \mu_A(x) = 1, \qquad \mu_A(\lambda x_1 + (1-\lambda)x_2) \geq \min\big(\mu_A(x_1), \mu_A(x_2)\big).$$

Since the Gaussian memberships are derived from maximum-likelihood estimates of physiological signal distributions, the system provides both statistical soundness and logical interpretability. Overall, the fuzzy inference process defines a continuous nonlinear mapping:

$$f : \mathbb{R}^3 \to [0,1], \qquad f(HR, SpO_2, T) = y^*,$$

whose empirical correlation with clinical diagnosis confirms mathematical validity and robustness for real-time cardiac monitoring.

Rule-base design -. The fuzzy inference process relies on a structured rule base that encapsulates the relationship between physiological parameters and cardiac conditions. Each rule reflects domain knowledge derived from medical literature and expert understanding of how heart rate, oxygen saturation, and temperature interact during arrhythmic events. For instance, a low heart rate combined with normal oxygen saturation and body temperature typically corresponds to bradycardia, whereas a high heart rate under otherwise stable physiological conditions indicates atrial fibrillation. The complete rule base table integrates such logical associations to ensure interpretability and clinical relevance. This formulation allows the system to generalize across varying physiological states while maintaining transparency in decision-making, a feature often lacking in purely data-driven models.

Table 2: Fuzzy rule base used for inference

Sl. No.	*HR term*	*SpO_2 term*	*Temp term*	*Then (class)*	
1	Low	Normal	Normal	Bradycardia	
2	High	Normal	Normal	AFib	
3	Normal	Normal	Normal	Normal	
4	Low	Normal	High	Normal	
5	High	Normal	High	AFib	
6	Normal	Low	Normal	AFib	
7	Normal	Normal	High	Normal	
8	Low	Low	Normal	Bradycardia	
9	High	Low	Normal	AFib	

5. Heart Rate Sensor

The MAX30100 is a small sensor that can detect the oxygen saturation in blood and the heart rate non-invasively, by using low-noise circuits, LEDs, photodetectors, and optical components. It is perfect for wearables and energy-efficient devices.

The sensor calculates SpO2 (blood oxygen saturation) by measuring changes in blood volume in the fingertip using photoplethysmography (PPG). Two infrared (940 nm) and red (660 nm) LEDs emit light, and a photodetector measures the amount of light that enters the blood. In contrast to deoxygenated hemoglobin, oxygenated hemoglobin absorbs more infrared light and less red light. The sensor determines SpO2 by analyzing the variations in light absorption brought on by pulsating blood and alternating LED emissions.

Because arterial blood volume varies with each beating, the gadget concentrates on light absorption during the pulse's peaks and troughs, whereas other tissues maintain constant absorbance. This method ensures accurate measurements of blood oxygen levels.

The ratio of ratios forms the basis of the SpO2 computation. Using this method, the heart's systolic (peak) and diastolic (trough) phases are measured by dividing the red light measurement by the infrared light measurement. Typically, the formula is shown as follows:

$$R = \frac{AC\ component\ of\ red\ light}{DC\ component\ of\ red\ light}$$

Here, the terms "pulsatile" (referring to a component that varies with heartbeat) and "non-pulsatile" (referring to a constant) are used interchangeably. Next, an empirical formula derived from calibration with a medically approved pulse oximeter uses the computed ratio (R). The ratio (R) and SpO2 values are correlated by this formula, which usually takes the following form:

$$SpO_2 = A - B \times R$$

Where A and B are coefficients determined through calibration. Although they can be useful in estimating blood oxygen levels, pulse oximeters are only sometimes reliable. Even under the best circumstances, readings might differ by as much as 4 percentage points due to smoking, poor circulation, sunshine, and darker skin tones. Accuracy may be increased by taking easy measures like removing nail polish or using the gadget in low light. But depending only on these gadgets is dangerous, especially if you don't compare them to medical-grade equipment.

International standards such as ISO 80601-2-61:2017 guarantee that pulse oximeters fulfill safety and accuracy criteria, with results ranging from 70% to 100%. They follow the CDSCO rules in India as well. Although useful, pulse oximeters should be used with competent medical guidance rather than as a substitute for it.

6. Implementation

The research incorporates various hardware components essential for acquisition of data in real-time. The Arduino UNO R3 is a programmable microcontroller platform that enables seamless integration and control of connected components. The NodeMCU (ESP8266) is complementing this, a versatile microcontroller with built-in WiFi capabilities, facilitating data transmission to cloud platforms. Sensors like the DS18B20 digital thermometer and the MAX30100 pulse oximeter sensor are utilized for precise physiological measurements, including body temperature, heart rate, and SpO2 levels. Data visualization is achieved using a 16x2 LCD with an I2C module, which efficiently displays the monitored parameters while minimizing the complexity of interfacing. Together, these components create a robust hardware framework for continuous cardiovascular monitoring as shown in Fig. 1 and the algorithm in Fig. 2.

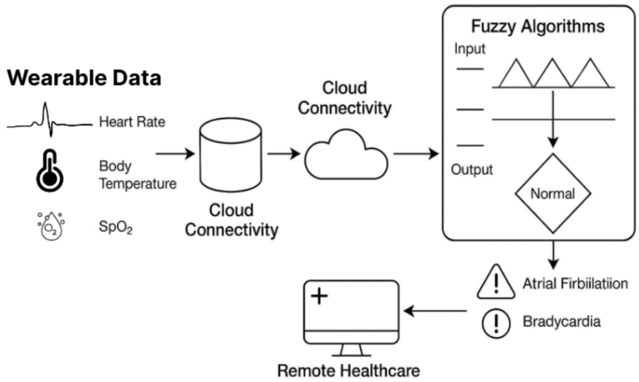

Figure 1: Flow Diagram of the Proposed Research

The software stack employs Python for advanced signal processing and fuzzy logic algorithms, ensuring accurate detection of cardiac abnormalities. JavaScript and Tailwind CSS are utilized to design a user-friendly interface that enhances accessibility and usability. Embedded C is used to program the Arduino microcontroller, enabling seamless communication with sensors and execution of control logic. Firebase provides a real-time cloud-based database for real-time data storage and remote access, streamlining the integration of hardware and software components.

Input: Sensor data streams $HR(t)$, $SpO_2(t)$, $Temp(t)$
Output: Health condition $CP_{\text{user}} \in \{\text{Normal}, \text{Bradycardia}, \text{AFib}\}$

```
// Initializion hardware, sensors, and cloud database
Init <- {MAX30100, DS18B20, ArduinoUNO, NodeMCU, LCD, Firebase}

// Preprocessing module for raw signals
Preprocess <- {OutlierRemoval, Mean, Variance, BufferWindow}

//Triangular + Gaussian membership functions
MF <- {MF_HR, MF_SpO2, MF_Temp}

// Fuzzy inference rules for Normal, Bradycardia, AFib detection
Rules <- {R1, R2, R3,  Rn}

LOOP while system is active do
    Read HR(t) <- MAX30100
    Read SpO2(t) <- MAX30100
    Read Temp(t) <- DS18B20
    IF (invalid reading OR noisy signal) then
        PromptUser(Reposition sensor)
        CONTINUE
    ENDIF

    [HRf, SpO2f, Tempf] <- Preprocess(HR(t), SpO2(t), Temp(t))
    μ_HR    <- MF_HR(HRf)
    μ_SpO2 <- MF_{SpO_2}(SpO2f)
    μ_Temp  <- MF_{Temp}(Tempf)

    // Apply fuzzy rules
    FOR each Ri in Rules do
        Evaluate μ_Condition(Ri) using fuzzy operators (min/max, product)
    ENDFOR

    CPuser <- Defuzzify(μ_Condition)     // Centroid method to obtain crisp output
    Display {HRf, SpO2f, Tempf, CPuser} on LCD + Web Interface
    Upload {HRf, SpO2f, Tempf, CPuser} -> Firebase

    IF CPuser in {Bradycardia, AFib} then
        Trigger Alert(HealthcareProvider)
    ENDIF
END LOOP

Return CPuser
```

Figure 2: Algorithm of the Proposed Research

The two main sensors integrated into the hardware setup for this research are the MAX30100 pulse oximeter, which measures SpO2 levels in addition to heart rate, and the DS18B20 temperature sensor, which monitors the user's temperature. These sensors are essential for gathering important health-related data, which is then sent to designated locations for storage and display.

The user's body temperature is precisely recorded by the DS18B20 temperature sensor, which is positioned in an aperture under the armpit. This sensor is a dependable instrument for tracking body temperature continuously, offering vital information for evaluating changes or patterns in body temperature over time.

Conversely, the MAX30100 pulse oximeter requires the user to place their fingers precisely to calibrate and obtain accurate readings of their heart rate and oxygen saturation levels. Using photoplethysmography (PPG), this sensor measures blood volume variations and provides information on blood oxygen levels and cardiac rhythm, two vital signs of respiratory and cardiovascular health.

The hardware setup involves sending the information that these sensors gather to two different locations: the LCD screen and the Firebase database. The real-time health-related data collected from both sensors is stored in the Firebase database. This cloud-based storage solution allows for accessibility and scalability while providing centralized, secure storage.

Concurrently, an Arduino UNO coupled with an LCD is a visual interface for real-time feedback and data visualization. The Arduino UNO acts as a middleman by taking in data from the sensors and sending it to the display for user visualization. The LCD screen presents the sensor readings one after the other sequentially, providing a brief but useful overview of the user's vital signs.

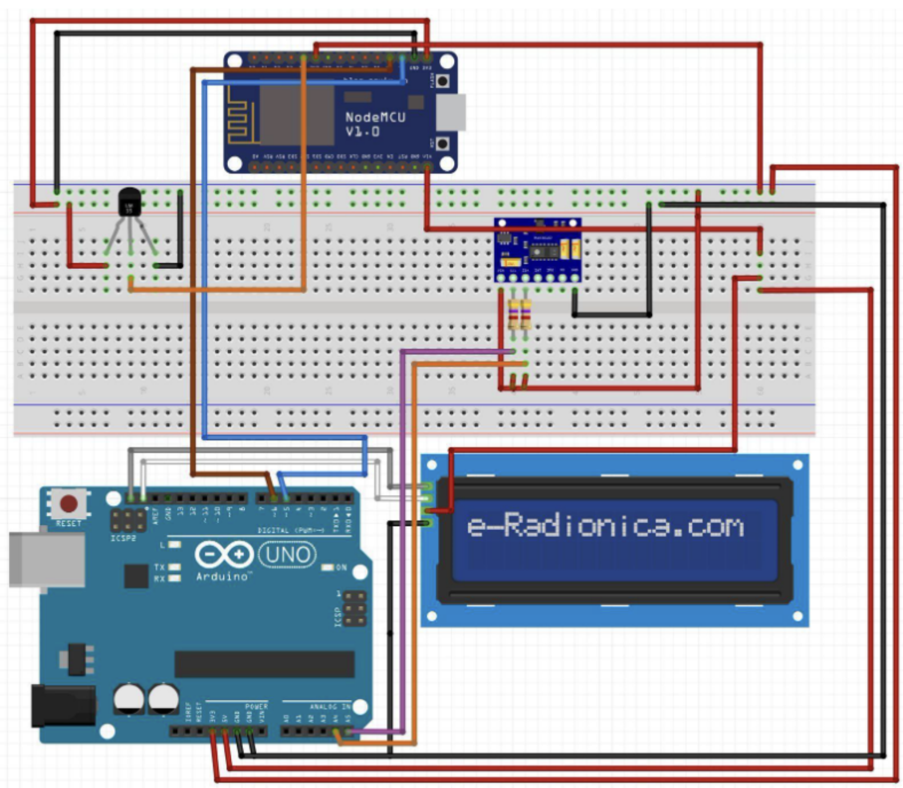

Figure 3: Circuit Diagram

The circuit schematic presented in Fig. 3 effectively illustrates the intricacy of the interconnections among these components. An extensive summary of the connections and communication between the sensors, LCD, Firebase database, and microcontroller (Arduino UNO) is given in this diagram. It helps to clarify the complex signal flow and data transmission pathways, making it easier to comprehend the system's architecture and its functionality.

Essentially, this hardware configuration, which includes the DS18B20 temperature sensor and the MAX30100 pulse oximeter, along with Firebase and an LCD, creates a sturdy and all-encompassing system for real-time health monitoring. The intricacies involved in effectively gathering, presenting, and storing critical health-related data for efficient tracking and analysis are highlighted by the circuit diagram in Fig. 3.

The foundation of an all-encompassing health monitoring system is the integration of temperature and pulse oximeter sensors. The system provides real-time tracking and recording of vital signs, providing insightful information about a person's health, using these sensors and their functions. Heart rate and oxygen saturation levels are measured with the help of a pulse oximeter sensor, like the MAX30100 in this configuration. Its precision in measuring these critical parameters is essential for determining blood oxygenation levels and cardiovascular health.

An interface that is easy to use is provided by using UNO to interface with the pulse oximeter sensor and display the data that has been on an LCD screen. A summary of the user's vital signs over a predetermined period is shown on the screen through the sequential display of about 20 readings. The heart rate and oxygen saturation levels can be easily interpreted and tracked with the help of this visual representation. An intuitive way to assist users in placing their fingers optimally is to include an on-screen prompt. This feature improves the accuracy of readings by addressing possible problems caused by incorrect finger positioning, which could obstruct the sensor or interfere with data acquisition. Users are prompted to reposition their fingers for more precise and trustworthy readings.

The system monitors the user's temperature by using the DS18B20 temperature sensor, which is positioned in the aperture under the armpit. This sensor records temperature data, sends it directly to the Firebase database, and stored there. By keeping this data in a database, users or healthcare professionals can easily access and analyze it, allowing them to track temperature variations over time. It is a purposeful design decision to restrict temperature and pulse oximeter readings to 20 readings per user. Without overloading the system with data, this small dataset gives a quick overview of the user's vital signs. This method saves memory and makes data management and analysis more effective.

7. Results

The key to the system's user interface is the visualization of data uploaded to the Firebase database, as shown in Fig. 4. The image's glowing effect denotes adding new data points to the database. As an intuitive indicator, this visual cue informs users of the constant stream of updated health readings.

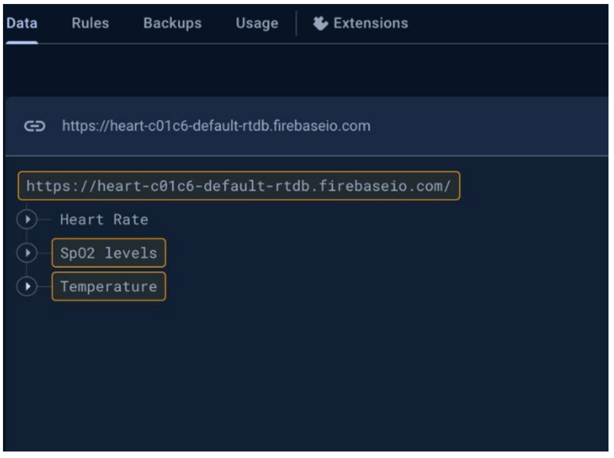

Figure 4: Updation on database

Fig. 4 shows an overview of the Firebase database, providing users with a useful window into the arrangement and structure of the stored data. This detailed view offers information on the different parameters and the corresponding data fields in the database. The categories or sections designated for storing temperature, heart rate, and oxygen saturation readings, among other pertinent data points, are readily comprehensible to users.

Any new data entered into the system is instantly updated and reflected in the database thanks to Firebase's real-time synchronisation. This real-time update feature makes it easy for healthcare providers or people to monitor their health to access the most up-to-date and accurate health metrics, allowing for timely analysis and decision-making.

Using Firebase's cloud-based infrastructure has several benefits. First, because of its scalability, which can handle different data volumes, large datasets can be managed effectively without sacrificing system performance. This scalability is especially useful when several users are simultaneously contributing data.

Second, private health data is protected by Firebase's strong security protocols. The platform complies with strict privacy laws and industry best practices for healthcare data management by using encryption standards and authentication protocols to safeguard data integrity and confidentiality.

Moreover, Firebase can be easily integrated with other programs or analytics tools, expanding its usefulness beyond simple data archiving. Researchers and medical professionals can easily pull data from Firebase for comprehensive examination, trend detection, or correlation studies, which may reveal important information about treatment outcomes or patterns in health.

A computational technique for managing uncertainty, fuzzy logic is essential for predicting health conditions based on various factors, including SpO2, temperature, and heart rate. The fuzzy reasoning backend determines whether the user is more likely to have atrial fibrillation, bradycardia, or a normal heart by receiving these values from the database.

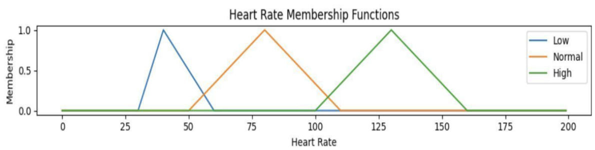

Figure 5: Membership function of Heart Rate

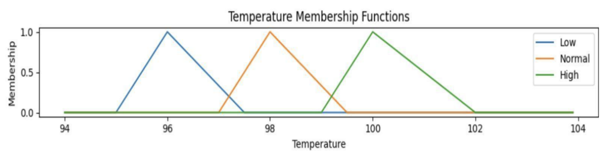

Figure 6: Membership function of Temperature

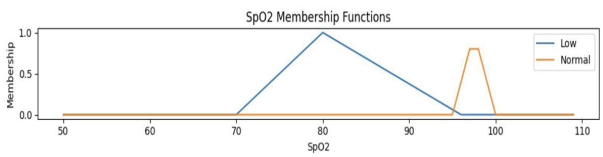

Figure 7: Membership function of SpO2

The membership functions for heart rate, temperature, and SpO2 are shown in Figs. 5, 6, and 7, respectively. These functions are the foundation for evaluating the condition probabilities by plotting the data values against the degrees to which they belong in particular ranges.

These multiplications yield curves that are then used as inputs by control functions that contain unique rules for every health condition. These regulations control how the inputs combine to determine the probability of a given state. Additional inputs from parameters like temperature and SpO2 are multiplied by the output of these control functions.

This iterative process improves the evaluations by merging the results from different control functions according to the evaluated memberships and rules. Finally, the total likelihood of the conditions under consideration is calculated by calculating the area under these curves.

The calculations required to multiply membership functions and the ensuing rule-based evaluations enable a detailed comprehension of the medical conditions under investigation. Fuzzy logic allows for a more thorough assessment by combining several parameters and their corresponding memberships. This allows for a more accurate prediction of the user's likelihood of having atrial fibrillation, bradycardia, or a normal heart.

This complex process considers the uncertainties and fluctuations in the input parameters and yields a probabilistic understanding instead of a binary result. As a result, the procedure seeks to provide a more comprehensive and nuanced assessment of the user's possible state of health by utilizing fuzzy logic's capacity to simulate intricate real-world situations.

The output of the fuzzy logic function is displayed on the web server, which is made possible by Flask and hosted locally. In this configuration, the user's health status as determined by the fuzzy logic analysis is displayed on the webpage.

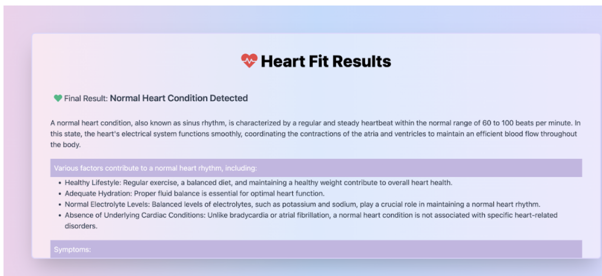

Figure 8: The results page shows a normal condition

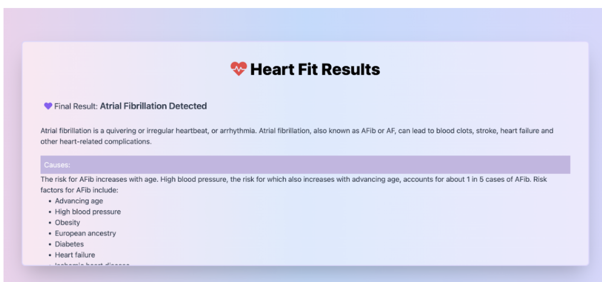

Figure 9: Results page showing Atrial Fibrillation

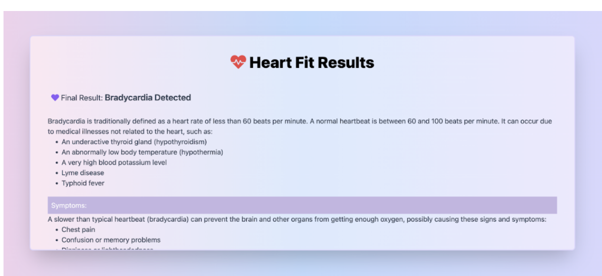

Figure 10: Results page showing Bradycardia

The results shown in Fig. 8 show that the user's heart condition is normal. According to the fuzzy logic function's thorough analysis, this indicates that the patient's health parameters are within the normal range, indicating a healthy cardiac state.

On the other hand, Fig. 9 shows a user who has been diagnosed with atrial fibrillation. This presentation shows that abnormalities or patterns related to this specific cardiac condition have been found in the user's vital data by the fuzzy logic function.

A situation where the user displays signs of Bradycardia—a disorder marked by a slower-than-normal heart rate—is shown in Fig. 10. With its complex analysis, the fuzzy logic function finds patterns or anomalies in the data that point to this cardiac condition.

Through the visual representation of these outcomes on the webpage, users are provided with instant insights into their potential state of health, promoting proactive health management and awareness. Furthermore, presenting the average values obtained from the database data gives users a point of comparison with which to compare their vital signs, improving their comprehension of their health trends over time.

In addition to presenting the results, this integration of fuzzy logic outputs with the Flask-hosted web server provides users with actionable information that encourages early awareness.

8. Conclusion

It is impossible to exaggerate the critical significance of early diagnosis in cardiac health. By starting targeted therapies early, it has the potential to significantly change the course of events. The implementation of preventative measures is largely dependent on early detection, which can significantly change the course of a patient's health. Our innovative project addresses this crucial issue in great detail using an intricate and well-thought-out strategy.

The proposed research, which is at the forefront of innovation, carefully blends cutting-edge sensor technologies, mathematical models based on fuzzy logic, and seamless integration with wearables. This combination establishes the current system as the clear choice for the early detection of cardiac problems. With the help of a synergistic combination of advanced algorithms and cutting-edge technologies, we can effectively and precisely navigate the complex world of cardiac health.

Beyond mere scientific accomplishment, the proposed framework is a force for transformation that is changing the way that people view healthcare. It commits to bringing in a time when early detection is the standard rather than just a possibility, upending preconceived notions and fostering a proactive attitude towards cardiac health care. It represents a vision of a proactive rather than reactive healthcare system in which early detection empowers individuals, improves outcomes, and forms the basis of a healthier society.

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ETHICAL APPROVAL

This study's use of human subjects complies with all applicable institutional and national rules and upholds the principles of the Helsinki Declaration. The study, which included verification of the advanced cardiac monitoring system at BMS Hospital, Bangalore, in collaboration with a cardiologist, and testing on a limited number of patients to assess its functionality. Informed consent was obtained from all participating patients before their involvement, ensuring the protection of their rights and confidentiality throughout the verification process.

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