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PAPER

Combining IoMT and XAI for Enhanced Triage Optimization: An MQTT Broker Approach with Contextual Recommendations for Improved Patient Priority Management in Healthcare

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ABSTRACT

The widespread adoption of the Internet of Things has significantly enhanced our daily lives across various dimensions. E-health has significantly benefited from advancements in the Internet of Things (IoT), particularly with the emergence of the Internet of Medical Things (IoMT). A sophisticated wireless sensor network produces a huge amount of data, requiring robust cloud-based hardware for precise processing and categorization. The IoMT allows for the extensive gathering of medical data from incoming hospital patients, enabling real-time monitoring of vital signs and health statuses. Nevertheless, effectively prioritizing patients in emergencies is challenging due to the importance and complicatedness of the data. To tackle this issue, an innovative solution involves integrating Explainable Artificial Intelligence into the IoMT ecosystem. By incorporating Explainable AI, the system enhances explainability, fostering trust and reliability in patient prioritization. This provides healthcare providers a more reliable prioritization mechanism that aligns with established medical guidelines. The study explores IoMT devices for collecting medical data from incoming patients, focusing on the MQTT protocol for lightweight devices, aiming to guide patients to the right department and prioritize emergency management through IoMT data analysis.

KEYWORDS

Artificial Intelligence, IoMT, Explainable AI (XAI), emergency department, contextual recommender system, MQTT Broker

1 INTRODUCTION

IoMT (Internet of Medical Things) refers to the interconnected network of medical devices and applications capable of collecting, transmitting, and analyzing health data.

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Prioritizing patients is crucial to healthcare, particularly when health resources are limited. XAI is an approach that emphasizes the transparency and interpretability of AI models. Combining IoMT and XAI can improve patient prioritization by providing clear explanations of the decisions made by AI algorithms.

Telemedicine is a pivotal solution for remotely overseeing and delivering care to individuals with chronic ailments. Healthcare practitioners can remotely evaluate, diagnose, and treat patients through telemedicine. This innovative approach has played a substantial role in elevating patient well-being, reducing hospital admissions, and easing the burden on emergency departments.

Telemedicine is advantageous in relieving pressure on emergency departments by empowering healthcare providers to assess and address non-emergency cases remotely. This, in turn, enables a more efficient allocation of emergency room resources, prioritizing immediate in-person care for patients with acute needs.

Triage is a fundamental procedure within the emergency department (ED), prioritizing patient care based on the severity of their conditions. It entails the initial clinical evaluation of patients to ascertain the urgency of their medical requirements and appropriately allocate resources. The primary objective of triage is to identify patients necessitating immediate medical attention, ensuring timely and suitable care. Throughout the triage process, healthcare professionals, including nurses or specially trained personnel, assess patients based on diverse factors such as their presenting symptoms, vital signs, medical history, and the nature of their injuries or illnesses. This evaluation aids in categorizing patients into distinct priority levels or triage categories.

Incorporating artificial intelligence (AI) and medical IoT devices [1] in smart hospitals holds immense potential to improve healthcare delivery significantly through data-driven decision-making. AI algorithms can analyze extensive medical data, encompassing patient records, medical literature, and diagnostic images. This empowers healthcare providers to make more precise and evidence-based decisions, ultimately leading to enhanced diagnoses, treatment plans, and patient outcomes. Moreover, AI systems can continuously monitor patient data from connected medical devices, facilitating early detection of warning signs for deteriorating health conditions and potentially averting complications or hospital readmissions.

In addition, AI plays a pivotal role in optimizing workflow by automating repetitive and time-consuming tasks such as data entry, documentation, and administrative processes. This streamlining of operations enables healthcare professionals to concentrate more on direct patient care, resulting in increased efficiency and reduced workload. AI algorithms can leverage individual patient characteristics, genetic data, and treatment history to generate personalized treatment plans, ensuring better outcomes and minimizing adverse medication reactions.

Furthermore, AI-powered analytics contribute to resource allocation and planning by predicting patient flow, demand, and resource utilization patterns. This optimization of resources, including beds, staff, and equipment, enhances operational efficiency and reduces costs [2]. In summary, the fusion of AI and medical IoT devices in smart hospitals holds great promise for transforming healthcare, improving patient outcomes, and revolutionizing the delivery of medical services.

Given these challenges, our research is centered on proposing a methodology that integrates several key elements:

- Remote Monitoring: Every patient is linked to Internet of Medical Things (IoMT) devices, allowing continuous monitoring of their condition in the waiting area, even when healthcare providers are occupied with other cases. This ensures the swift detection of any sudden deterioration, facilitating timely intervention.

- Efficient Diagnostics: Using connected devices, non-urgent patients can undergo preliminary diagnostic assessments remotely, reducing the need for prolonged in-person evaluations. This strategy liberates doctors' time and resources, enabling a focus on urgent cases and leading to a more effective utilization of healthcare services.
- Triage using MQTT Broker: Connected devices offer valuable insights into the appropriate medical service a patient should seek. Based on this information, urgent cases can be identified, and necessary laboratory tests can be promptly initiated. This element aids in prioritizing urgent cases, expediting appropriate care, and enhancing overall efficiency in the emergency department.

2 THEORETICAL BACKGROUND AND RELATED WORKS

2.1 Combining IoMT-driven data with XAI

The general framework for IoMT-driven patient prioritization using XAI can implement:

- Data Collection with IoMT: Utilize IoMT devices to collect diverse and real-time health data from patients [3]. This can include data from wearables, implantable devices, sensors, and electronic health records (EHR).
- Data Preprocessing and Integration: Clean, preprocess, and integrate the collected data to create a comprehensive and standardized dataset. This may involve dealing with missing values, normalizing data, and ensuring interoperability between different IoMT devices.
- Feature Selection and Engineering: Identify relevant features that contribute to patient prioritization. This may involve domain knowledge and statistical methods to select the most informative variables. Feature engineering may also enhance the predictive power of the model.
- Model Development: Train machine learning models, such as classifiers or risk prediction models, using the preprocessed data. Common models include decision trees, random forests, support vector machines, or deep learning models.
- Explainable AI Integration: Choose an XAI technique that provides transparent insights into the model's decision-making process. Techniques like LIME (Local Interpretable Model-agnostic Explanations), SHAP (Shapley Additive explanations), or decision rule extraction methods can be employed [4].
- Model Validation and Testing: Validate the model using appropriate validation techniques, such as cross-validation, and test its performance on independent datasets.
- Explainability Validation: Evaluate the interpretability of the model's explanations. This involves assessing whether the provided explanations are understandable and align with medical knowledge.
- Deployment and Continuous Monitoring: Deploy the model into the healthcare system, integrating it with existing workflows. Implement continuous monitoring to ensure the model performs reliably and adapts to patient populations or data distribution changes.
- Clinician Collaboration: Involve healthcare professionals in the development and validation process to gain their insights and ensure that the model aligns with clinical practices.
- Feedback Loop and Iterative Improvement: Establish a feedback loop where insights from clinicians and the model's performance can be used to improve the model over time [5].

2.2 IoMT and contextual information

The Internet of Medical Things (IoMT) and contextual information are intimately linked in healthcare. IoMT devices, such as wearables and remote monitoring systems, generate real-time medical data. At the same time, contextual information encompasses the wider aspects of a patient's life, including lifestyle, environment, and daily activities. Integrating these two elements provides a more complete understanding of an individual's state of health. By considering the medical data provided by IoMT devices and contextual factors, healthcare professionals can personalize treatment plans, use predictive analytics for early intervention, and make more informed decisions. This holistic approach supports improved patient care, strengthens communication, and contributes to population health management while requiring careful consideration of privacy and security aspects.

2.3 Context-aware recommender systems

IoMT is an acronym for the Internet of Medical Things, which refers to interconnected devices and systems in the healthcare sector that collect and share medical data. IoMT-driven patient prioritization involves leveraging IoMT technologies to analyze and prioritize patients based on various criteria. These may include factors such as the severity of their condition, real-time health data, historical health records, and other relevant information obtained from medical devices connected to the IoMT. By integrating data from various medical devices and sensors, healthcare providers can gain a more comprehensive, real-time understanding of a patient's health status. This information can then be used to prioritize patients according to the urgency of their needs, optimizing resource allocation and improving the overall delivery of healthcare.

Efficient and optimized solutions have emerged in healthcare with advancements in technology. Smart healthcare systems require integrated techniques like AI, IoT, and machine learning for data management and improved services [6]. AI-based robots in surgery, medical imaging diagnostics, IoT applications for temperature management, and instrument health enhance smart hospital management [7]. Researchers focus on smart domains, proposing architectures to address challenges and provide better results and facilities. [1] explores AI and IoT-based smart hospital systems, highlighting their impact on healthcare and the hurdles faced during development.

The healthcare sector aims to integrate technologies for patient monitoring and data management. Remote patient monitoring apps provide cost-effective healthcare services, but data management poses challenges. Cloud-based healthcare applications store patient records but face security and availability issues. To address these challenges, [2] proposes an intelligent IoT-based distributed framework for remote healthcare services. The model interconnects system entities using IoT, employs a Distributed Database Management System for secure data availability, and ensures record security through Blockchain. The proposed model is tested with real clinical data, and the results are thoroughly discussed.

The Internet of Things (IoT) encompasses intelligent devices and systems that interact and communicate with each other, environments, objects, and infrastructures. RFID and sensor network technologies are poised to address this evolving landscape. [3] outlines developing and implementing a smart health help system that combines IoT, Artificial Intelligence, and Android Technology. This innovative system offers technical support to aid patients in emergencies, assisting nurses and doctors with minimal investments. [3] focuses on government-funded hospitals with high patient volumes, aiming to alleviate the challenges doctors and nurses face in delivering care.

IoT has made significant strides in enabling a smarter world with diverse services and abundant data. The emergence of smart Multiple Sensorial Media (MulSeMedia) systems, cloud technology, and IoT has sparked substantial interest in "smart healthcare" across various sectors. This research addresses security and privacy issues in AI-driven IoT (AIIoT) and proposes effective measures to tackle these concerns. The study employed a qualitative research design, gathering information from relevant secondary sources. [4] The proliferation of AI-driven IoT has introduced numerous sensors and devices to the internet, raising security and privacy concerns. The study recommends implementing well-defined architecture standards, encompassing interfaces and data models, to enhance user privacy and security in AI-driven IoT environments.

The primary aim of [5] is to design a patient health monitoring system focusing on transmission nature. A wireless sensor network tracks patient health parameters transmitted via the GPRS interface. This system caters to patients who require continuous observation without being in a life-threatening condition. When critical conditions arise, the system generates an alarm notification for the doctor. The research aims to develop modules for physician diagnosis through patient telemonitoring, incorporating medical and environmental sensors to monitor the patient's well-being and surroundings. Sensor data is transmitted to a server via mobile devices or PCs. This study proposes a GPRS-based remote medical care monitoring device that provides real-time online patient health data. All health-related information is directed to a web server, enabling physicians to monitor patient's conditions on smartphones. The results demonstrate the effective use of Internet of Things (IoT) devices for patient health monitoring, considering power consumption concerns. The proposed system offers simplicity, low power consumption, and high convenience for healthcare professionals and nursing patients.

In Sub-Saharan Africa, healthcare facilities are often limited and encounter challenges such as overcrowded waiting areas and error-prone manual patient data capture. However, by skillfully integrating technology, it becomes feasible to establish a healthcare system that ensures prompt diagnosis and access to treatment. In reference [8], an integrated patient triage and capacity recommender system for outpatient departments is presented [9, 10]. This system prioritizes patients based on vital signs, syndrome, chief complaint, and arrival time, facilitating efficient scheduling. Vital signs are captured by bio-sensors, while nurses input syndrome and chief complaints through a graphical user interface. Each patient's acuity level corresponds to an estimated safe waiting time for treatment. The system also notifies nurses when the hospital's capacity is reached, preventing excessive waiting times. Providing information to patients about capacity levels empowers them to seek care at less crowded facilities, thereby reducing healthcare facility costs by eliminating overtime expenses.

Generally, the current state of recommender systems in healthcare can be categorized in different key aspects:

- Personalized Treatment Plans: Recommender systems were being used to suggest personalized treatment plans based on individual patient characteristics, medical history, and genetic information. These systems aimed to improve the effectiveness of treatments and minimize adverse reactions to medications [6, 7].
- Clinical Decision Support: Recommender systems were integrated into clinical decision support tools, assisting healthcare professionals in making informed decisions about patient care. These systems analyzed a vast amount of medical

data, including electronic health records, to provide real-time recommendations for diagnosis and treatment [8, 9].
- Patient Engagement and Education: Recommender systems were applied to recommend personalized health information to patients, fostering engagement and empowering them to make informed decisions about their health. Health-related content, such as articles, videos, and preventive measures, were suggested based on individual health profiles [11, 12]
- Chronic Disease Management: Recommender systems played a role in chronic disease management by providing personalized interventions and lifestyle recommendations to individuals with conditions like diabetes, cardiovascular diseases, and obesity [13, 14].
- Telemedicine and Remote Monitoring: In the context of telemedicine, recommender systems were utilized to prioritize and schedule virtual appointments based on patient needs and urgency. Remote monitoring systems used recommendations to alert healthcare providers to potential issues and enable early intervention.
- Research and Clinical Trials: Recommender systems were employed to match eligible patients with appropriate clinical trials, facilitating patient recruitment for research studies.

Table 1 presents a summary of contributions in the field of healthcare and IoT applications.

Table 1. Summary of contributions

References	Contribution Method	Handled Issues
[15]	The introduction of an IoT system to the medical field using Sigfox, a low-power communication network for indoor location monitoring used as a hospital network. The implementation of a proof-of-concept (PoC) to evaluate the effectiveness of medical devices and patient safety management.	• Quality medical services • Accuracy of sending and receiving signals of various targets
[16]	Framework to monitor patient with chronic diseases located far from the hospital using telemedicine techniques	• Real time monitoring of patient far from the hospital
[17]	The automation of the process of remote triage by a lightweight mobile-friendly, and capable architectures of assigning triage scores to a broad spectrum of medical conditions	• Overcrowding in emergency departments
[18]	Emergent triage via an explorative data analysis of symptoms, comorbidities, and other parameters, comparing different machine learning algorithms for case severity detection	• Remote data and information exchange risk mitigation and appropriate medical facilities
[19]	Effectively handling prioritization in hospital emergencies involves adjusting dynamic operations and interactions with various stakeholders in response to changes in their execution context.	• Drawing insights from data collected through Mobile Communication Operators (MCOs) deployed in ambulances, emergency rooms could be adequately equipped to handle individuals in need, such as those involved in road accidents or other incidents.

3 RESEARCH CONTRIBUTION

3.1 Motivation

Relying solely on artificial intelligence methods may result in basic classification and user recommendations [20, 21]. However, incorporating contextual data from IoT, along with the application of explainable artificial intelligence, particularly in Feature Selection and Engineering, has the potential to enhance the outcomes of the classification process.

The most important components we include in our research study are:

- Artificial Intelligence Techniques could include machine learning algorithms, neural networks, or any other AI models designed to perform specific tasks.
- Contextual Information from IoT: Internet of Things (IoT) devices generate vast contextual data. Integrating this information into your AI models can provide a richer understanding of the environment or system you are analyzing. For example, in a smart home scenario, integrating data from sensors on doors, windows, and thermostats can provide contextual information that helps the AI system make more informed decisions.
- The decision-making process of AI models are more transparent and understandable to humans. This is especially important in critical applications, where users need to trust and comprehend the decisions made by the AI system. Feature selection and engineering play a role in creating models that are not only accurate but also interpretable [22].
- Feature Selection: Choosing a model's most relevant features (variables) is critical. It helps simplify the model, reduce overfitting, and improve generalization to new data. In the context of IoT, you may have many sensors, and not all of them contribute equally to the model's predictive power. Feature selection helps identify the most informative ones [23].
- Feature Engineering: This involves creating new features from existing ones to improve the model's performance. It could include transformations, combinations, or other modifications to the input features. For example, creating lag features (values from previous time points) can help capture temporal patterns in a time-series IoT dataset.

3.2 Demonstration of the choice of XAI tools

Absolutely, in the context of healthcare and context-aware recommendation systems, identifying and analyzing the most important features or variables becomes paramount for supporting healthcare providers in reliable patient prioritization. Here is why it is crucial:

1. Urgency and Criticality: Healthcare providers often need to prioritize patients based on the urgency of their medical conditions. Identifying key features contributing to urgency, such as vital signs, medical history, or specific symptoms, helps make more informed and accurate prioritization decisions.
2. Optimizing Resource Allocation: By understanding the most influential variables, healthcare providers can optimize the allocation of resources, such as medical staff and facilities, to promptly attend to patients with more critical needs.

3. Emergency Response: In emergencies, quick and accurate patient prioritization can be a matter of life and death. Feature analysis helps develop context-aware models that consider the dynamic and real-time nature of medical conditions.
4. Personalized Medicine: Context-aware recommendation systems can consider individual patient characteristics, preferences, and medical histories. Understanding the importance of various features allows for a more personalized approach to patient care and prioritization.
5. Transparency and Trust: Giving healthcare providers insights into the factors influencing prioritization builds trust in the recommendation system. It gives them confidence in the system's ability to consider relevant information for decision-making.
6. Compliance with Regulations: In healthcare, there are often regulatory requirements and standards for patient prioritization. Feature analysis helps ensure the recommendation system aligns with these standards and provides transparent decision-making processes.
7. Data-Driven Decision Support: Leveraging important features empowers healthcare providers with data-driven decision support. This is especially valuable in busy healthcare environments where providers may deal with a large volume of patient information.
8. Continuous Improvement: Regular analysis of feature importance allows for continuous improvement of the recommendation system. As new data becomes available and medical practices evolve, the system can be adapted to maintain effectiveness.

3.3 Contribution

In summary, the paper presents the following key contributions:

- We introduced and executed the prototype phase of an MQTT Broker that categorizes incoming inputs into distinct topics.
- We suggest an advanced approach that integrates context-aware recommendation systems.
- For this method, we utilized a dataset that already encompasses Internet of Medical Things (IoMT) variables.

4 THE PROPOSED APPROACH

4.1 Our problem

Conventional emergency departments encounter constraints that impede the timely and efficient provision of care as illustrated in Figure 1, encompassing:

- Overcrowding: Factors such as a surge in patient numbers, limited resources, and inadequate staffing contribute to the overcrowding of emergency departments. This, in turn, leads to prolonged wait times for patients, adversely affecting their access to prompt care.

- Inefficient deployment of connected objects: The ineffective integration and utilization of connected objects can hinder the prioritization of urgent cases. Consequently, patients in critical condition may face extended waiting periods due to non-urgent cases. This delay can have a substantial impact on patients with life-threatening conditions.

4.2 Aim of the study

By integrating triage and recommender systems into the IoMT ecosystem [23], healthcare providers can efficiently prioritize and manage urgent data from connected devices. This integration improves patient outcomes, reduces response times, and improves healthcare interventions [19]. Figure 2 presents the main architecture of our proposed framework. This study aims to enhance the triaging process system by introducing an innovative approach that classifies each medical condition into four emergency triage levels. The proposed framework focuses on addressing diverse chronic diseases, such as heart chronic disease, hypertension, Alzheimer's, cerebrovascular issues, chronic kidney problems, chronic obstructive pulmonary disease, congestive heart failure, coronary artery conditions, renal insufficiency, pulmonary embolism, and diabetes. To achieve this objective, the framework integrates two essential components: the first component utilizes medical data from the Internet of Medical Things (IoMT). In contrast, the second component employs machine learning algorithms.

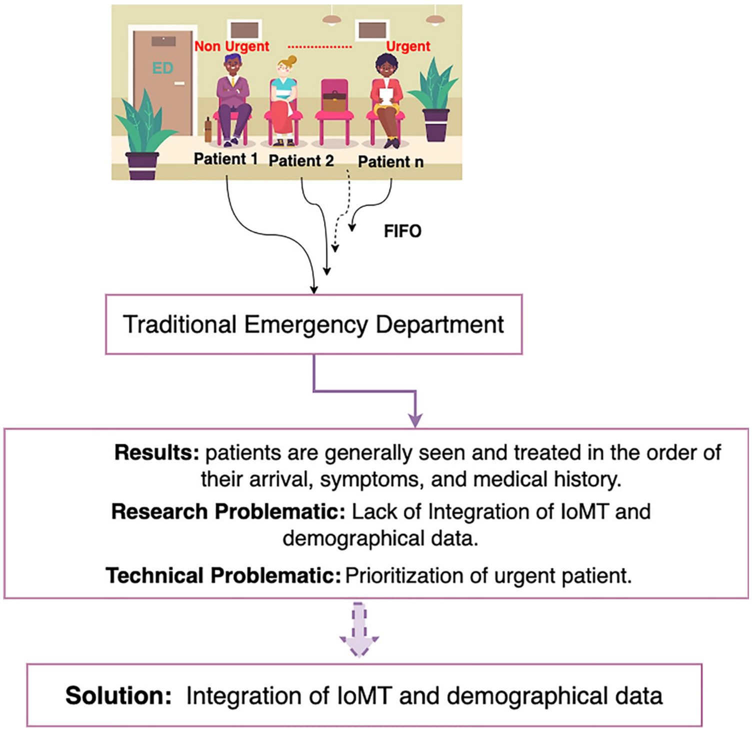

Fig. 1. Our research and technical problem

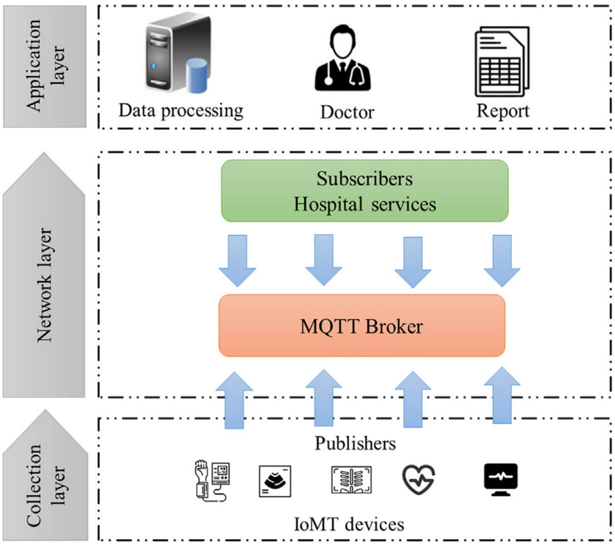

Fig. 2. Architecture of the proposed framework

4.3 Our proposed method

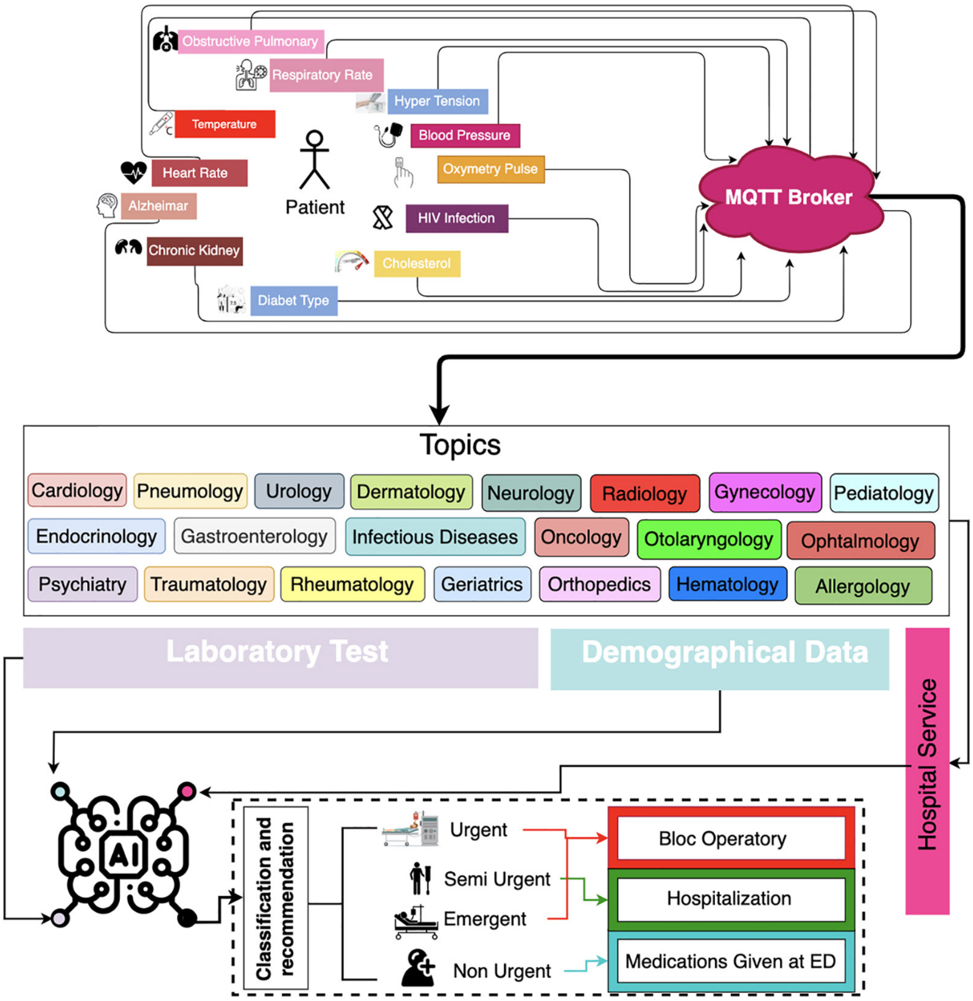

Fig. 3. The main architecture of our proposed approach

Our approach is based on three modules as shown in Figure 3:

- MQTT Broker: First, we utilize data from medical-connected objects, including signals such as heart rate, respiratory rate, systolic blood pressure, diastolic blood pressure, and pulse oximetry. These data inputs are then transmitted to an MQTT broker, who determines the appropriate department for the patient's transfer. For instance, if a patient exhibits high blood pressure, and considering that hypertension is typically evaluated using systolic and diastolic blood pressure values, the output would indicate a transfer to the cardiology department.
- Laboratory Test: Furthermore, we also examine whether the patient has undergone specific laboratory tests such as Arterial Blood Gases, Blood Alcohol Concentration, and Basic Metabolic Panel. The results of these tests enhance our algorithm's ability to identify specific chronic diseases affecting the patient. Blood tests can assist in deciding whether the patient has high cholesterol, which refers to elevated cholesterol levels in the blood.
- Demographical Data: The final step involves incorporating demographic data and various medical conditions into the analysis. This includes factors such as obstructive pulmonary disease, chronic kidney disease, HIV infection, hypertension, high cholesterol, obesity, cerebrovascular disease, Alzheimer's disease, alcohol consumption level, cancer, congestive heart failure, coronary artery disease, depression, renal insufficiency, pulmonary embolism, sleep apnea, and osteoporosis. Considering these additional factors, the algorithm can provide a complete estimation of the patient's health situation.

5 RESULTS AND DISCUSSION

5.1 Data pre-processing

Data pre-processing plays a crucial role in the Internet of Medical Things (IoMT) data, which often involves handling numerical values from various medical sensors and devices. In IoMT, the raw data collected from these devices may contain noise, outliers, missing values, or inconsistencies due to sensor inaccuracies or signal disruptions. Data pre-processing is the initial step to clean, transform, and prepare this raw data for meaningful analysis and interpretation. It involves data cleaning to eliminate erroneous values, data normalization to scale variables consistently, and imputation to handle missing data points. Moreover, in the context of IoMT, pre-processing may also encompass time-series data alignment and synchronization to ensure temporal coherence. First, we start with handling missing values; for that, we identify and handle missing data points. Common techniques include data imputation (replacing missing values with estimates like the mean or median) or removal of rows or columns with missing data. Then, we move to the outlier detection and treatment; we detect and handle outliers, data points that significantly deviate from the norm. Outliers can be corrected, removed, or retained based on the nature of the data and the analysis goals. The data transformation we proceed with is divided into two points.

- Scaling and Normalization: Scale numerical features to the same range and normalize them to a standard distribution. This ensures that different variables in our experimental study contribute equally to the analysis.
- Feature Engineering: We employ machine learning algorithms to perform various feature engineering tasks to progress to the prediction phase. Subsequently, during the phase of Medical Connected Objects, we compare the values generated

by patient-connected equipment with age-specific normal values to determine whether patients exhibit values above or below the expected range.

5.2 Exploratory data analysis and results

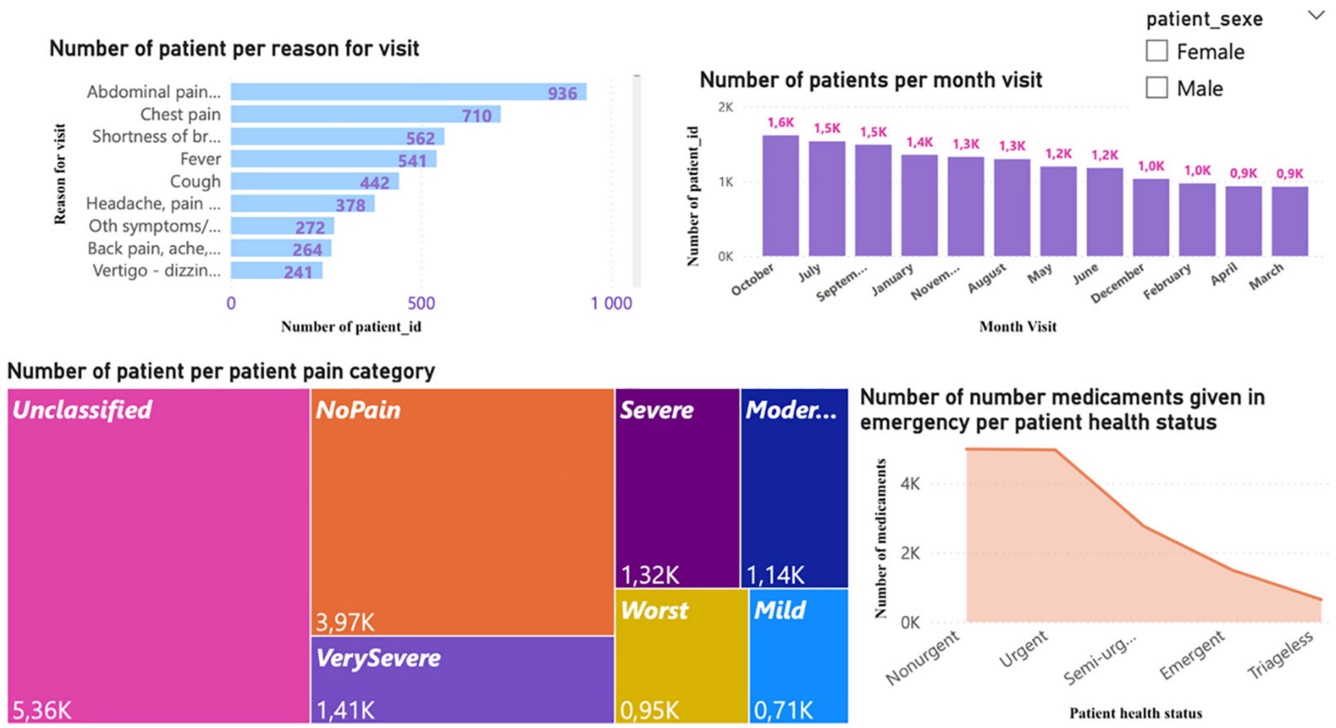

Fig. 4. Patient flow in the emergency department for all genders

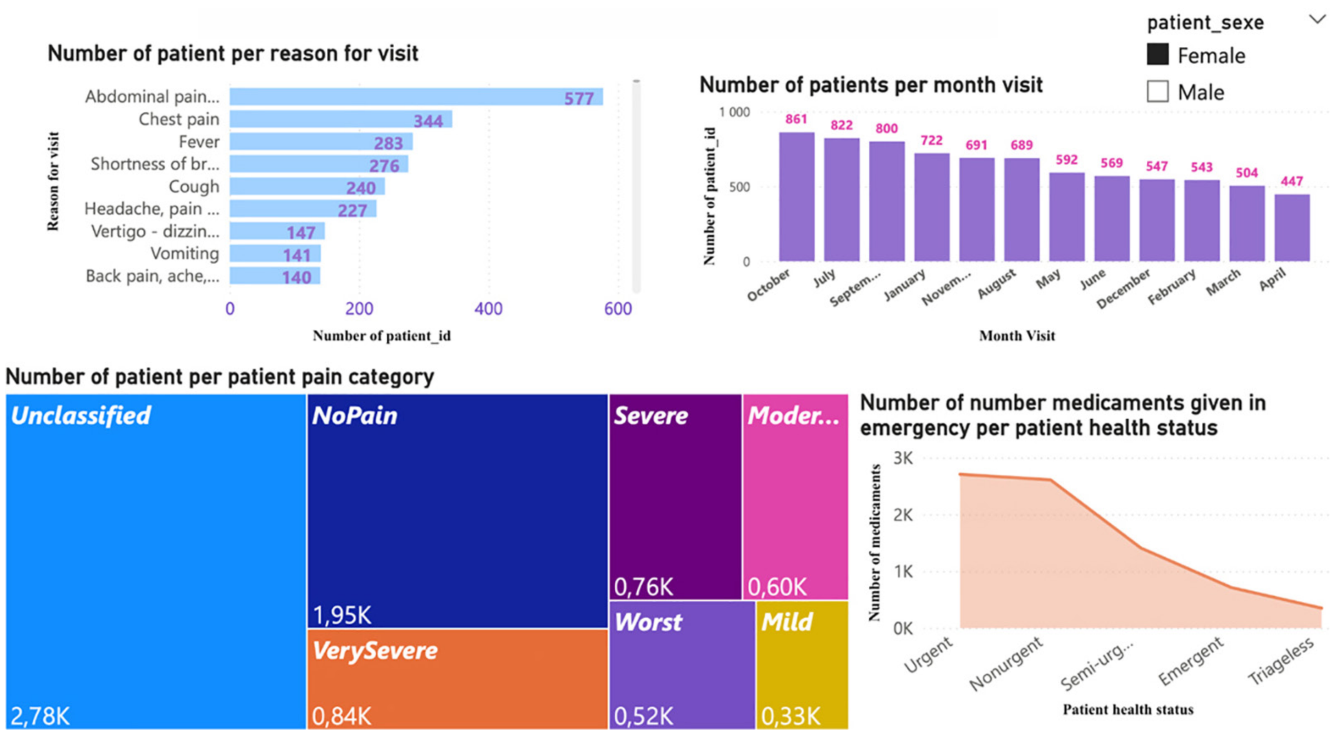

Fig. 5. Patient flow in the emergency department for female gender

It is visible in Figures 4, 5 and 6 that there is a relationship between abdominal pain and urgent health status, which is significant as abdominal pain can often be an indicator of serious underlying health issues. When a person experiences sudden or severe abdominal pain, it may require immediate medical attention, as it could be a symptom of conditions such as appendicitis, gallbladder problems, kidney stones, or other gastrointestinal disorders that require urgent evaluation and treatment. The urgency of addressing abdominal pain with regard to a person's health status highlights the importance of recognizing potential warning signs and seeking professional medical advice when needed. Ignoring or neglecting such symptoms can lead to delayed diagnosis and treatment, which may worsen the underlying condition and result in complications.

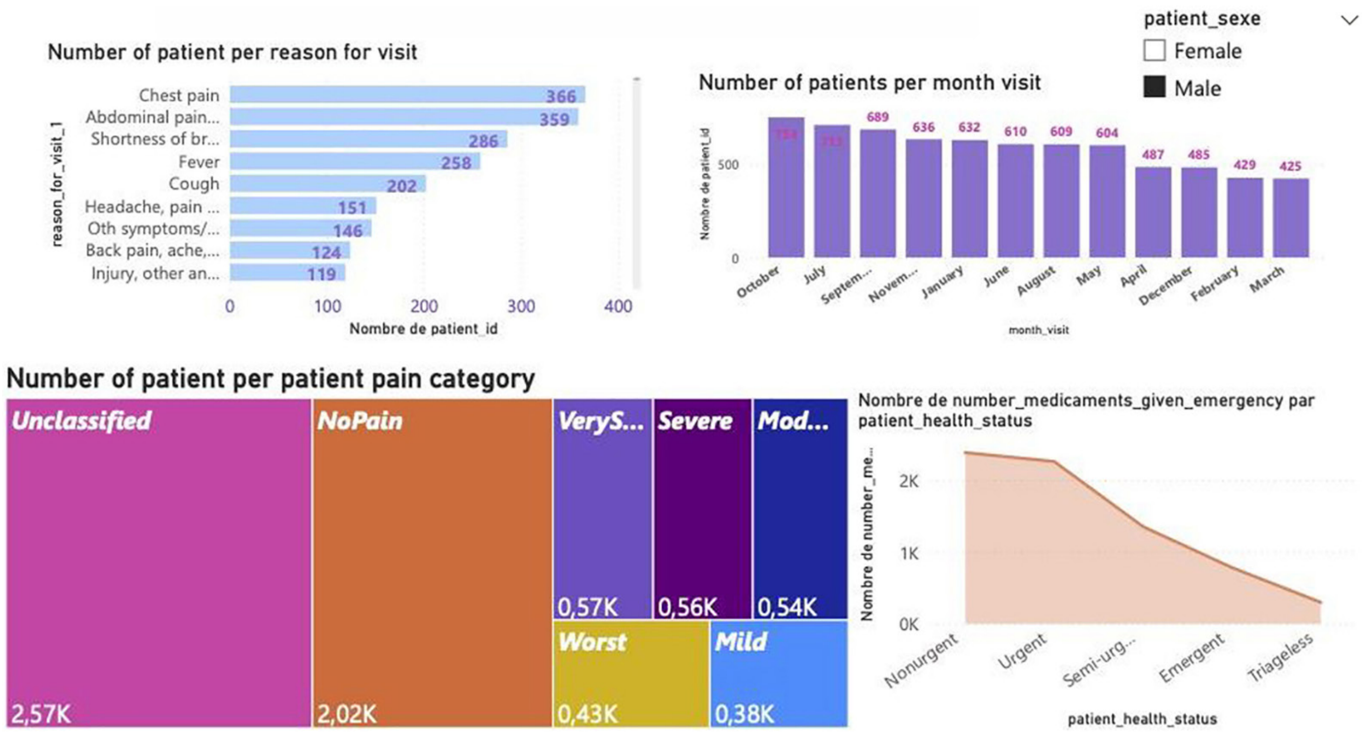

Fig. 6. Patient flow in the emergency department for male gender

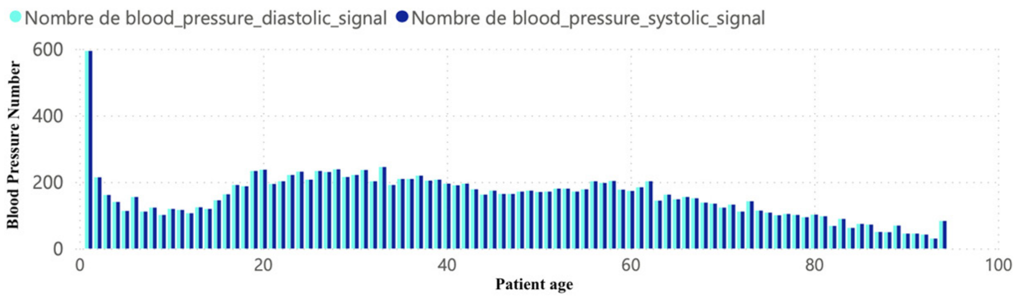

Fig. 7. Correlation between diastolic and systolic blood pressure

The relationship between age and blood pressure is well-established, and it is common to increase with age. However, the correlation between diastolic and systolic blood pressure and age can vary, and the patterns may differ between individuals, as mentioned in Figures 7 and 8. In many individuals, both systolic and diastolic blood pressure tend to rise with age. This is partly due to the aging process. The increase in systolic blood pressure is often more pronounced with age compared to diastolic blood pressure. Table 2 shows the gathered results for patient classification using different machine learning algorithms.

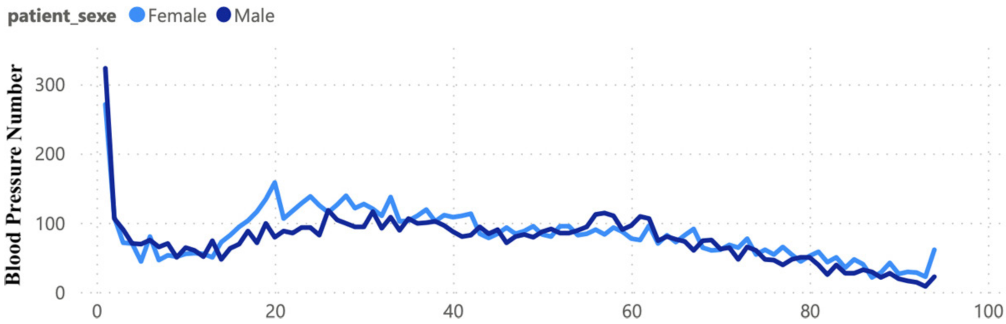

Fig. 8. Correlation between blood pressure diastolic and patient age

Table 2. Results for patient classification using different machine learning algorithms

Algorithm	Accuracy
LogisticRegression	88.13%
RandomForestClassifier	89.03%
DecisionTreeClassifier	73.69%
MultinomialNB	67.22%
SGDClassifier	72.21%
ComplementNB	75.51%
GaussianNB	50.73%
SVM	86.20%

6 DISCUSSION

The Internet of Medical Things (IoMT) and contextual information are crucial in enhancing patient priority management within healthcare systems. Here is a demonstration of how these technologies contribute to more effective and efficient patient care:

- **Real-time monitoring through IoMT:** IoMT devices, such as wearable sensors and medical IoT devices, continuously collect and transmit patient health data in real time. Vital signs, medication adherence, and other relevant health metrics are monitored, providing healthcare professionals with immediate insights into a patient's condition [24, 25].
- **Early detection of critical changes:** Through IoMT, healthcare providers receive instant alerts in case of abnormal readings or critical changes in a patient's health parameters. This early detection allows prompt intervention and prevents potential emergencies, contributing to proactive and personalized healthcare.

- **Contextual information integration:** Contextual information, including patient history, lifestyle, and environmental factors, is integrated into the patient's health records. This comprehensive view enables healthcare professionals to understand the broader context of a patient's health, facilitating more informed decision-making.
- **Predictive analytics for patient prioritization:** IoMT systems can identify patterns and trends in patient data, which enables healthcare providers to predict potential health risks or deteriorations, allowing for prioritized intervention for high-risk patients.
- **Smart allocations and resource optimization:** Patient priority management is optimized by dynamically allocating resources based on real-time patient needs and risk assessments. Emergency responses, hospital bed allocations, and healthcare staff assignments are streamlined for maximum efficiency.
- **Enhanced communication and coordination:** IoMT facilitates seamless communication among healthcare professionals, ensuring that relevant contextual information is shared promptly. This fosters collaborative decision-making, reducing response times and improving overall patient outcomes.
- **Improved patient engagement and adherence:** IoMT-enabled devices empower patients to participate actively in their healthcare management. Contextual information, such as daily routines and preferences, is used to tailor treatment plans, promoting better patient engagement and adherence to medical recommendations.
- **Continuous learning and improvement:** IoMT systems continuously gather data, enabling healthcare providers to analyze outcomes and refine patient management strategies. This iterative process contributes to ongoing improvements in patient care protocols.

7 CONCLUSION

The increasing population density necessitates innovative solutions to manage the surge in patients, leading to the adoption of Internet of Medical Things (IoMT) technologies in healthcare services, both in hospitals and at patients' homes. IoMT facilitates access to healthcare services wirelessly, benefiting elderly individuals, chronic disease patients, and others in need. However, the rapid evolution of IoMT devices generates a large amount of data, posing challenges in data management and transmission. In addressing this challenge, we propose a solution in this paper integrating Explainable Artificial Intelligence into the Internet of Medical Things (IoMT) ecosystem. By incorporating Explainable AI, the entire system is elevated to a new level of explainability, fostering heightened trust and reliability in the crucial process of patient prioritization. This innovative integration allows healthcare providers to navigate the prioritization process with greater confidence, knowing that the decisions are both data-driven and comprehensible. Furthermore, the research underscores the drawbacks of conventional emergency systems, delves into context-aware recommendation systems within smart healthcare, and introduces a novel system utilizing contextual data from IoMT to aid specialists in recognizing critical patients. The study explores IoMT devices for collecting medical data from incoming patients, with a focus on the MQTT protocol for lightweight devices, aiming to guide patients to the right department and prioritize emergency management through IoMT data analysis.

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