A Context-Aware Framework to Manage the Priority of Injured Persons Arriving at Emergencies

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Abstract—Integrating the Internet of Medical Things (IoMT) in the Hospital system has modified the traditional medical service from a reactive system based on hospitalization and diseases to a preventive and interoperable system based mainly on the interactive data flow between patients and health professionals. Medical data is collected and processed using medically connected objects (MCOs). According to gathered data, the new medical system should be able to sort patient states based on urgent and critical vital signs, and consequently, priorities are defined. In this paper, we focus on managing priority in hospital emergencies to adapt dynamic operations and interactions with different stakeholders according to the changes in their execution context. Indeed, based on data sensed from MCOs implemented in ambulances, emergency rooms might be prepared to receive injured persons like victims of road accidents or other incidents. Therefore, we design a context-aware monitoring framework for injured people based on gathered medical data to manage priorities.

Keywords—IoMT, MCOs, context-aware, priority management, ambulance, hospital

1 Introduction

The population density is increasing exponentially day after day. Consequently, in the traditional hospitalization services, hospitals and clinics should take measures to support this development and take charge of many incoming patients. Therefore, this situation urges the health industries to innovate new solutions and alleviate the tasks in hospitalization services.

In this context, recently connected objects are widely used and implemented in various applications and use cases, mainly transportation, Automation systems, agriculture, and healthcare. In the healthcare field, medical-connected objects are deployed for remote healthcare monitoring purposes, such as tracking elderly patients [1], pregnant women [2], and patients with disabilities [3] and controlling the evolution related to their chronic diseases. Medical connected devices are also used for preventive medicine, namely the cases of the pandemic [4]. The use of these technologies represents what is called the Internet of Medical Things (IoMT).

This quick evolution gives birth to many IoMT devices implemented in different applications and generating a great amount of data. Subsequently, the challenge is to manage the gathered data. Furthermore, the transmission of data in a continuous way may lead to the exhaustion of the server or the congestion of the network [5]. Moreover, on the one hand, for medical applications that require data transfer in real-time to the server, the discontinuity of data flow could be destructive to the service. However, on the other hand, the transmission and data processing permanently can incur delays and lead to overlaps in health centers. Furthermore, this situation may result in a late response, making the process hard to detect and respond to emergencies [6].

In this paper, we focus on addressing the priority management based on IoMT-gathered data to access hospital emergencies. Gathered data from connected medical sensors are used to make medical decisions related to the patient state. Then, a hospital system should be able to sort patient states based on urgent and critical vital signs, and thus priorities can be defined.

Connected medical objects, such as wearable devices, remote monitoring systems, and smart health appliances, can revolutionize healthcare delivery by improving patient outcomes, increasing efficiency, and reducing costs. However, the success of connected medical objects depends on the strength and effectiveness of the health system that supports them. Here are some reasons why the health system is crucial in the context of connected medical objects:

- ✓ Integration: Connected medical objects generate a vast amount of data. It is essential to integrate it with existing health records and systems. The health system needs to have the infrastructure and technology to manage this data and ensure that it is accessible and usable by healthcare professionals. The percentage of data generated by connected medical objects can vary widely depending on the device type, the data collection frequency, and the number of patients using the devices. However, these devices can generate a significant amount of data. For example, a wearable device that monitors a patient's vital signs, such as heart rate, blood pressure, and oxygen saturation, can generate thousands of data points daily. If millions of patients use this device, the data generated can quickly become overwhelming. According to a report by Grand View Research, the global wearable medical devices market size was valued at 12.6 billion in 2020 and is expected to grow at a compound annual growth rate (CAGR) of 26.4% from 2021 to 2028. This growth is driven by the increasing adoption of wearable devices for remote patient monitoring, disease management, and fitness tracking. As more patients use these devices, the amount of data generated will continue to grow, creating new challenges and opportunities for the healthcare industry.
- ✓ Interoperability: Connected medical objects come from different manufacturers and may use different data formats and communication protocols. The health system needs to ensure that these devices can communicate seamlessly with existing health systems.
- ✓ Security and privacy: Connected medical objects may collect and transmit sensitive patient data, such as medical history, vital signs, and other health-related information. The health system needs to have robust security and privacy policies to protect this data from unauthorized access and maintain patient confidentiality.

- ✓ Quality assurance: Connected medical objects must meet quality standards to ensure they are safe, reliable, and effective. The health system needs to have regulations and standards in place to assess and monitor the quality of these devices and ensure that they meet the required standards.
- ✓ Training and education: Connected medical objects require different skills and knowledge from healthcare professionals to operate and interpret data. The health system needs to train and educate healthcare professionals to ensure they can use these devices effectively and provide the best care possible.

The health system plays a critical role in the success of connected medical objects. It needs the infrastructure, technology, regulations, policies, and training to support these devices and ensure that they provide the best possible patient care. Our objective in this study is to address multiple areas that are lacking. Our contributions consist of the following:

- Firstly, we highlight a limitation of the traditional emergency system.
- Secondly, we provide a comprehensive overview of context-aware recommendation systems and their application in smart healthcare systems.
- Thirdly, we introduce a new system that employs contextual information collected through connected medical objects (IoMT) to assist specialists in identifying the most critical patient.
- Our goal is to illustrate how contextual information and the Internet of Medical Things (IoMT) can improve the management of patient priority.

The remainder of this paper is organized as follows: the hospital models are reviewed in the second section. Then, in the third section, some related work to the challenges of using connected devices within an IoMT system is reported. Afterward, in the fourth section, our proposed framework is presented. Finally, a conclusion and future works are presented in the fifth section.

2 Theoretical background

2.1 Smart hospitals

With the great evolution of information and communication technology (ICT), the concept of a smart hospital is increasingly widespread. Indeed, a smart hospital refers to the IoT use cases in healthcare. IoT devices are connected through a wireless network to improve and enhance their services [6]. Indeed, in the past, numerous efforts were made to apply ICT in the medical field, starting with the concept of a "digital hospital" at the beginning of the 2000s in Korea. This integration aimed to transform analog hospital workflows using papers to record patients' medical histories to digitalization in computers [7]. Afterward, the concept of an "intelligent hospital" was born with Radio Frequency Identification (RFID) integration in early 2009. The implementation of RFID tags allowed real-time location tracking of patients and health professionals in various hospital spaces, such as operating rooms, hospital wards, and emergencies [8].

A smart hospital now represents an ecosystem where connected devices can perform tasks and operations related to e-health under a healthcare server [9]. The concept of smart hospitals was used in various use cases along with new technology and its properties to minimize the risk of disease contamination and spread [10]. Consequently, wirelessly connected devices for patient monitoring replaced physical contact.

Furthermore, elderly persons represent a significant proportion of hospital patients. Generally, this category of patients suffers from chronic diseases requiring careful and critical monitoring. In this context, numerous researchers propose monitoring elderly patients by a smart hospital system such as [11], [12], and [13]…

Nonetheless, in [14] authors deal with another aspect of the healthcare system that concerns the sleeping posture of the hospitalized patient. Thus, they propose a real-time recognition algorithm to detect the patient's sleeping posture. Because unsuitable sleeping is a major factor causing bad sleep quality or other serious consequences in the patient's health, authors propose to remotely monitor the patient's posture while sleeping using Edge computing-based smart hospital bed.

In conclusion, although smart technology and connected medical devices enable hospitals to monitor patients and administer adequate care remotely; nevertheless, this makes generated data management more complex and challenging.

2.2 Context-aware recommender system

In the Internet of Things (IoT) realm, context awareness refers to devices and systems that can comprehend and react to their physical and digital context. In emergency patient scenarios, context-aware IoT systems have the potential to enhance care efficacy by delivering pertinent information and alerts to healthcare providers in real time. For example, wearable devices with sensors can monitor the vital signs of an emergency patient and transmit this data to a centralized system that healthcare providers can access. This would allow healthcare providers to monitor the patient's condition and intervene remotely. Additionally, context-aware IoT systems could alert healthcare providers of potential risks or complications, such as an allergic reaction, based on the patient's medical history and current condition. Overall, utilizing context-aware IoT systems in emergency patient care can improve patient outcomes and enhance the efficiency of the healthcare system by providing real-time data and alerts to healthcare providers.

The use of medically connected objects in context-aware applications in healthcare is increasingly popular due to their capacity to provide real-time information and insights into a patient's health status. Medical-connected objects such as wearables and sensors can gather data on a patient's vital signs, medication usage, and other health-related information. Context-aware applications can then use this data to provide healthcare providers valuable insights into a patient's health [15], allowing for more informed treatment decisions and care management. For example, a context-aware application could alert a healthcare provider if a patient's vital signs indicate an impending health emergency.

An emerging field of research involves using context-aware systems to aid patient work [16]. To assess the effectiveness of these systems in enhancing patient work, self-management practices, and health outcomes in individuals with chronic diseases, randomized controlled trials (RCTs) are necessary. Understanding the contextual information of health data is crucial for reliable and efficient analysis and interpretation [17]. This is especially important in an IoT-based health monitoring system where large amounts of data are collected from various sources and devices. Contextual information includes any information that can provide additional meaning and understanding to the data being collected. For example, the time and location of data collection, the patient's medical history, and the specific device used to collect the data can all provide important context that can aid in accurate analysis and interpretation. By incorporating contextual information into an IoT-based health monitoring system, the system can more accurately identify patterns and trends, detect anomalies, and make more informed decisions about patient care. Additionally, contextual information can be used to personalize treatment plans and interventions, improving the overall effectiveness of the healthcare system.

Authors in [18] offer a comprehensive and detailed technical analysis of deploying secure smart health services. It covers every aspect of the process, from collecting sensor data related to individuals' medical conditions or immediate environment to transmitting the data over wireless networks and storing and analyzing the information in the appropriate health information systems. By providing this information, the article equips practitioners with a complete understanding of the potential vulnerabilities and solutions in the technical aspects of smart healthcare.

3 Related works

The technological evolution in smart and wearable sensors increases their integration in the healthcare domain. Thus, real-time stable and reliable communication is indispensable because it is based on the gathered data to make critical decisions. In [19], the need for QoS in smart hospitals was discussed. The authors created a middleware for healthcare 4.0 that considers the QoS for sensor data in a hybrid operating room. This middleware coordinates data from multiple sensors and uses deep imaging sensors and real-time location tags to reduce the jitter of sensors. The implementation aims to follow up and control surgeries in real-time and provide medical applications with relevant data.

In [20], the authors discussed the challenge of decision-making in emergency medical services (EMS) under limited time, missed data, and unstructured priority. Via a survey, they analyzed the requirement of a smart EMS (SEMS) and implemented SEMS. They also addressed and developed the concept of context awareness in the EMS to improve personalized care in emergencies and during the patient's stay in the hospital.

In [21], authors dealt with coronavirus patients suffering from severe infection and highlighted the importance of using the IHTCOVID-19 prioritization score for transferring patients between hospitals, called inter-hospital transfer (IHT). Hence, they proposed establishing a single coordination center to manage the priority of patient transfers between hospitals using ethical guidelines to make decisions. Applying IHTCOVID-19 aims to reduce the IHT times and variability in decision-making.

As the prediagnostic is a very good indicator of the patient's state of health, authors in [22] proposed installing a sensor system inside ambulances to gather patients' vital signs and send the collected data to the hospital via the Internet. On the hospital side, they developed a database to store the transferred data. The proposed system also includes audio and video monitoring to improve the diagnosis rate of patient cases. On the other hand, in [23], the authors proposed a communication system between ambulances and hospitals to reduce delays and route ambulances. The system also aims to make ambulances send the signal to nearby traffic signal posts to save time and lives. In [24], authors explore various similarity measurements that are employed in the recommender system.

4 Proposed approach

4.1 Research problematic

Nowadays, with the increasing number of road accidents and incidents, hospitals can need more resources and staff available to attend to patients, especially when many cases arrive simultaneously. Traditional emergency systems based on a first come first served are no longer reliable. Therefore, managing the priority of patients arriving at a hospital emergency department is complex and challenging. The first challenge faced is determining the level of urgency for each patient under time pressure, as some may require immediate attention while others may be able to wait. This situation may be difficult to assess, especially when the patient needs to communicate or provide accurate information about their condition. On the other hand, limited resources or limited capacity can lead to delays and longer wait times.

Furthermore, a second challenge is to balance the needs of patients with different types of injuries or illnesses unless a patient might require specialized care that cannot be readily or instantly available, then managing the pressure of the emergency room staff to quickly triage patients and assign them to the appropriate level of care.

Consequently, smart healthcare systems are increasingly being implemented in hospitals to address the challenges above.

Internet of Medical Things (IoMT) technologies can benefit injured individuals in several ways. One way IoMT can be used for injured individuals is through wearable devices and sensors that can monitor their vital signs and physical activity in real-time. These devices can alert medical professionals to any changes in the individual's condition, which can help to ensure that they receive timely and appropriate medical care. For example, wearable devices with sensors can monitor heart rate, blood pressure, and oxygen levels and alert medical professionals if these vital signs become abnormal. This can be especially useful for individuals who have suffered a traumatic injury and are at risk of complications.

Another way in which IoMT can be used for injured individuals is through the use of telemedicine technologies. These technologies allow individuals to connect remotely with healthcare professionals, such as doctors, nurses, and physical therapists, for consultations and treatments. This can be especially useful for injured individuals who cannot travel physically to a medical facility due to their injuries. Telemedicine technologies can include video conferencing, messaging, and other forms of communication that allow individuals to receive medical care remotely as depicted in Figure 1.

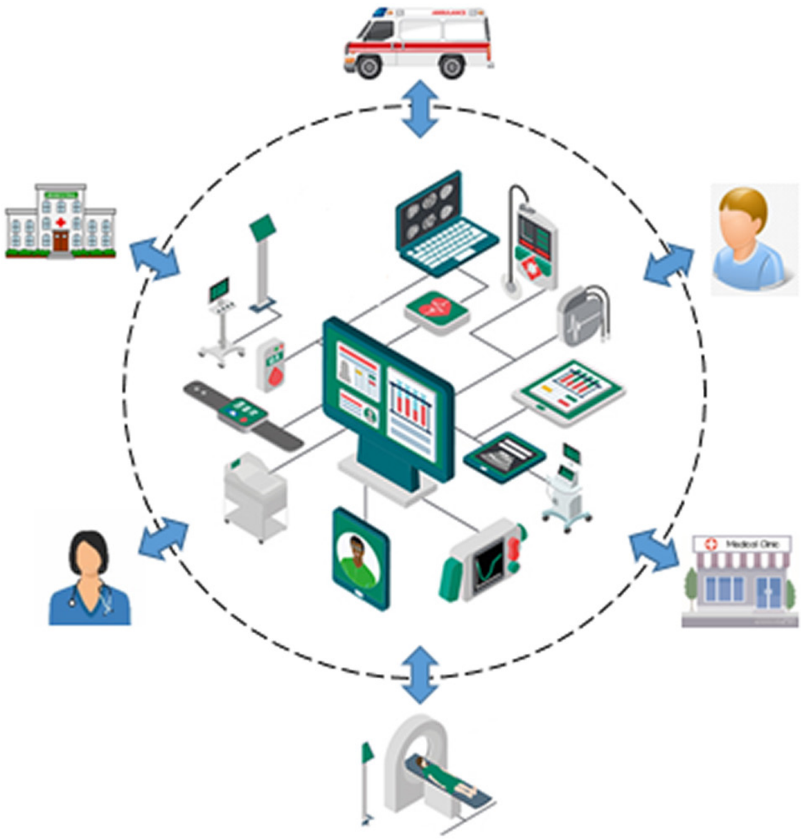

Fig. 1. Stakeholders of a medical system

Overall, IoMT technologies can be a valuable tool for injured individuals, helping to ensure that they receive timely and appropriate medical care and improving their overall health and well-being.

Our work aims to develop a smart context-aware system that can collect medical information about the hospitalized patient in the ambulance before arriving at the hospital. The use of medically connected objects in ambulances promotes communication between the ambulance staff and the hospital staff, further improving and accelerating the overall patient care process. Hence, based on gathered patient data, the system utilizes real-time data modeling and ontological knowledge representation to detect critical situations and decide if the patient's case is emergent, urgent, or semi-urgent. The design of our context-aware system is composed of three main components, as shown in Figure 2:

1. The Data Manager is responsible for data collection and storage.
2. Context-Aware Management, where data is analyzed, and priorities are managed.
3. The Emergency Manager is responsible for defining which service is recommended to each patient before arrival.

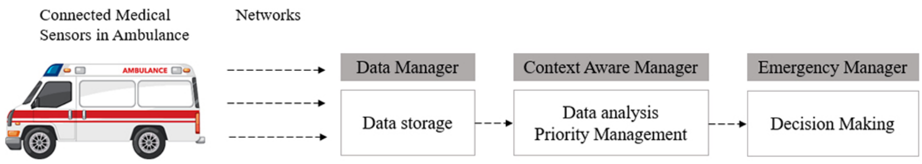

Fig. 2. Our global overview system

Furthermore, information such as heart rate, blood pressure, temperature, respiratory rate, and oxygen levels can help professionals prepare the necessary materials and services for the patient before their arrival, like blood transfusions, surgeries, and other treatments. Additionally, using IoMT devices in ambulances allows for continuous monitoring of vital signs. The follow-up of these parameters provides important information about the patient's overall health and alerts healthcare professionals if any abnormalities occur. The analysis of data from medical settings takes place reactively.

In the following, we highlight the key advantage of our context-aware system based on IoMT: the ability to predict the type of care a patient will need before they arrive at the hospital.

4.2 Methodology and overall approach

In this study, a combination of literature review and case study analysis is conducted. We started with a comprehensive literature review to gather information on the current use of IoMT in ambulances, including the implementation, benefits, and limitations. This information will be used to identify the key issues and challenges facing the use of IoMT in ambulances. Our approach is based on three modules as shown in Figure 3:

Data acquisition. This module consists of the use of a medical ambulance with a connected object that focuses on three main parts:

Data listening interface. This interface takes as input the set of patient information captured from the connected medical equipment that can capture a variety of a patient's current health status, which can be transmitted wirelessly to healthcare providers for monitoring and analysis. IoT medical-connected objects can improve patient outcomes by allowing for more frequent and convenient monitoring of vital signs. It can also track trends over time to help identify potential health issues.

- ✓ An oximetry pulse measures the oxygen saturation level in the blood, typically taken using a pulse oximeter. The device attaches to a finger or earlobe and uses infrared light to measure the amount of oxygen in the blood.
- ✓ Temperature is a measure of the body's heat level. It is typically measured in degrees Fahrenheit (°F) using a thermometer.
- ✓ Blood pressure measures the force of blood against the walls of arteries as the heart pumps it around the patient's body. It is divided into two types: systolic pressure, which represents the pressure in the arteries when the heart beats. The second one is called diastolic pressure and represents the pressure in the arteries when the heart rests between beats.

✓ Heart rate measures the heart's rhythm and can indicate a person's physical fitness level and overall health.
✓ Respiratory rate is the number of breaths a person takes per minute. It is a vital sign to assess a person's lung function and overall health.

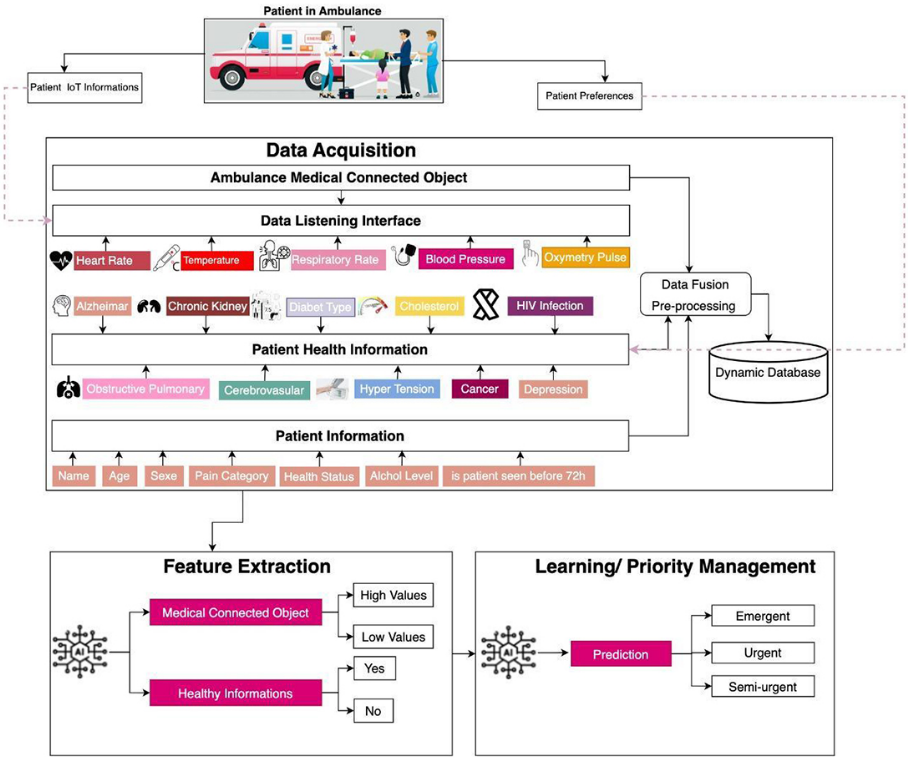

Fig. 3. Our proposed approach

Patient health information. This interface takes as input the set of patient health information, including their medical history and current condition, to determine if a patient is suffering from a chronic disease like Alzheimer's disease, Chronic Kidney, Diabetes type level, Cholesterol, hypertension, and so on. The purpose behind using this interface is because there is a strong correlation between the values collected by the medical objects and the patient's chronic diseases. For example, there is a strong correlation between heart rate and hypertension, also known as high blood pressure. Hypertension can cause an increase in heart rate, and a high heart rate can also contribute to hypertension. This is because hypertension can cause the heart to work harder to pump blood, leading to an increase in heart rate, while a high heart rate can cause the blood vessels to constrict, which can increase blood pressure. Hypertension and high heart rate are risk factors for heart disease, so it is important to manage both conditions.

Patient information. This interface takes as input the set of patient information, including their personal histories like age, sex, and alcohol level. Age and all medically connected objects seen in the first interface are strongly correlated. We gather all these data from interfaces to a dynamic database.

Feature extraction. Using machine learning algorithms, we extract several feature engineering to move to the prediction step. Then in the phase of Medical Connected Object, we compare patient-connected equipment values generated and normal values depending on patient age to know if patients have higher or lower values.

Learning and priority management. This phase is the last step in our process; it predicts the patient's health status based on the features used.

5 Experimentation results

Table 1. Performance of the proposed approach

Model	Before Self-Training	After Self-Training
Logistic Regression	41.34%	99.93%
Random Forest Classifier	40.91%	100.00%
Decision Tree Classifier	37.76%	100.00%
Multinomial Naive Bayes	37.83%	67.38%
SGD Classifier	38.36%	96.00%
Complement Naive Bayes	37.02%	69.18%
Gaussian Naive Bayes	40.28%	100.00%
Support Vector Machine	41.59%	97.38%
Average	**39.38%**	**91.23%**

5.1 Experimental data

Experimental data is a crucial component that involves several steps, starting with pre-processing to clean and prepare the data for analysis. This can involve removing outliers, dealing with missing values, and normalizing the data to ensure that it is comparable across different samples. Once the data has been pre-processed, the next step is often feature extraction. This involves identifying the most relevant features or variables in the data likely to predict the outcome of interest. Finally, once we have pre-processed the data and extracted relevant features, we can use machine learning techniques such as classifier training to build predictive models. The process is highlited in Figure 4. This involves selecting an appropriate algorithm and tuning its parameters to maximize the accuracy of our predictions. The goal of classifier training is to build a model that can accurately predict the outcome of interest based on the available data and generalize well to new, unseen data.

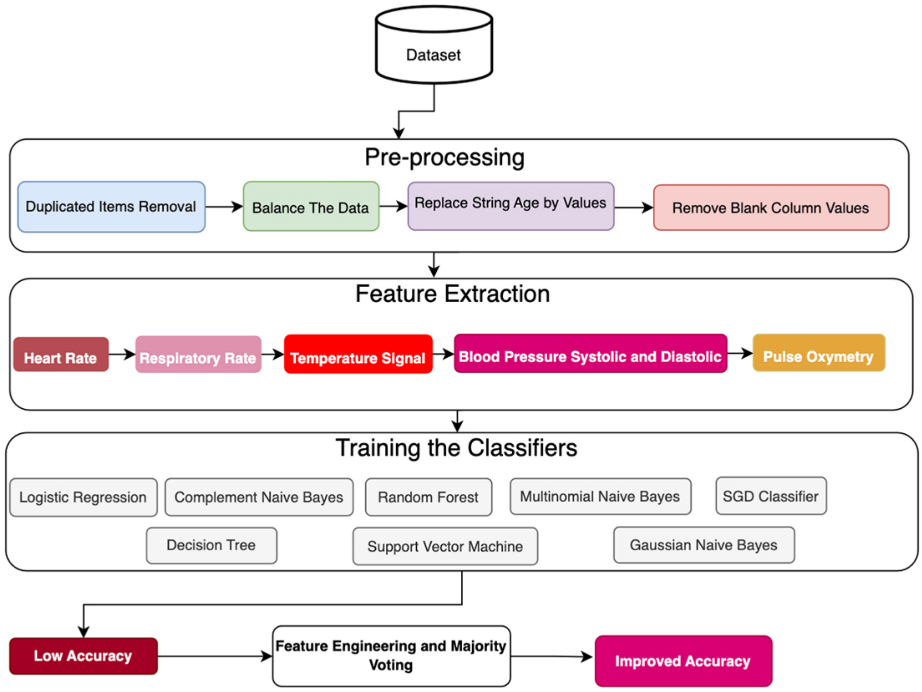

Fig. 4. The general overview of our model

Data pre-processing. Refining the data by applying techniques such as stop-word elimination, tokenization, lower casing, sentence segmentation, and punctuation removal is necessary. By removing unnecessary details from the data, we can reduce its size. To achieve this, we developed a standardized processing function that removes empty and blank rows and text in the column age as mentionned in Table 2.

Table 2. Transition steps in data pre-processing

Before Pre-Processing	After Pre-Processing
Under one year	1
94 years and over	94
DOPP or DOPPLER	
P, Palp, DOP or DOPPLER	60

Feature extraction. Feature extraction is selecting and transforming relevant information from raw data to create a set of features that can be used for machine learning or statistical analysis. In the case of physiological data, such as heart rate, respiratory rate, temperature, and blood pressure, feature extraction can help identify patterns and trends in the data that may be related to specific health conditions or physiological states.

Training classifiers. We employed several classifiers to perform majority voting, including the maximum of algorithms that produced identical predictions or classifications. In machine learning, ensemble methods like majority voting are often used to combine the predictions of multiple classifiers with improving the classification model's overall accuracy and robustness.

- First, we train multiple classifiers (Linear Regression, Complement Naive Bayes, Random Forest, Multinomial Naive Bayes, Support Vector Machine, Gaussian Naive Bayes, SGD Classifier, and Decision Tree Classifier). As mentioned in Table 1. Using the same dataset but with different algorithm configurations, hyper-parameters or feature selection methods, for example.
- Then, when predicting a new instance, each classifier would make its prediction or classification based on the input data.
- Finally, the majority voting approach would combine the predictions of all the classifiers and choose the class that is predicted by the most classifiers as the final prediction. In other words, the class with the most votes is selected as the final output.

5.2 Experimental architecture

Data collection process. Table 3 mentions the details of the collected dataset.

Table 3. Dataset details

Title	Description	Type
patient_id	The patient numbers	Patient Information
patient_age	The patient ages	
patient_sexe	The patient sex	
patient_race	The patient races	
heart_rate_signal	The number of times a patient's heart beats per minute.	Patient IoMT Collected Information
respiratory_rate_signal	The number of times a patient breathes per minute.	
blood_pressure_ systolic_signal	The force of blood against artery walls when the heart beats and the pressure when the heart rests.	
blood_pressure_ diastolic_signal	The measure of the force of blood against the walls of the arteries.	
pulse_oximetry_signal	The measure of the oxygen saturation level of a patient's blood.	
ambulance_time	The time taken for a patient inside the ambulance to arrive at the hospital.	

(Continued)

Table 3. Dataset details *(Continued)*

Title	Description	Type
patient_alchol_level	The patient alcohol level	Patient Health Information
is_patient_suffer_alzheimar	is a boolean column "Yes" or "No", which mentions if the patient suffers from Alzheimer's disease.	
is_patient_suffer_cancer	is a boolean column "Yes" or "No", which mentions if the patient suffers from cancer disease.	
is_patient_suffer_cerebrovacular	is a boolean column "Yes" or "No", which mentions if the patient suffers from cerebrovascular disease.	
is_patient_suffer_chronic_kdney	is a boolean column "Yes" or "No", which mentions if the patient suffers from kidney disease.	
is_patient_suffer_depression	is a boolean column "Yes" or "No", which mentions if the patient suffers from depression disease.	
is_patient_suffer_diabet_L1	is a boolean column "Yes" or "No", which mentions if the patient suffers from diabetes level 1.	
is_patient_suffer_diabet_L2	is a boolean column "Yes" or "No", which mentions if the patient suffers from diabetes level 2.	
is_patient_suffer_diabet_L0	is a boolean column "Yes" or "No", that mentions if the patient suffers from diabetes.	
is_patient_suffer_pulmonary_embolism	is a boolean column "Yes" or "No", which mentions if the patient suffers from pulmonary embolism disease.	
is_patient_suffer_obesity	is a boolean column "Yes" or "No", which mentions if the patient suffers from obesity disease.	
is_patient_suffer_apnea	is a boolean column "Yes" or "No", which mentions if the patient suffers from apnea disease.	
is_patient_suffer_osteoporosis	is a boolean column "Yes" or "No", which mentions if the patient suffers from osteoporosis disease.	
is_patient_suffer_hyper_tension	is a boolean column "Yes" or "No", which mentions if the patient suffers from hypertension disease.	
is_patient_suffer_HIV_infection	is a boolean column "Yes" or "No", which mentions if the patient suffers from HIV infection disease.	
is_patient_suffer_high_cholesterol	is a boolean column "Yes" or "No", which mentions if the patient suffers from high cholesterol disease.	
is_patient_suffer_renal_insufficiency	is a boolean column "Yes" or "No", which mentions if the patient suffers from renal insufficiency disease.	
is_patient_suffer_coronary_artery	is a boolean column "Yes" or "No", which mentions if the patient suffers from coronary artery disease.	
is_patient_suffer_congestiveheart_failure	is a boolean column "Yes" or "No", which mentions if the patient suffers from congestive heart failure disease.	
is_patient_suffer_chronic_obstructive_pulmonary	is a boolean column "Yes" or "No", which mentions if the patient suffers from chronic obstructive pulmonary disease.	
patient_health_status	The patient's health status	

5.3 Evaluation and results

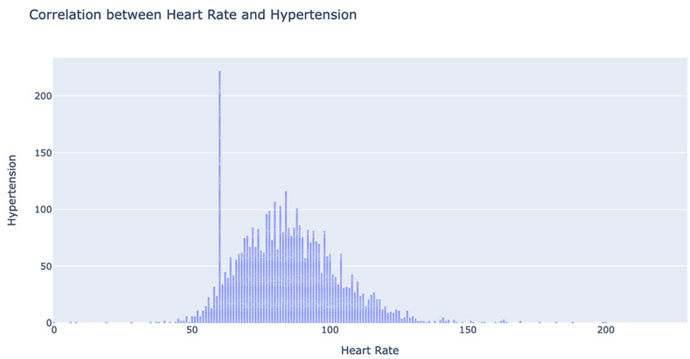

Fig. 5. Correlation between heart rate and hypertension

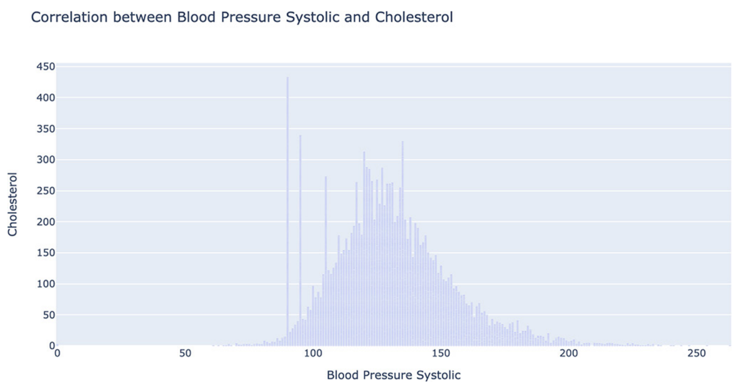

Fig. 6. Correlation between blood pressure systolic and cholesterol

6 Distinctions

This section evaluates the proposed method for prioritizing patient injuries using medical IoT devices compared to other established methods. Medical-connected objects such as wearable sensors, remote monitoring devices, and medical imaging equipment can collect and transmit patient data in real time, allowing healthcare professionals to make more informed decisions about patient prioritization. We suggest a novel approach similar to triage systems prioritizing patient injuries to accomplish this. This method categorizes patients into varying priority levels based on the severity of their injuries. Other existing techniques include using predictive analytics and artificial intelligence algorithms to analyze patient data and identify those at the highest risk for poor outcomes as mentioned in Table 4. These approaches can help healthcare professionals make more accurate patient outcomes predictions and prioritize care accordingly. However, it is important to consider factors such as data security and privacy and the potential for bias in the algorithms used to analyze patient data.

Table 4. Comparisons between our proposed approach and other approaches for managing patient priority

Study	Patient Features							Goal	Limitation
	HR	**T**	**RR**	**BP**	**OP**	**CD**	**PI**		
[25]	✓	×	✓	✓	×	✓	✓	The objectives of the work are to develop a smart system for predicting patient context, collecting data, and triggering emergency alerts. The system includes a real-time ontology-based data model with an emergency mechanism for locating patients and notifying the nearest hospital.	The proposed framework's generality and distribution can be improved by implementing multiple components as autonomous agents.
[26]	✓	✓	×	✓	×	✓	✓	This paper aims to create an ontology to monitor and communicate crucial medical information of a patient with brain tumor. By gathering data and using reasoning techniques, a high-level framework has been developed, which can be employed to develop context-aware applications.	The proposed framework does take into consideration one chronic disease which is a brain tumor.
[27]	✓	✓	✓	✓	✓	✓	×	The suggested framework proposes an approach that gathers medically connected object measures like heart rate, temperature signal, respiratory rate, blood pressure, oximetry pulse, and some chronic disease.	The proposed framework does not take into consideration two chronic diseases: Alzheimer's and Anemia.
[28]	✓	✓	×	✓	×	×	×	The paper presents a novel context-aware service system for safe driving that detects a driver's health status and offers assistance. It's the first of its kind and features an assessment model that minimizes service use and adapts to risky conditions based on assessments.	The proposed framework considers two chronic diseases, which are Alzheimer's disease monitoring and Anemia detection.
[29]	✓	×	✓	×	×	×	×	This review introduces intelligent speech technology (IST), implemented on an application case of IST. It also proposes a novel medical voice analysis system architecture.	The few available high-quality datasets make the study of IST less reliable.
[30]	✓	✓	×	✓	✓	×	×	The study proposes a scheduler and resource allocation using mobile edge computing (MEC) for efficient emergency health monitoring system.	The prediagnostic step is not present in this approach.
[31]	✓	✓	×	✓	✓	×	×	The context-aware framework for u-healthcare applications aims to decrease network traffic by using the environment and patient condition data processing components. It offers users and hospitals services such as location data, alert messages, and updates on patient status.	The proposed framework does not consider patient information, like if there is a chronic disease and the patient's age.
Our Proposed Approach	✓	✓	✓	✓	✓	✓	✓	Our framework categorizes characteristics into three components: patient data (age, gender, ethnicity), patient health information (chronic illnesses, alcohol addiction, obesity), and medical device measurements (heart rate, temperature, pulse oximetry).	The proposed framework has potential benefits but limited access to medical dataset is a drawback due to confidential patient information.

7 Conclusion

The time a patient or an injured person takes to reach the hospital in case of an incident or accident plays a crucial role in deciding the person's fate. This is why it is important to have a prediagnostic step before the arrival at the hospital. This study aims to help health professionals provide care to hospitalized patients as quickly as possible and save lives. In this paper, we propose an approach consisting of connected ambulances equipped with connected medical devices to detect and collect a patient's vital signs, such as temperature, blood pressure, heart rate, respiratory rate, and oximetry pulse. After collecting data via MCOs installed in the ambulance, data is transferred to the hospital server to allow health professionals to prepare emergency rooms adequately.

Moreover, the gathered data allows the system to manage hospitalized person priority based on critical cases. The study concludes that our approach provides an effective method to improve the efficiency and accuracy of medical services. Furthermore, implementing our context-aware recommender system can significantly improve patient outcomes and reduce the burden on emergency departments. Future research should focus on the scalability and cost-effectiveness of using MCOs and the recommender system in different healthcare and hospital departments.

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