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Classification of Heart Disease Using Fuzzy C-means Algorithm (FCM) in an Internet of Things Environment

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Abstract - **Heart diseases ailments persist as a significant source of global morbidity and mortality. Timely identification and precise categorization of these ailments play a pivotal role in enabling efficacious treatment and preventive measures. Leveraging technological advancements, The Internet of Things has evolved into a potent tool for monitoring and managing healthcare systems. This paper endeavors to investigate the utilization of the fuzzy C-means (FCM) algorithm for the classification of cardiac disorders within an IoT framework, with the primary objective of attaining favourable predictive outcomes. This pursuit involves a comparative assessment against pre-existing outcomes within the database to ascertain the algorithm's efficacy.**

Index Terms - **Heart diseases, IoT, Preventive measures, Fuzzy C-means algorithm (FCM), Classification.**

INTRODUCTION

After the emergence of the Internet of Things, the medical field has witnessed significant expansion and development and revolutionizing the landscape of healthcare practices. IoT is an integrated system of physical devices, sensors, and data communication mechanisms is profoundly impacting the healthcare sector by facilitating the smooth amalgamation of diverse medical equipment, thereby revolutionizing the field, data sources, and processes. This integration empowers healthcare providers and stakeholders to leverage real-time data, remote monitoring, and intelligent analytics for enhancing patient care, optimizing resource utilization, and driving proactive medical interventions.

The amalgamation of IoT technology with the healthcare sector has given rise to interconnected healthcare ecosystems, commonly termed the Internet of Medical Things (IoMT). Within this context, devices in the medical realm, along with wearable and implantable technologies, engage in mutual communication as well as interaction with central healthcare systems, generating a continuous flow of patient-related data.

This wealth of data not only allows for comprehensive patient monitoring but also facilitates the development of personalized treatment plans, predictive analytics, and early intervention strategies.

Moreover, the IoT's impact extends beyond patient care to encompass various aspects of the healthcare industry. Administrative processes, supply chain management, medical research, and public health monitoring are among the domains benefiting from IoT applications. The ability to collect, transmit, and analyse data in real-time offers insights into disease trends, enhances medical research through the accumulation of large-scale data sets, and improves operational efficiency across healthcare institutions.

As IoT-enabled medical devices continue to proliferate, addressing challenges related to data privacy, security, interoperability, and regulatory compliance becomes paramount. Balancing the potential benefits of IoT with the safeguarding of patient information and ensuring the reliability of interconnected systems are critical considerations. Within the scope of the Internet of Things (IoT) environment, the examination of extensive heart disease data assumes paramount importance. Central to this analytical endeavor are classification algorithms, which serve as pivotal tools for extracting insights from the copious data generated.

One such algorithm that merits attention is the fuzzy C-means (FCM) algorithm, renowned for its application in clustering and pattern recognition tasks. What distinguishes FCM from conventional algorithms is its integration of fuzzy logic principles, which engender the capacity for probabilistic assignments and the accommodation of data uncertainties.

By concurrently considering multiple parameters, FCM adeptly discerns underlying patterns and effectuates the classification of distinct heart ailments.

This algorithm undertakes the analysis of Heart Rate Variability (HRV) features, alongside other pertinent clinical data, thereby achieving precision in the distinction of diverse cardiac conditions.

The realm of scientific inquiry has exhaustively delved into the utilization of fuzzy logic algorithms for the purpose of categorizing cardiac disorders. Illustratively, the research undertaken by Nancy A. et al. [1] clarifies the integration of fuzzy logic principles and fog computing within the context of the Internet of Things (IoT) environment to enhance the diagnostic accuracy of heart diseases. The conceptualized intelligent healthcare framework, bolstered by fuzzy inference and deep learning mechanisms, attains a remarkable precision level by percentage of approx 99%. This achievement is accompanied by a strategic reduction in latency, achieved through data analytics processing at the fog layer. This innovative approach surpasses conventional cloud-based methodologies, thus unveiling substantial potential for time-sensitive healthcare applications. Similarly, in another study conducted by Zhengchun H. et al. [2], the application of the fuzzy C-means (FCM) algorithm is combined with Heart Rate Variability (HRV) analysis to differentiate between individuals who are in good health and those who suffering from congestive heart. These comprehensive inquiries collectively underscore the prowess of the FCM algorithm in effectively classifying heart ailments, thereby illuminating its promise in facilitating precise diagnostic procedures and informed treatment selections.

The amalgamation of IoT environment with FCM algorithms yields a multitude of advantages. Immediate monitoring and ceaseless data accumulation facilitate prompt detection of cardiac irregularities, allowing healthcare providers to intervene without delay. FCM's adeptness at handling uncertain and imprecise data augments the precision of disease categorization, acknowledging the intricacies and variances inherent in heart conditions. Moreover, the FCM methodology powered by IoT facilitates categorizing risks, strategies for tailored care, and improved patient results.

However, challenges in the realms of data security, interoperability, and scalability necessitate resolution to ensure the efficacious integration of IoT-enabled FCM algorithms within healthcare contexts. Ongoing endeavors are directed toward mitigating these challenges and refining the FCM approach.

This involves the incorporation of additional physiological parameters and the expansion of heart disease classification's purview within the IoT framework.

IOMT IN HEALTHCARE

The realm of the Internet of Medical Things (IoMT) represents an amalgamation of medical devices and applications, seamlessly interconnecting with healthcare information technology systems through network technologies.

This synergy seeks to alleviate the strain on healthcare systems by facilitating patient-physician connectivity, enabling secure transmission of medical data, and subsequently curtailing unnecessary hospital visits. According to the discerning analysis by Frost & Sullivan, the global IoMT market reached a valuation of $22.5 billion in 2016, manifesting a noteworthy compound annual growth rate of 26.2%.

Within the purview of the IoMT market, reside intelligent devices like wearables and medical/vital monitors, meticulously designed for healthcare utilization whether worn on the body, employed within domiciliary settings, or deployed in community, clinic, or hospital environments. This expansive domain also encompasses the provisioning of real-time location services, telehealth provisions, and other ancillary services [3].

IoMT (Internet of Medical Things) involves the utilization of internet-connected medical devices to collect health data and provide information about the health of individuals [4]. When it comes to measuring heart disease, here are some examples of commonly used connected devices in the field of IoMT:

I. Heart Rate Monitors

These wearable contrivances, typified by smartwatches or wristbands, perpetually gauge an individual's heart rate. Their utility extends to the identification of irregular heart rhythms, surveillance of physical exertion, and tracking overall heart rate trends.

FIGURE 1 EXAMPLE OF HEART RATE MONITORS [5].

II. Electrocardiographs (ECG)

These instruments capture the electrical behavior of the heart. They possess the capability to identify irregular heart rhythms, evaluate cardiac well-being, and track indications of cardiac issues.

FIGURE 2 ELECTROCARDIOGRAM [6].

III. Pulse Oximeters

A Pulse Oximeter functions as a medical tool intended to assess an individual's blood oxygen saturation level. This process involves emitting light through the skin and measuring the amount of hemoglobin bound with oxygen in the bloodstream.

Furthermore, the device provides information about the individual's heart rate. Pulse oximeters are extensively utilized in medical settings, especially during surgical interventions or for patients dealing with respiratory disorders, to monitor both oxygen levels and overall health status. Additionally, they are conveniently available for personal usage within the comfort of one's own home.

FIGURE 3 EXAMPLE OF PULSE OXIMETER.

IV. Implantable Medical Devices

Refers to medical instruments or apparatuses that are designed to be surgically implanted inside the human body or living organisms for diagnostic, therapeutic, monitoring, or assistive purposes. These devices are typically intended to interact with biological systems, tissues, or organs, either temporarily or permanently, to provide medical benefits. Implantable devices are used across various medical disciplines to manage or treat specific conditions, monitor physiological parameters, or enhance bodily functions. Such devices may include pacemakers, insulin pumps, cochlear implants, and neural stimulators, among others. The development, design, and application of implantable devices are central to modern medical advancements and contribute significantly to patient care and well-being [7].

FIGURE 4 EXAMPLE OF IMPLANTABLE MEDICAL DEVICES.

PROPOSED ARCHITECTURE (IOMT)

The Internet of Medical Things (IoMT) denotes the interconnected framework encompassing medical devices and applications that amass and interchange healthcare data through the internet. The envisaged IoMT architecture intended for patient diagnosis entails the amalgamation of diverse IoT devices, sensors, and software solutions to enable remote monitoring, data accumulation, scrutiny, and diagnosis of patients' health conditions. This architecture strives to augment healthcare provisioning by furnishing real-time insights, elevating patient outcomes, and mitigating the load on healthcare establishments.

I. IoT Devices and Sensors

The bedrock of the proposed architecture consists of a comprehensive array of IoT devices and sensors that can be affixed to patients or seamlessly integrated into medical apparatuses. These devices encompass wearable health monitors (e.g., smartwatches, fitness bands), medical implants, monitors for vital signs, glucose monitors, temperature sensors, ECG monitors, pulse oximeters, among others. These devices perpetually amass patient-specific data and channel it to the central system.

II. Connectivity

The IoMT architecture hinges upon resilient connectivity solutions to securely and instantaneously relay data. Depending on the context, it has the ability to leverage a range of communication technologies such as Wi-Fi, Bluetooth, mobile networks, or a combination of these, ensuring uninterrupted data flow between the devices and the central system [8].

III. Data Aggregation and Management

The amassed data originating from diverse IoT devices undergoes consolidation and administration within either a centralized database or a cloud-based platform. This repository functions as a storehouse for patient health data, offering scalable storage to accommodate the extensive information stream generated by IoMT devices.

IV. Data Security and Privacy

Considering the delicate character of medical information, prioritizing the security and privacy of data remains a paramount concern. The IoMT architecture integrates potent encryption methodologies, access control mechanisms, and authentication protocols to shield patient data against unauthorized access or breaches.

V. Edge Computing

For the purpose of latency reduction and the augmentation of real-time decision-making, the architecture can incorporate edge computing. Certain data processing and analytical functions are executed in close proximity to the IoT devices themselves, thereby alleviating data load on the central system and facilitating expedited response times [9].

VI. Artificial Intelligence and Machine Learning

Embedded within the IoMT architecture are artificial intelligence (AI) and machine learning (ML) algorithms designed to dissect the voluminous pool of collected patient data. These algorithms possess the capability to discern patterns, identify anomalies, and prognosticate potential health issues, thereby assisting healthcare providers in rendering precise diagnoses and timely interventions.

VII. Patient Interface and Mobile Applications

The IoMT architecture encompasses patient interfaces, such as mobile applications and web portals, which empower patients to access their health information, receive notifications, and interact remotely with medical professionals.

These applications also foster communication with healthcare experts and furnish patients with health education resources.

VIII. Healthcare Provider Portal

For healthcare practitioners, the IoMT architecture incorporates a dedicated portal that furnishes a comprehensive overview of patient data, trends, and analyses.

This portal permits physicians and caregivers to remotely monitor patients, track progress, and make informed decisions grounded in real-time data.

IX. Integration with Electronic Health Records Systems

In order to ensure care continuity and seamless fusion with existing healthcare workflows, the IoMT architecture can be seamlessly integrated with Electronic Health Records (EHR) systems. This integration providers information about of individual's comprehensive medical background, encompassing data procured through IoMT devices, within their prevailing EHR framework.

The proposed architecture of the Internet of Medical Things (IoMT) for patient diagnosis within a medical IoT framework presents an all-encompassing and interconnected framework that confers empowerment to both patients and healthcare providers alike. Through the strategic utilization of IoT devices, cutting-edge data analytics, and the integration of AI/ML algorithms, all fortified by a foundation of secure connectivity, this architectural paradigm has the potential to reshape the healthcare landscape. It does so by enabling remote monitoring, early-stage diagnostics, and the formulation of individually tailored treatment strategies, ultimately culminating in the augmentation of patient outcomes and the refinement of healthcare dispensation.

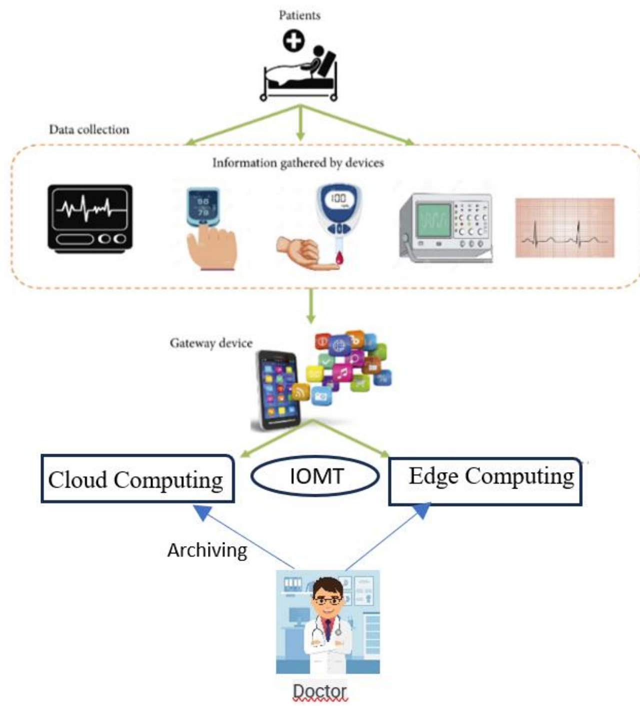

Figure 5 Proposed Architecture (IOMT).

The proposed IOMT architecture (see Figure 5) represents a cutting-edge solution for remote patient monitoring, offering real-time and continuous measurement of various physiological factors, including ECG.

Through seamless integration of medical sensors, IoT technologies, edge computing, and cloud computing, this architecture transforms healthcare delivery by enabling proactive interventions and personalized patient care. By harnessing the power of advanced data analytics and maintaining stringent data security measures, the IOMT architecture promises to revolutionize patient monitoring and enhance overall health outcomes.

EXPERIENCE AND IMPLEMENTATION

I. IoT Data Collection

In the pursuit of empirical insights, the selection of data emerges as a pivotal cornerstone. For this, we opted for the Heart Disease Dataset curated by David W. Aha, accessible through the UCI Machine Learning directory [10]. This dataset encapsulates variables that potentially exert influence on heart disease susceptibility.

The data assemblage emanates from an assemblage of four distinct establishments situated across diverse cities: Cleveland, Hungary, Switzerland, and the VA Long Beach

The central point of any IOMT experimentation faces a difficulty arising from the lack of highly advanced medical instruments and sensors capable of accurately measuring patients' physiological indicators. These instrumentalities are pivotal for the acquisition of real-time and all-encompassing data, propelling researchers to unravel the intricate tapestry interweaving heart health and assorted variables. The incipient nature of medical IoT technologies and their limited accessibility complicate the pursuit of IOMT-based studies. Hence, to surmount these hurdles, our recourse rested in collaborating with a validated reference database like the UCI Machine Learning directory.

Each database contains 76 attributes, we used only 14 attributes (see Table1), this attribute reduction was suggested by a domain expert. Thus, it is possible to take into account only these most impacting factors in the context of diagnosis prediction:

TABLE I
AN OVERVIEW OF THE UCI DATASET ATTRIBUTES

Attribute	Type	Description
Age	Continuous	Age in years
Cp	Discrete	Chest pain type (4 values)
Trestbps	Continuous	Resting blood pressure (in mm Hg on admission to the hospital)
Chol	Continuous	Serum cholestoral in mg/dL
Fbs	Discrete	Fasting blood sugar > 120 mg/dL 1 = true; 0 = false
Restecg	Discrete	Resting electrocardiographic results (values 0,1,2)
Thalach	Continuous	Maximum heart rate achieved
Exang	Discrete	Exercise induced angina (1 = yes; 0 = no)
Oldpeak	Continuous	ST depression induced by exercise relative to rest
Slope	Discrete	The slope of the peak Exercise ST segment (values 0,1,2)
Ca	Discrete	Number of major vessels (0–4) colored by flourosopy
Thal	Discrete	Nature of defect, values (0–3)
Target	Discrete	Presence or absence of heart disease, values (1,0)

- *Age:* Age emerges as the most formidable precipitant in the trajectory of cardiovascular or heart disease progression, showcasing a nearly tripling risk increment with each successive decade of existence. Notably, the incipience of coronary fatty streaks might even be witnessed during adolescence, heralding the commencement of this complex process. Alarmingly, statistics reveal that a substantial 82% of individuals succumbing to coronary heart disease are aged 65 or above, accentuating the pronounced risk associated with advancing years. Moreover, an additional layer of risk pertains to stroke, with its jeopardy doubling per decade commencing from the age of 55.
- *Gender:* Gender delineates an influential demarcation in heart disease vulnerability, with men poised at a heightened risk in comparison to premenopausal women. Post-menopause, discussions regarding women's risk comparability to men have ensued; however, recent insights from WHO and the United Nations engender dissent. Interestingly, women afflicted with diabetes manifest a proclivity for heart disease surpassing that in their diabetic male counterparts [11].
- *Angina (Chest Pain):* Angina materializes as an outcome of insufficient oxygen-rich blood supply to the heart muscle, triggering a spectrum of sensations ranging from pressure to compression within the chest. This discomfort occasionally reverberates across the shoulders, arms, neck, jaw, or back, resembling the sensation of indigestion.
- *Resting Blood Pressure:* The culmination of persistently high blood pressure escalates the risk of arterial impairment, particularly for heart-supplying arteries.
- *Serum Cholesterol:* The peril posed by elevated levels of low-density lipoprotein (LDL) cholesterol, colloquially referred to as the "bad" cholesterol, is most pronounced in the narrowing of arteries. Moreover, the risk profile is further exacerbated by elevated triglyceride levels, a blood fat variant influenced by diet, that augments the propensity for heart attacks.
- *Fasting Blood Sugar:* Dysfunctional insulin production or responsiveness fosters a surge in blood sugar levels, augmenting the susceptibility to heart attacks. This cascade underscores the intricate interplay between metabolic pathways and cardiovascular health.
- *Resting ECG:* A Resting ECG, or Electrocardiogram, is a non-invasive medical test that records the electrical activity of the heart while a person is at rest [12].
  It involves placing electrodes on the skin at specific locations on the chest, arms, and legs to measure the electrical impulses generated by the heart as it beats.
- *Maximum Heart Rate Reached:* Remarkably mirroring the risk amplification observed with high blood pressure, an escalation in cardiovascular risk is proportionate to heart rate elevation.
- *Maximum Exercise ST Segment:* A treadmill ECG stress test deviates from the norm when there is a horizontal or descending ST segment depression exceeding or equalling 1 mm at intervals of 60–80 Ms.
- *Thal:* Is a common abbreviation for thalassemia, which is a group of inherited blood disorders characterized by an abnormal production of haemoglobin, the protein in red blood cells responsible for carrying oxygen. Thalassemia results in anemia, as affected individuals have fewer healthy red blood cells than normal.

II. Methodology

The heart disease database includes various heart related features, including age, sex, blood pressure, cholesterol levels, and electrocardiogram readings.

The dataset underwent preprocessing to address missing data, standardize feature values, and ready it for use in classification tasks.

The Fuzzy C-Means algorithm was implemented in Python using the scikit-fuzzy library. The algorithm was trained on the pre-processed dataset, and the cluster centroids were determined to classify each data point with fuzzy membership values.

III Training and Testing Datasets in Python

Is a fundamental step in building machine learning models. Python provides several popular libraries, such as scikit-learn, for handling machine learning tasks.

- *Import necessary libraries:* First, we need to import the required libraries, including scikit-learn for machine learning operations and other relevant libraries for data manipulation and visualization.
- *Load and preprocess the dataset:* It's essential to import our dataset into a Pandas DataFrame and perform any required preprocessing steps.
- *Split the dataset into training and testing sets:* Means to partition our dataset into two separate subsets, one for training a machine learning model and the other for testing the model's performance. The training set is used to train and build the model, while the testing set is used to evaluate how well the model generalizes to new, unseen data. This process is crucial for assessing the model's ability to make accurate predictions on real-world data by simulating its performance on data it hasn't been exposed to during training.

ANALYSIS OF EXPERIMENTAL RESULTS

The proposed algorithm fuzzy c-means has been implemented. We have used a datasets about heart disease from the UCI machine learning repository (1025 instances). We chose for the training phase (80 %) and for the testing phase (20 %).

I. Confusion Matrix

A Confusion Matrix is a performance evaluation tool used in machine learning and statistics to assess the accuracy of a classification model. It is particularly useful for binary classification problems, where the outcome can be categorized into two classes, such as positive/negative, true/false, or yes/no. The Confusion Matrix is a square matrix that helps evaluate the performance of a classification model by comparing its predicted class labels to the actual class labels found in the dataset.

The Confusion Matrix comprises four crucial elements:

- *True Positives (TP):* Instances correctly predicted as positive.
- *True Negatives (TN):* Instances correctly predicted as negative.
- *False Positives (FP):* Instances incorrectly predicted as positive.
- *False Negatives (FN):* Instances incorrectly predicted as negative.

The significance of the Confusion Matrix is rooted in its capacity to provide essential data for the appraisal of a classification model's performance. It enables the computation of several pivotal evaluation metrics, such as:

- *Accuracy:* This metric quantifies the overall correctness of the model's predictions and is computed as (True Positives + True Negatives) divided by (True Positives + True Negatives + False Positives + False Negatives).
- *Precision:* Is determined as True Positives divided by (True Positives + False Positives). It signifies the proportion of accurate positive predictions among all predicted positive instances, indicating how well the model discriminates true positives.
- *Recall:* Is computed as True Positives divided by (True Positives + False Negatives). This metric represents the proportion of correctly identified positive instances among all actual positive instances, assessing the model's capacity to capture true positives.
- *F1 Score:* The F1 Score serves as a harmonized combination of precision and recall, expressed as 2 * (Precision * Recall) divided by (Precision + Recall). It offers a balanced assessment of the model's performance by considering both false positives and false negatives [13].

Through the examination of the Confusion Matrix and the computation of these assessment metrics, we can attain a more profound comprehension of the classification model's capabilities and limitations. This knowledge is crucial for fine-tuning the model, selecting appropriate thresholds, and optimizing its performance for the specific task at hand. Additionally, the Confusion Matrix aids in identifying potential class imbalances and detecting scenarios where the model may excel at predicting one class but struggle with the other, allowing for targeted improvements and adjustments.

TABLE II
THE CONFUSION MATRIX

		Class predicted by the model	
Real class		***Class 0***	***Class1***
	Class 0	388	34
	Class 1	44	559

II. Evaluation Metrics

To assess the accuracy of the FCM algorithm and its comparison with other classification methods, we can employ a range of evaluation metrics, encompassing accuracy, precision, recall, F1-score, and overall accuracy.

Accuracy = 947 / 1025 = 0,924

Precision = 559 / 603 = 0,927

Recall = 559 / 593 = 0,943

F1 Score = 2 * (0,927 * 0,943) / (0,927 + 0,943) = 0,935

III. Discussion:

In our study, we conducted a comprehensive analysis of the performance of our fuzzy c-means (FCM) classifier in comparison with other classification algorithm such us the k-nearest neighbours (KNN) algorithm. The results obtained from the FCM classifier demonstrated significant promise (Accuracy = 92,4 %), showing its effectiveness in handling complex and overlapping data distributions. Through its ability to assign membership degrees to data points, the FCM classifier proved to be robust in dealing with uncertainty and noise, resulting in improved accuracy and reduced misclassifications. Moreover, the FCM classifier exhibited superior performance in scenarios where data clusters exhibited irregular shapes or when dealing with datasets containing vague boundaries. In contrast, the KNN algorithm, while known for its simplicity and ease of implementation, showed limitations in handling such intricate data patterns (Accuracy = 87 %). Our findings highlight the superiority of the FCM classifier in classification tasks, particularly in datasets with complex structures, underlining its potential as a valuable tool in various real-world applications, ranging from medical diagnosis to pattern recognition and beyond.

CONCLUSION

In conclusion, this research has demonstrated the immense value and potential of the On-Body Medical Internet of Things (IOMT) model in revolutionizing remote patient monitoring. The IOMT architecture, with its integration of medical sensors and IoT technologies, offers a groundbreaking solution for continuous and personalized healthcare, especially in the context of heart disease management. By enabling remote monitoring of patients, IOMT bridges the gap between healthcare providers and individuals, ensuring timely interventions and proactive healthcare measures.

Furthermore, the utilization of Cloud Computing as part of the IOMT infrastructure presents a reliable and secure means of data storage and management. The Cloud's vast storage capacity and accessibility allow for centralized and scalable storage of patient data, facilitating data sharing and collaboration among healthcare professionals while adhering to strict privacy and security protocols.

The integration of Edge Computing into the Internet of Medical Things (IOMT) architecture is crucial for facilitating real time data processing and analysis at the network's edge. This decentralized approach reduces latency and bandwidth requirements, ensuring timely responses and immediate actions in critical medical situations. Edge Computing enhances the overall efficiency and responsiveness of the IOMT system, significantly benefiting remote patient monitoring.

The selection of the Fuzzy C-Means (FCM) algorithm as the classification model further contributes to the success of this research. FCM's unique ability to handle uncertainty and accommodate overlapping data makes it an ideal choice for the intricate nature of heart disease classification. By incorporating soft clustering and partial memberships, FCM delivers more nuanced and interpretable results, ensuring accurate patient classifications even in complex scenarios.

The selection of the Fuzzy C-Means (FCM) algorithm as the classification model in this study proves to be a judicious choice. FCM's ability to handle uncertainty, accommodate overlapping data, and introduce soft clustering demonstrates its prowess in accurately classifying patients with heart ailments. FCM, through its ability to capture subtle variations and accommodate partial memberships within clusters, exceeds the limitations of traditional algorithms, leading to a more nuanced and interpretable classification process.

The success of the FCM algorithm in this research lies in its adaptability to the complexities of medical datasets, including the intricate relationships between diverse physiological factors and heart diseases. Moreover, FCM showcases remarkable robustness to noisy data, a common challenge in healthcare datasets, ensuring reliable and consistent patient classifications.

As this work moves toward implementation in real-world healthcare settings, it holds the potential to transform patient care and improve health outcomes on a global scale. By harnessing the power of IOMT, Cloud Computing, Edge Computing, and Fuzzy C-Means algorithm, the medical community can embark on a transformative journey towards precision medicine and optimal heart care, thereby enhancing the quality of life for patients and revolutionizing the landscape of cardiovascular healthcare.

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