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A Multi-Layer Adaptive Architecture Driven by Case-Based Reasoning for Post-Discharge Care

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Abstract

This paper presents an adaptive system for post-discharge physiological monitoring that addresses the challenges of heterogeneous and imperfect data collected in home environments. The proposed framework integrates sensing layer adaptation with a case-based reasoning algorithm recommender (CBR-AR) to enable context-aware selection of data analysis strategies. Instead of relying on a fixed processing pipeline, the system characterizes incoming physiological data and dynamically selects appropriate preprocessing and detection methods based on prior cases stored in a meta-dataset. Rough set theory is incorporated to determine attribute importance and improve similarity-based case retrieval under uncertainty. A system architecture is developed to connect wearable sensing, mobile data management, and cloud-based analytical modules. The sensing layer includes adaptive mechanisms for signal prioritization and sampling rate control, allowing the system to balance data quality, energy consumption, and bandwidth constraints. The analysis layer operationalizes adaptive strategy selection through the CBR-AR framework and executes the selected methods for abnormality detection. A case study using ECG data demonstrates the workflow of the system, where an LSTM-based model is selected and applied to detect arrhythmia-related patterns. The study serves as a functional illustration of how the system adapts to specific data conditions rather. The proposed approach provides a foundation for future integration with higher-level reasoning to assist clinical decision-making in post-discharge care.

Keywords
Adaptive Analysis, Case-Based Reasoning, Analysis Strategy Selection, Physiological Signal Analysis, Post-Discharge Care System

1. Introduction
Hospital readmission remains one of the most persistent and costly challenges facing the American healthcare system. According to the Agency for Healthcare Research and Quality's Nationwide Readmissions Database, the United States recorded approximately 32.9 million inpatient discharges in 2022, the most recent year for which nationally representative data are publicly available, and roughly 13.3% of those patients were readmitted within 30 days of discharge (AHRQ 2024). This represents an estimated 3.74 million readmission events in a single year. Among FFS Medicare beneficiaries, who tend to be older, carry greater comorbidity burdens, and rely more heavily on post-acute care transitions, the risk-adjusted hospital readmission rate reached 15.4% in fiscal year 2024 (MedPAC 2026). Suboptimal communication of discharge instructions has been identified as a major contributor to hospital readmission. Recent evidence shows that deficiencies in patient education at discharge are associated with increased risk of treatment failure and readmission (Beck et al. 2021). Patients who are not adequately informed about their medications and care plans often demonstrate poor adherence and limited understanding of their treatment, which can compromise recovery after discharge. Beyond communication issues, many post-discharge patients have limited access to continuous health monitoring, making it difficult to detect early signs of deterioration. Inadequate post-discharge support and lack of accessible follow-up mechanisms may hinder patient's transition from hospital to home and weaken the continuity of post-discharge care (Jesus et al., 2024). As a result, patients often rely on hospital revisits as

the primary means of obtaining timely care. However, the cost and inconvenience associated with in-person visits can reduce adherence to recommended follow-up care, further increasing the risk of delayed treatment and readmission. Mobile health systems and IoT-based monitoring solutions have been introduced to enable continuous and remote healthcare services. Smart mobile devices allow patients to actively participate in their health management, while IoT technologies extend these capabilities by integrating wearable sensors and wireless communication for real-time physiological data collection and analysis. However, deploying such systems in real-world environments introduces several practical challenges that directly affect their reliability and usability:

- **Data quality:** Wearable sensor data are often incomplete or unreliable due to non-wear periods, user behavior, and sensor artifacts. Wearable sensor data is affected by motion artifacts, poor adhesion, and noise, which reduce signal stability and limit their diagnostic applicability (Iqbal et al. 2021). Furthermore, real-world wearable datasets frequently exhibit missing data, data entry errors, and variability caused by user interaction, requiring additional validation and processing to ensure reliability (Van Der Donckt et al. 2024).
- **Energy consumption and communication fault tolerance**: In wearable environments, sensors are required to operate continuously under limited battery capacity, making energy efficiency a critical design factor. Lon-term monitoring is often hindered by limited battery life and transmission vulnerabilities (Iqbal et al. 2021), particularly since wireless communication dominates the energy budget compared to local processing Ahmmed et al. (2025). These system interaction further impact data availability, as system interaction such as insufficient frequency of data synchronization leads to non-random data loss (Braem 2024). Such communication-related disruption can lead to structured data loss, which directly affects system performance, including downstream analysis and decision-making.
- **Algorithm selection for data analysis:** Even if data quality issues are mitigated and sensing systems operate reliably under energy and communication constraints, another challenge emerges at the analysis stage. The same type of physiological signal may not be effectively interpreted using a single fixed method across all conditions. Variations in signal characteristics influence preprocessing and feature extraction strategies (Charlton et al. 2022), while in practice, automated analytical pipelines still need to navigate diverse data characteristics and modeling choices (Castro et al. 2025). In clinical prediction tasks, there is a persistent need for flexible and adaptive strategies.

This paper proposes a multi-layer adaptive architecture for post-discharge care that integration sensing layer adaption with case-based reasoning- driven analysis strategy selection. The system is designed for heterogeneous and imperfect data conditions in home-based environments, enabling data-driven adjustment from acquisition to interpretation. Through the proposed CBR-AR system, analysis strategy can be selected based on data characteristics. The system enables past cases to be compared and used for decision-making under varying conditions. Furthermore, the rough set-based weighting mechanism further optimizes the selection process by capturing the relative importance of different attributes, supporting the alignment between data conditions and analytical methods.

2. Related Work on Emerging Technologies

2.1 IoT Based Remote Smart Health Monitoring Service System

IoT-based remote health monitoring systems have been widely studied as a way to extend healthcare services beyond hospital settings. In the past several decades, development in sensing technology has provided masses of portable and flexible methods of collecting physiological data from patients, which make an integral system possible. Existing studies adopt multi-layer architectures that integrate sensing, communication, and cloud-based processing. Mohapatra et al. (2025) and Abu-Jassar et al. (2025) both demonstrate systems combining wearable sensors with cloud services to enable real-time transmission, storage, and visualization for remote monitoring. At a broader level, Whig et al. (2025) and Alsabah et al. (2025) highlight that IoT ecosystems that comprise interconnected sensors, cloud platforms, and high-speed networks form a common foundation for smart healthcare systems, with increasing integration of AI, big data analytic for healthcare applications. To address data quality issues, Mohapatra et al. (2025) incorporate sensor fusion and anomaly detection to enhance reliability, while Van Der Donckt et al. (2024) proposes data validation pipelines and visualization-based methods to identify missing data patterns and assess biases.

For energy efficiency and communication reliability, prior work emphasizes system-level optimization. Ahmmed et al (2025) demonstrate that reduction data transmission through compressed sensing can significantly lower energy consumption in wearable systems. This improves resource efficiency in wearable monitoring by optimizing sensor sampling rates, demonstrating that lower sampling frequencies can substantially reduce data volume, storage cost, and power consumption while preserving clinically relevant accuracy. (Bent and Dunn, 2021). This improves energy efficiency in wearable ECG monitoring by using deep reinforcement learning to adaptively control sampling rates, achieving significant reductions in computation and data transmission energy while maintaining accurate real-time signal analysis (Demirel et al. 2023).

2.2 Data-dependent Physiological Signal Analysis and Method Selection

Physiological signal analysis and home-based healthcare is not a single, well-defined problem with a universal optimal solution. Instead, it merges from a heterogeneous set of data conditions that vary across sensing modalities, acquisition environments, and clinical objectives. Even with a single modality such as photoplethysmography (PPG), measurements are affected by wearable configurations, motion conditions, and physiological and environmental factors, leading to variability in signal quality. Consequently, different preprocessing and analysis techniques are required to reliably derive physiological parameters such as heart rate and blood oxygen saturation (Charlton et al. 2022). This indicates that methodological diversity is driven by variations in the underlying data characteristics. This heterogeneity becomes more pronounced when extending beyond contact-based sensing. Hassanpour and Yang (2025) show that remote vital sign monitoring incorporates a wide range of modalities, including vision-based, radar-based, and ambient sensing. Each has distinct sensitivities to environmental factors such as lighting, occlusion, and noise. In response, multi-modal fusion and multi-task learning approaches have been developed to compensate for these types of limitations and enhance accuracy. This further reinforces the view that physiological signal analysis is a data-conditioned problem, where method selection is inherently tied to operating context. This suggests that when signal quality is relatively stable and feature representations are informative, conventional machine learning approaches remain effective.

At the level of analytical pipelines, existing studies also demonstrate the different data conditions naturally lead to different methodological choices. For example, Qananwah et al. (2024) develop a PPG-based arrhythmia classification framework that relies on structured preprocessing, handcrafted feature extraction, and classical machine learning models such as support vector machines and k-nearest neighbors, achieving high classification performance on preprocessed PPG signals. The dependence of model performance on data conditions is formally captured in algorithm selection literature. Tornede et al. (2022) define algorithm selection as the task of mapping each problem instance to the most suitable algorithm based on its characteristics, and further show that even algorithm selectors themselves can exhibit complementary strengths, motivating meta-level selection strategies. In medical applications, this challenge is further reflected in the growing adoption of automated machine learning. Castro et al. (2025) report that AutoML has been widely applied to clinical prediction tasks, but key components such as model selection and data preprocessing remain important challenges, even within automated pipelines. Moreover, the limited integration of explainable AI highlights an additional constraint in healthcare settings, where transparency and interpretability are critical for decision support.

Beyond model centric approaches, case-based reasoning (CBR) provides an alternative paradigm that directly links data conditions to decision-making through similarity-based retrieval. Noll et al. (2025) describes how CBR can operate on heterogeneous clinical data, including both structured and unstructured data, while maintaining interpretability through similarity-based reasoning and explainable similarity metrics. Similarly, Shojaee-Mend et al. (2024) show that combining fuzzy ontology with CBR enables effective reasoning over imprecise and linguistic clinical features, supporting diagnostic decisions in domains where data are incomplete, subjective, or weakly structured.

3. Analysis and Design of the Adaptive Post-discharge Monitoring System

3.1 Functional System Design

The funcional decomposition model of the proposed system is depicted in the IDEF0 diagram in Figure 1. It structures across four sequential functional blocks labled A1 through A4. The notation follow stardard (Input, Control, Output, Mechanism) conventions, where top arrows represent control constraints, left arrows represent inputs, right arrows represent outputs and bottom arrows represent mechanisms.

The first functional block A1, physiological data acquisition, starts with selected sensors and is controled by sensing procedure guideline and sensor managing rules. The sensing platform acts as a mehanism, while the sensor data charateristics, such as sampling frequency, and raw physiological data flow out as the output into the downstream processes. Data Characterization block A2 received the raw physiological data from A1 and processes it to extract data characteristics, such as data availability. The analysis strategy selection block A3 integrates three concurrent inputs: sensor and physiological data characteristics, as well as patient baseline characteristics. A CBR(Case-Based Reasoning) Algorithm Recommender acts as the main computational mechanism for selecting appropriate analytical strategy for processing data. The output, selected algorithm(s), along with the raw physiological data, are passed to the A4 abnormalities detection block. The output, analyzed results, includes the detection results and corresponding performance. When evidence suggests underperforming, a new sensor configuration suggestion is fed back to the A1 functional block for better future performance.

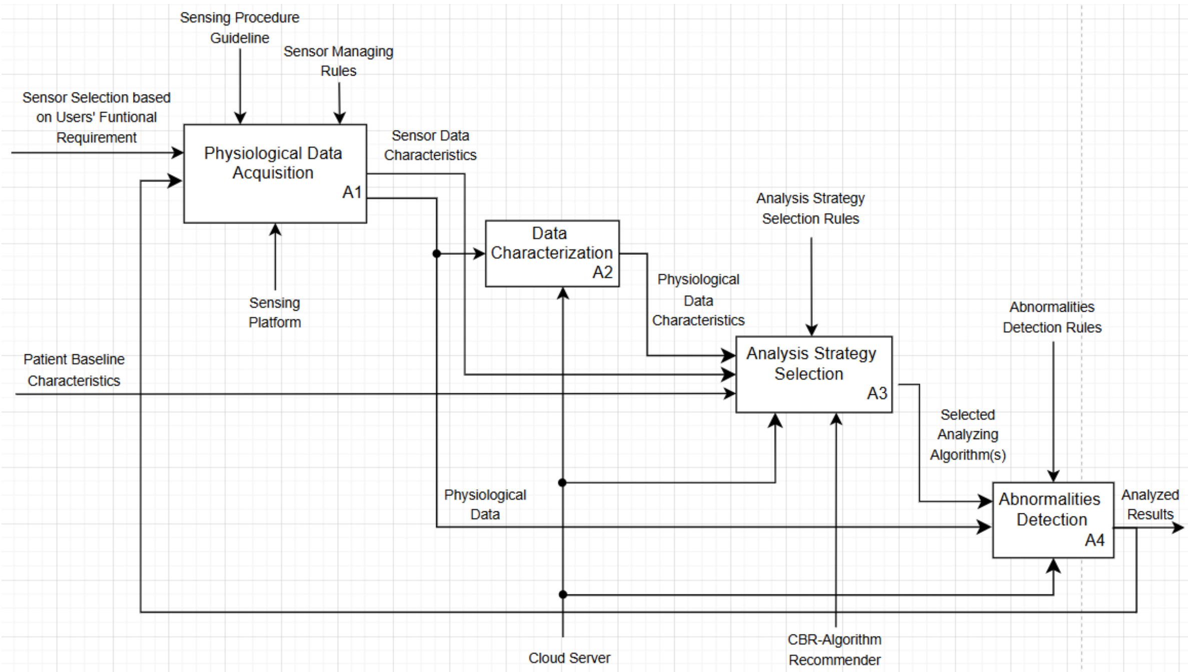

Figure 1. IDEF0 functional decomposition of the proposed system

3.2 System Architecture of the Proposed System

Figure 2 shows the system architecture of the proposed post-discharge care system. There are five components: a Mobile Platform hosting the Sensing Layer Adaptatioon, a Cloud Server hosting the Model Layer Adaptation, a Wireless Sensing Network, as well as two human actors, a post-discharge patient and a professional medical staff member. The Wireless Sensing Network forms the data acquisition foundation. It comprises three subcomponents: a sensor information module that tracks sensor status and configurations; a wearable sensors category that includes sensors that can collect data throughout the day; and a non-wearable sensors category including sensors with spot or intermittent measurements. Patients interact with this layer directly by wearing and using sensors for data collection, while the Mobile Platform's Sensor Management module governs hardware behavior through monitoring and adaptation. The adaptation of acquisition parameters in response to changing operational contexts provides optimal data quality and will be discussed in detail in Chapter 4. The Mobile Platform operates as the local intermediary between the patient and the cloud server. The Local Data Management module stores user information, user settings, and collected physiological data, and it transmits this data upward to the cloud while receiving incoming sensor-collected data for local retention. The Result Receive Module accepts analyzed results returned from the cloud. The post-discharge patient update baseline information and the Notification Center push notifications and clinical guidance down to the patient.

The Cloud Server hosts the analytical backbone of the system, structured across three sequential processing modules that collectively transform raw physiological data into clinically interpretable outputs. Upon receiving collected data from the Mobile Platform, the Data Characterization module classifies the incoming signal by data type, computes descriptive statistics, and flags missing or erroneous values. The output feeds into the Model Layer Adaptation, which performs analysis strategy selection through a Case-Based Reasoning - Algorithm Recommender (CBR-AR). The CBR-AR draws on a database of prior cases to recommend the most contextually appropriate analytical pathway for a given physiological data profile. Preprocessing Strategy Selection determines the sequence of signal conditioning operations, including noise removal, differencing, and missing data handling. Detection Strategy Selection identifies the appropriate detection method from a set of candidate approaches. Following strategy execution, the Abnormality Detection module runs the selected algorithm on the preprocessed data. Afterwards, the results are transmitted back to the Mobile Platform to notify the post-discharge patient.

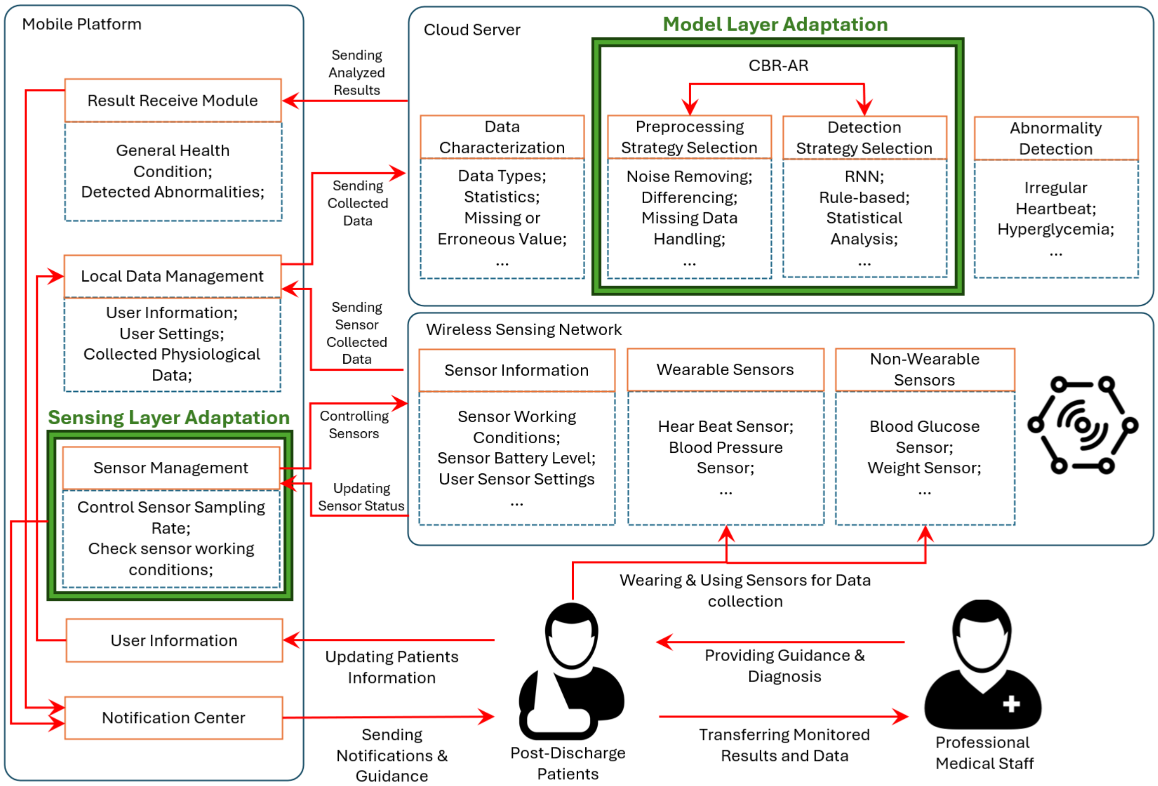

Figure 2. System architecture of the proposed post-discharge care system

4 Smart Sensing Subsystem for Data Acquisition

4.1 Sensor Management and Data Acquisition Framework

Health data acquisition acts as the fundamental part of the proposed whole system. To detect the abnormal health status of the patient accurately, there should be a certain number of sensors for acquiring different types of data. Real-time data from sensors causes huge storage and accessibility problems in the long run, so a smart sensing subsystem is necessary for managing sensors and collecting physiological data. The framework of the Sensor Management module within the Mobile Platform, as shown in Figure 3, is structured into three primary functional domains: Fundamental Management, Fault-Tolerance Sensing, and Sampling Rate Control. This subsystem facilitates a bidirectional interface with the Wireless Sensing Network. Communication between these two subsystems is maintained through continuous sensor status updates and responsive sensor control commands.

Fundamental Management module serves as the foundational utility layer, overseeing the core operational health of the sensing hardware. Within this block, the Sensor Calibrator ensures hardware precision while the Usage Monitor track system run-time metrics. To maintain system reliability, the Sensor Alert function trigger notifications based on hardware malfunctions detected by the status monitor. Most notably, the Power Monitor and Signal Checking components serve as critical diagnostic tools. The Power Monitor tracks the energy consumption rates, while Signal Checking evaluates data integrity across varying frequencies. Data from these two functions serves as the primary input for the reward-based adaptive logic in sampling rate controlling. To ensure system resilience and data continuity, Fault-Tolerance Sensing block manages data flow during periods of network instability or high latency to minimize the effect of corrupted data. Local Buffer acts as a temporary relay station for system settings and physiological data in case of data resampling. Simultaneously, the Bandwidth Monitor continuously assesses the available transmission capacity. The Signal Priorities Controller then determines the transmission priority to prevent data loss. The Sampling

Rate Control block implements a closed-loop learning mechanism for dynamic sampling rate adjustment with a goal of optimizing the tradeoff between data resolution and energy efficiency.

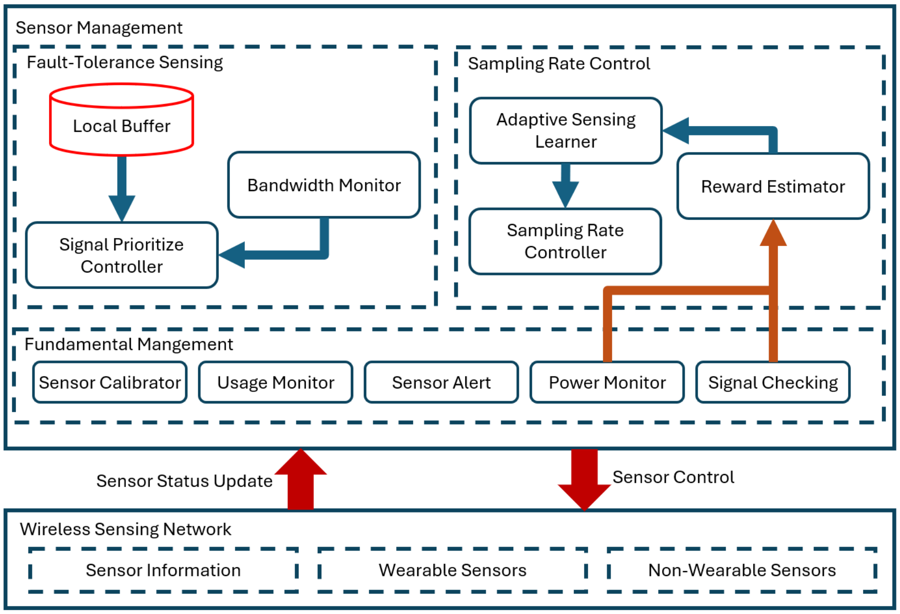

Figure 3. Internal Mechanism of the Sensing Layer Adaptation Module

4.2 Sensing Layer Adaptation

The Sensing Layer Adaptation contains two components: Fault-Tolerance Sensing and Sampling Rate Control. Fault-Tolerance Sensing block ranks the different types of sensor-collected data based on their priority. When the bandwidth becomes unstable or low, the signal prioritize controller allows the sensor management layer to receive the more important types of physiological data first. Therefore, the more important data has a lower chance of containing errors. The priority of the data type is stored in the local buffer database. Based on different sensor types and settings, the priority of different data types can be adjusted.

The second component, Sampling Rate Control, determines the size of the data stream, quality of the signal and sensor usage time. To achieve the optimal balance among these three factors, an adaptive sensing mechanism is proposed. The controller adjusts the sampling rate of each sensor to maximize the reward estimator. A performance score estimate function for $\boldsymbol{i}$th sensor is defined as:

$$\boldsymbol{R^i(\theta_i) = \alpha^i R^i_{energy}(\theta_i) + \beta^i R^i_{quality}(\theta_i) + \gamma^i R^i_{bandwidth}} \tag{1}$$

In Equation (1), $\boldsymbol{\theta_i}$ represents the sampling rate of the $\boldsymbol{i_{th}}$ sensor. The coefficients $\boldsymbol{\alpha^i}$, $\boldsymbol{\beta^i}$, $\boldsymbol{\gamma^i}$ denote weight factors that determine the relative contribution of the three sub score estimation functions: $\boldsymbol{R^i_{energy}(\theta_i)}$, $\boldsymbol{R^i_{quality}(\theta_i)}$ and $\boldsymbol{R^i_{bandwidth}}$. The values of the three weight factors are affected by the hardware of the smart sensing system. For example, a sensor equipped with a higher battery capacity will lead to a lower $\boldsymbol{\alpha}$ to balance the score function. The energy score, $\boldsymbol{R^i_{energy}(\theta_i)}$, reflects energy consumption over a specific temporal interval as reported by the Power Monitor function. The signal quality score, $\boldsymbol{R^i_{quality}(\theta_i)}$ is returned by the Signal Checking function**.** During the initial sensing phase, the sampling rate starts at a high baseline based on the IEEE standard. Consequently, the quality of the signal is assessed by comparing the returned signal data at different sampling rates. The signal data is kept temporarily in the local buffer data storage. The bandwidth score, $\boldsymbol{R^i_{bandwidth}(\theta_i)}$, depends on the size of the data stream, which remains a direct function of the sensor sampling rate. In addition, the weight factor of the $\boldsymbol{R^i_{bandwidth}}$ is based on the priority of the data type.

5. Adaptive Strategy Selection for Condition Monitoring and Symptom Detection

5.1 Strategy Pool for Physiological Signal Analysis

Physiological data collected from patient-operated sensors in home environments are inherently diverse, noisy, and often inconsistent in quality. Variations in sensor types, user conditions, and environmental factors lead to significant differences in data characteristics. As a result, relying on a single fixed analysis pipeline is often insufficient to ensure robust and accurate interpretation across diverse scenarios. To address this challenge, a case-based strategy pool is introduced as a flexible repository of candidate analysis methods, designed to accommodate heterogeneous data conditions and varying analytical requirements. Specifically, the system dynamically selects appropriate strategies for both preprocessing and abnormality detection based on data characteristics. For instance, a specific type of continuous data from wearable sensors requires noise reduction and feature extraction for data preprocessing and predictive learning models for abnormality detection. In contrast, another type of discrete data requires minimal preprocessing and can be effectively analyzed using rule-based methods.

5.2 Case-based Strategy Selection with Rought Set Weighting

The case-based strategy pool mentioned earlier is operationalized in this section as a case-based reasoning (CBR)-Algorithm Recommender (AR), which enables systematic mapping from data characteristics to appropriate analysis strategies. After collecting the physiological data, the data is transmitted to the cloud server for further processing. Within the cloud server, a data characterization model first summarizes the properties of data. This information is then passed to the proposed CBR-AR system, which performs adaptive strategy selection for downstream analysis based on the existing experience without testing all algorithms with the new data. The proposed system relies on a meta-dataset that captures the relationship between data characteristics and suitable analysis strategies. This meta-dataset is constructed from prior cases, where each case encodes descriptive features of the input data along with the corresponding selected analysis strategy and its performance. These meta-features in the meta-dataset are characterized by the instances and attributes in the meta-dataset, which are employed by the proposed method to find the suitable algorithm (Pimentel & de Carvalho, 2019).

Compared to static algorithm selection methods based on conventional meta-learning, the CBR-based method has several advantages: (1) provides flexibility in incorporating new strategies without requiring full model retaining, (2) supports reasoning under partially matching fuzzy condition (Lindner & Studer, 1999). To further handle uncertainty in evaluating strategy suitability, rough set theory is employed as a mathematical framework for modeling vagueness and supporting adaptive weighting in the recommendation process.

5.2.1 Architecture of the Case-based Reasoning Algorithm Recommender

The workflow architecture of the CBR-AR system designed for automated data analysis and strategy selection is illustrated in Figure 4. The CBR-AR contains two main functional regions: a centralized case database and a series of processes for new case creation. The system executes the solution-finding process for a new problem based on previous problems and solutions with human domain experts integrated into the verification loop. The case base C_i, formulated as a meta-dataset, acts as the system's long-term memory with structured problem-solution associations from prior analyses. Each case includes a set of metadata D_i and the corresponding solution S_i, indexed for a total of n cases. The metadata D_i consists of two categories of descriptors, baseline metadata B_j and meta-features F_k. B_j includes baseline information such as a patient's weight and age, and F_k contains sensor data such as sensor type and extracted features from raw physiological data such as data availability. The solution stores prior algorithmic recommendations by analysis strategy A_h and detection performance P_h.

Incoming data from a new collected dataset enters through an automatic characterization tool, which extracts baseline metadata b_j and meta-features f_k. These descriptors constitute a newly formed case, designated C_{new}. The case then passes through a retrieval step, where the system queries the case base to identify historically analogous cases and returns a list of candidate solutions ranking by similarity score. Details of the case retrieval process are discussed in the next section. The recommendation is then subjected to case verification, which includes a self-verification process and a joint evaluation with a medical expert and/or a data science engineer if the case is flagged by the system. During the self-verification process, the system evaluates the detection performance after deploying the recommended strategy on the new case. If the performance is below a predefined threshold, the system uses the second-highest similarity score to select an alternative candidate solution. If, after a few cycles, the result is still unsatisfactory, the case is flagged as a pending case and feedback is sent to sensor management to provide recommendations for the next day's data collection, including sensor configuration adjustments. If the result remains unsatisfactory after adjustments on the following day, the case is flagged for human evaluation. A new solution created by domain experts and its detection performance will then be updated to retain the case in the case base.

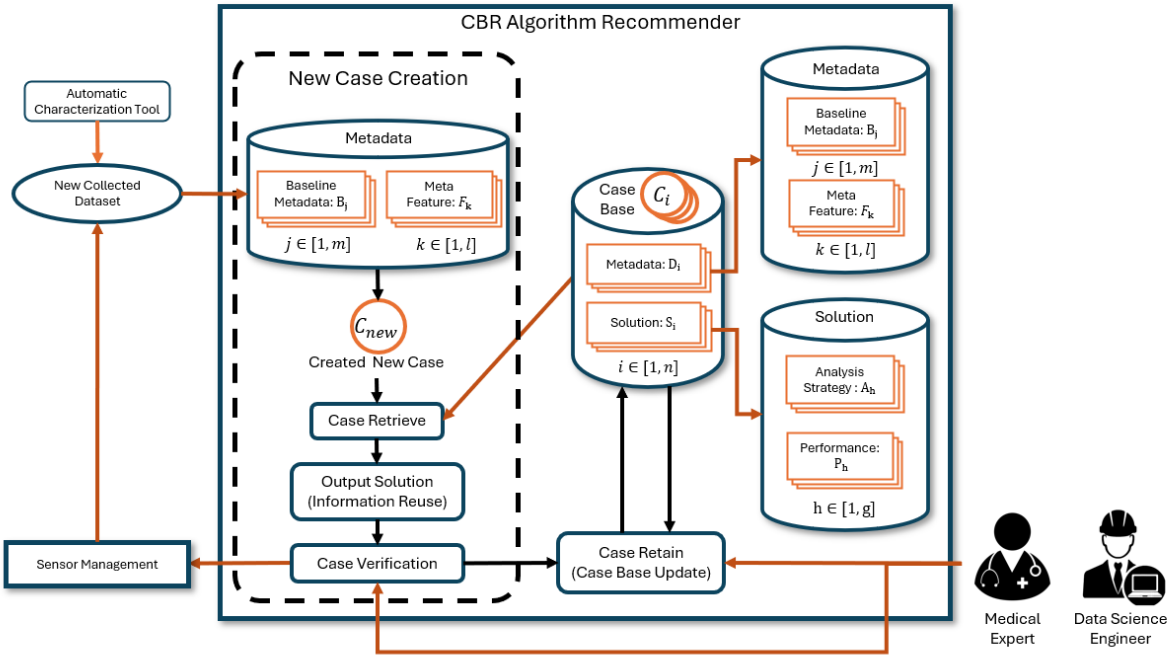

Figure 4. Workflow architecture of the CBR-AR system

5.2.2 Rough Set-Based Similarity for Case Retrieval

As discussed in the previous section, CBR is employed to select the appropriate strategy for a new classification task based on prior cases. These cases are represented using a rough set-based decision system that contains cases as objects U, metadata as conditional attributes C, and solutions as decision attributes D. For a new case, similarity-based retrieval is performed to identify relevant historical cases. The similarity relationship between two objects u_1 and u_2 can be defined as:

$$Sim(u_1, u_2) = \frac{\sum_{i=1}^{n} w_i S_{a_i}(u_1, u_2)}{\sum_{i=1}^{n} w_i} \tag{2}$$

where w_i denotes the weight factor of attribute a_i, and $S_{a_i}(u_1, u_2)$ measures the similarity between two cases with respect to that attribute. Selected n attributes are used for calculation. Attribute-level similarity is computed using normalized distance for numerical attributes and exact matching for symbolic attributes.

The attribute weights are determined based on rough set theory, which evaluates the classification capability of each attribute. Given a subset of conditional attribute $P \subseteq C$, which induces an indiscernibility relation over the case base, the weight w_i for each attribute $p_i \in P$ is computed as (Pawlak 1982; Bahga & Madisetti, 2012):

$$w_i = \frac{card\big(POS(P, D)\big)}{card(U)} - \frac{card\big(POS(P - \{p_i\}, D)\big)}{card(U)} \tag{3}$$

Where $POS(\cdot)$ denotes the positive region and $card(\cdot)$ denotes set cardinality. Continuous attributes are discretized prior to weight computation to avoid a zero-weight value.

6. Case Study of Post-Discharge Patient with Heart Arrhythmia

The case study is intended to illustrate the workflow of the proposed adaptive system. In the case study, the proposed system provides service to a post discharge patient who had heart arrhythmia problems. Heart Arrhythmia is one of the major health problems in the world. Heart arrhythmia refers to irregular electrical heartbeat signals which include

single ectopic occurrence, and continuous arrhythmia. Electrocardiogram (ECG) heartbeat signal is crucial for cardiovascular disorders (CVDs) diagnosis which can be collected by ECG sensor simply and non-invasively.
The post-discharge patient is a 52 years-old male who is diagnosed with heart failure. He decides to use the proposed system for the assistance of the monitor and recovery of heart diseases. He wears an ECG sensor for heartbeat data collection. The collected time-series heartbeats signal is preprocessed and then sent to the CBR-AR system for selecting the analysis strategy. The data are then analyzed to determine abnormalities, and the new case is then retained. The rest of the section includes adaptative analysis strategy selection through case representation and retravel, as well as heart arrhythmia detection by the selected strategy.

6.1 Strategy Selection using CBR-AR System

In this section, the use case of CBR-AR is described. Table 1 shows a synthetic illustrative example of the case baes. As mentioned in Chapter 4, the case base is in the form of a decision table $\boldsymbol{T}$, where $\boldsymbol{T} = (\boldsymbol{U}, \boldsymbol{C} \cup \boldsymbol{D})$**.** The case base contains 10 cases, where $\boldsymbol{U} = \{\boldsymbol{u_1}, \boldsymbol{u_2}, \dots, \boldsymbol{u_{10}}\}$. For each case, the conditional attribute set used for rough set analysis consists of meta features extracted from the ECG heartbeat data, expressed as $\boldsymbol{P} = \{\boldsymbol{c_2}, \boldsymbol{c_3}, \boldsymbol{c_4}, \boldsymbol{c_5}\}$**.** The decision attributes $\boldsymbol{D} = \{\boldsymbol{d_1}, \boldsymbol{d_2}\}$ are the solutions of each case. Baseline metadata such as age $\boldsymbol{c_1}$**,** is included in the case representation for descriptive purposes but are not involved in the rough set computation**.** Attributes $\boldsymbol{c_4}$and $\boldsymbol{c_5}$ are discretized into three categories {High, Medium, Low} for further computation. $\boldsymbol{c_4}$ is categorized as low (≤ 0.05), medium (0.05–0.15], and high (> 0.15). $\boldsymbol{c_5}$ is categorized as low (≤ 0.20), medium (0.20–0.50], and high (> 0.50).

Table. 1 Synthetic Illustrative Case Base for Demonstrating the CBR-AR Workflow

Case $\boldsymbol{U}$	Age $\boldsymbol{c_1}$	Signal Type $\boldsymbol{c_2}$	Sampling Rate (hz) $\boldsymbol{c_3}$	Data Missing Rate $\boldsymbol{c_4}$	Noise Index $\boldsymbol{c_5}$	Preprocessing Strategy $\boldsymbol{d_1}$	Detection Strategy $\boldsymbol{d_2}$
1	45	ECG	125	0.09	0.35	Bandpass	CNN-LSTM
2	66	ECG	250	0.22	0.41	Signal Cleaning	CNN-LSTM
3	89	ECG	250	0.12	0.56	Signal Cleaning	CNN-LSTM
4	70	ECG	250	0.1	0.21	Bandpass	LSTM
5	55	PPG	50	0.16	0.12	Moving Average	Rule-based
6	67	PPG	250	0.2	0.18	Moving Average	Rule-based
7	71	PPG	250	0.25	0.25	Moving Average	Rule-based
8	54	PPG	250	0.03	0.3	Smoothing	Peak Detection
9	60	PPG	250	0.06	0.51	Artifact Removal	Random Forest
10	59	PPG	250	0.14	0.22	Smoothing	Peak Detection

Based on the table, the positive regions are shown below:

$$\boldsymbol{POS}(\boldsymbol{P}, \boldsymbol{D}) = \{\{u_1\}, \{u_2\}, \{u_3\}, \{u_4\}, \{u_5\}, \{u_6\}, \{u_7\}, \{u_8\}, \{u_9\}, \{u_{10}\}\}$$

$$\boldsymbol{POS}(\boldsymbol{P} - \{\boldsymbol{c_2}\}, \boldsymbol{D}) = \{\{u_6\}, \{u_8\}, \{u_1\}, \{u_5\}\}$$

$$\boldsymbol{POS}(\boldsymbol{P} - \{\boldsymbol{c_3}\}, \boldsymbol{D}) = \{\{u_2\}, \{u_3\}, \{u_7\}, \{u_8\}, \{u_9\}, \{u_{10}\}, \{u_5, u_6\}\}$$

$$\boldsymbol{POS}(\boldsymbol{P} - \{\boldsymbol{c_4}\}, \boldsymbol{D}) = \{\{u_1\}, \{u_3\}, \{u_5\}, \{u_6\}, \{u_9\}\}$$

$$\boldsymbol{POS}(\boldsymbol{P} - \{\boldsymbol{c_5}\}, \boldsymbol{D}) = \{\{u_1\}, \{u_2\}, \{u_5\}, \{u_8\}, \{u_6, u_7\}\}$$

Based on Equation 3, the weight factor w_i can be calculated where $\boldsymbol{w_1} = 0.6, \boldsymbol{w_2} = 0.2, \boldsymbol{w_3} = 0.5$, and $\boldsymbol{w_4} = 0.4$. A new case generated based on the ECG heartbeat data is shown as below:

Case $\boldsymbol{U}$	Age $\boldsymbol{c_1}$	Signal Type $\boldsymbol{c_2}$	Sampling Rate (hz) $\boldsymbol{c_3}$	Data Missing Rate $\boldsymbol{c_4}$	Noise Index $\boldsymbol{c_5}$
new	52	ECG	125	0.18	0.22

The similarity between the new case and existed case can be obtained from Equation (2). The result is shown in **Table** 2 where $\boldsymbol{u_4}$ is the most similar to the new case. Therefore, the recommended strategy for preprocessing is bandpass and for detection is LSTM.

Table 2. Case retrieval results ranked by similarity (descending order)

Case No.	Similarity	Preprocessing Strategy d_1	Detection Strategy d_2
4	0.81	Bandpass	LSTM
1	0.77	Bandpass	CNN-LSTM
2	0.66	Signal Cleaning	CNN-LSTM
3	0.81	Signal Cleaning	CNN-LSTM
6	0.52	Moving Average	Rule-based
5	0.53	Moving Average	Rule-based
10	0.46	Smoothing	Peak Detection
7	0.33	Moving Average	Rule-based
8	0.26	Smoothing	Peak Detection
9	0.52	Artifact Removal	Random Forest

6.2 Strategy Execution Example: LSTM as a Time-Series Analysis Strategy

Based on the strategy selection result obtained from the CBR-AR module, this section demonstrates the execution of the selected LSTM strategy using ECG time-series data. To illustrate, a publicly available ECG dataset is employed. The data for training the model is originally combined from MIT-BIH Arrhythmia Database (Amaral et al., 2000) and PTB Diagnostic ECG Database (Kreiseler et al., 1995). The dataset is resampled at 125Hz and divided into a short period of 1second based on the R-R time interval (Kachuee et al., 2018). The ECG heartbeat data have labeled into one of five categories: $\boldsymbol{N}, \boldsymbol{S}, \boldsymbol{V}, \boldsymbol{F}, \boldsymbol{Q}$, where $\boldsymbol{N}$ represents the normal beats, $\boldsymbol{S}$ represents the supraventricular ectopic beats, $\boldsymbol{F}$ represents the fusion beats and $\boldsymbol{Q}$ represents the unknown beats. There are 87554 samples of training data and 21892 samples of test data, with 20% of the training data used for validation.

The model takes time-series heartbeat segments as well as the patient's baseline metadata stored in the case base as inputs and produces a probability vector [P(N), P(S), P(V), P(F), P(Q)], which represents the likelihood of each heartbeat category. Table 3 shows the overall results of heart arrhythmia classification. In this case, the probability of supraventricular ectopic beats is the highest at 60.245%, while the probabilities of normal beats, ventricular ectopic beats, and fusion beats are 20.851%, 14.902%, and 39.987%, respectively. These results indicate a high likelihood of abnormal cardiac activity.

Table 3. Overall Classification Results of Heartbeats of the User in Two Hours

Predicting Results of the Arrhythmia Type Classification
Probability of Normal Beats (N): 0.20851
Probability of Supraventricular Ectopic Beats (S): 0.60245
Probability of Ventricular Ectopic Beats (V): 0.14902
Probability of Fusion Beats (F): 0.39987
Probability of Unknown Beats (Q): 0

	Normal Beats	Suparventrical Ectopic Beats	Ventricular Ectopic Beats	Fusion Beats	Unknown Beats
Accuracy	0.99	0.84	0.96	0.86	0.99

These results are then passed to subsequent modules in the system, such as notification generation, enabling further interpretation and adaptive response. In this way, the LSTM model serves as an execution component within the overall CBR-AR framework, transforming raw physiological signals into structured information for downstream reasoning.

7. Conclusion and Future Work

This paper presents an adaptive system for post-discharge physiological monitoring that integrates sensing layer adaptation with case-based analysis strategy selection. The system is designed to operate under heterogeneous and imperfect data conditions commonly observed in home-based health care environments. The case study demonstrates the functionality of the system workflow, specifically how raw physiological data are characterized, how analysis strategies are selected through the proposed CBR-AR mechanism, and how the selected model (e.g. LSTM) is executed within the pipeline. A central aspect of the proposed system is the use of a meta-dataset stored in the case base to link data characteristics with analysis strategies. This allows prior experience to be reused in a structured way and supports adaptive decision-making under varying data conditions. The integration of rough set-based weighting further enhances the retrieval process by capturing the relative importance of different attributes in distinguishing suitable strategies. Together, these components form a flexible mechanism for aligning data conditions with analytical methods in a systematic manner.

Beyond the current scope, this work also establishes a foundation for extending the system toward more comprehensive clinical reasoning. The outputs generated by the analysis layer, such as probabilistic abnormality detection results, can be further interpreted as higher-level health indicators and incorporated into downstream reasoning processes. This opens the path toward integrating data-driven models with knowledge-based representations which enables the system to support more structured interpretation of patient conditions. In a broader context,

References

Abu-Jassar, A. T., Attar, H., Amer, A., Lyashenko, V., Yevsieiev, V. and Solyman, A., Remote Monitoring System of Patient Status in Social IoT Environments Using Amazon Web Services Technologies and Smart Health Care, *International Journal of Crowd Science*, vol. 9, no. 2, pp. 110-125, 2025.

Agency for Healthcare Research and Quality, Introduction to the HCUP Nationwide Readmissions Database (NRD) 2022, Available: https://hcup-us.ahrq.gov/db/nation/nrd/NRDIntroduction2022.pdf, December, 2024.

Ahmmed, P., Garceau, E., Latif, T., Brewer, A., Dieffenderfer, J., Valero-Sarmiento, J. M., Pamula, V. R., Van Helleputte, N., Van Hoof, C., Verhelst, M. and Bozkurt, A., Preclinical Evaluation of a Wearable Wristband With Compressed-Sensing Based Photoplethysmography, *IEEE Transactions on Biomedical Engineering*, vol. 72, no. 5, pp. 1596-1604, 2025.

Alsabah, M., Naser, M. A., Albahri, A. S., Albahri, O. S., Alamoodi, A. H., Abdulhussain, S. H., and Alzubaidi, L., A comprehensive review on key technologies toward smart healthcare systems based IoT: technical aspects, challenges and future directions, *Artificial Intelligence Review*, vol. 58, no. 343, 2025.

Bahga, A. and Madisetti, V. K., Analyzing massive machine maintenance data in a computing cloud, *IEEE Transactions on Parallel and Distributed Systems*, vol. 23, no. 10, pp. 1831–1843, 2012.

Becker, C., Zumbrunn, S., Beck, K., Vincent, A., Loretz, N., Müller, J., Amacher, S. A., Schaefert, R. and Hunziker, S., Interventions to Improve Communication at Hospital Discharge and Rates of Readmission, *JAMA Network Open*, vol. 4, no. 8, pp. 1–23, 2021.

Bent, B. and Dunn, J. P., Optimizing sampling rate of wrist-worn optical sensors for physiologic monitoring, *Journal of Clinical and Translational Science*, vol. 5, no. 1, e34, 2021.

Bousseljot, R., Kreiseler, D. and Schnabel, A., Nutzung der EKG-Signaldatenbank CARDIODAT der PTB über das Internet, *Biomedizinische Technik*, vol. 40, no. 1, pp. 317, 1995.

Braem, C. I. R., Yavuz, U. S., Hermens, H. J. and Veltink, P. H., Missing Data Statistics Provide Causal Insights into Data Loss in Diabetes Health Monitoring by Wearable Sensors, *Sensors*, vol. 24, no. 5, pp. 1526, 2024.

Castro, G. A., Barioto, L. G., Cao, Y. H., Silva, R. M., Caseli, H. M., Machado-Neto, J. A., Cerri, R., Villavicencio, A., and Almeida, T. A., Automated Machine Learning in Medical Research: A Systematic Literature Mapping Study, *Artificial Intelligence in Medicine*, vol. 171, pp. 103302, 2026.

Charlton, P. H., Kyriacou, P. A., Mant, J., Marozas, V., Chowienczyk, P., and Alastruey, J., Wearable Photoplethysmography for Cardiovascular Monitoring, *Proceedings of the IEEE*, vol. 110, no. 3, pp. 355–381, 2022.

Demirel, B. U., Chen, L. and Al Faruque, M. A., Data-driven Energy-efficient Adaptive Sampling Using Deep Reinforcement Learning, *ACM Transactions on Computing for Healthcare*, vol. 4, no. 3, Article 19, 2023.

Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R. and Stanley, H. E., PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals, *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000.

Hassanpour, A. and Yang, B., Contactless Vital Sign Monitoring: A Review towards Multi-Modal Multi-Task Approaches, *Sensors*, vol. 25, no. 15, pp. 4792, 2025.

Iqbal, S. M. A., Mahgoub, I., Du, E., Leavitt, M. A., and Asghar, W., Advances in healthcare wearable devices, *npj Flexible Electronics*, vol. 5, no. 9, 2021.

Jesus, T. S., Stern, B. Z., Lee, D., Zhang, M., Struhar, J., Heinemann, A. W., Jordan, N. and Deutsch, A., Systematic review of contemporary interventions for improving discharge support and transitions of care from the patient experience perspective, *PLoS ONE*, vol. 19, no. 5, e0299176, 2024.

Kachuee, M., Fazeli, S. and Sarrafzadeh, M., ECG Heartbeat Classification: A Deep Transferable Representation, *Proceedings of the IEEE International Conference on Healthcare Informatics (ICHI)*, pp. 443-444, New York, NY, USA, 2018. doi: 10.1109/ICHI.2018.00092.

Lindner, G. and Studer, R., Ast: Support for algorithm selection with a cbr approach, *Principles of Data Mining and Knowledge Discovery*, pp. 418–423, 1999.

Medicare Payment Advisory Commission (MedPAC), March 2026 report to the congress: Medicare payment policy, Chapter 3 Hospital inpatient and outpatient services, Available: https://www.medpac.gov/wp-content/uploads/2026/03/Mar26_Ch3_MedPAC_Report_To_Congress_SEC.pdf, March 2026

Mohapatra, A. G., Mohanty, A., Nayak, S., Menfash, H. A., Alqahtani, H., Al-Sharaei, A. M., Allaf, R. and Nafie, F. M., IoT-driven remote health monitoring system with sensor fusion enhancing immediate medical assistance in distributed settings, *Alexandria Engineering Journal*, vol. 120, pp. 627-636, 2025.

Noll, R., Berger, A., Facchinello, C., Stratmann, K., Schaaf, J. and Storf, H., Enhancing diagnostic precision for rare diseases using case-based reasoning, *Journal of the American Medical Informatics Association*, vol. 33, no. 1, pp. 98–111, 2026.

Pawlak, Z., Rough sets, *International Journal of Computer & Information Sciences*, vol. 11, pp. 341–356, 1982.

Pimentel, B. A. and de Carvalho, A. C. P. L. F., A new data characterization for selecting clustering algorithms using meta-learning, *Information Sciences*, vol. 477, pp. 203–219, 2019.

Qananwah, Q., Ababneh, M., and Dagamseh, A., Cardiac Arrhythmias Classification Using Photoplethysmography Database, *Scientific Reports*, vol. 14, pp. 3355, 2024.

Shojaee-Mend, H., Ayatollahi, H., and Abdolahadi, A., A Fuzzy Ontology-Based Case-Based Reasoning System for Stomach Dystemperament in Persian Medicine, *PLoS ONE*, vol. 19, no. 10, e0309722, 2024.

Tornede, A., Gehring, L., Tornede, T., Wever, M., and Hullermeier, E., Algorithm Selection on a Meta Level, *Machine Learning*, 2022.

Van Der Donckt, J., Vandenbussche, N., Van Der Donckt, J., Chen, S., Stojchevska, M., Brouwer, M. D., Steenwinckel, B., Paemeleire, K., Onganae, F., and Hoecke, S. V., Mitigating data quality challenges in ambulatory wrist-worn wearable monitoring through analytical and practical approaches, *Scientific Reports*, vol. 14, pp. 17545, 2024.

Whig, P., Kouser, S., Bhatia, A. B. and Alkali, Y., Role of IoT in developing smart healthcare monitoring systems, *Mining Biomedical Text, Images and Visual Features for Information Retrieval*, Academic Press, pp. 99-118, 2025.

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