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College of Science and Technology

AFRICAN CENTER OF EXCELLENCE IN INTERNET OF THINGS

An Intelligent IoT-Enabled System for Real-Time Ambulance-Based Patient Health Monitoring

A dissertation submitted in partial fulfilment of the requirements for the award of Master of Science degree in Internet of Things: Embedded Computing Systems

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January, 2025

Declaration

I HABIMANA Jean Claude, Masters' student from African Center of Excellence in internet of things, at University of Rwanda. I declare that this research thesis is my own original work and it has never been presented before anywhere in the world.

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Bonafide certificate

This is to certify that this submitted Research Thesis work report is a record of the original work done by HABIMANA Jean Claude (**Ref. No: 221031800**), MSc. IoT-ECS Student at the University of Rwanda / College of Science and Technology / African Center of Excellence in Internet of Things, the Academic year 2021/2023.

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Abstract

This study developed an IoT-enabled system integrated with machine learning for real-time ambulance tracking and patient health monitoring, emphasizing data security. The system continuously captures vital signs such as temperature, heart rate, and oxygen saturation, improving care coordination between ambulances and hospitals. Due to ethical and logistical constraints, the machine learning model was trained using secondary data from patients transported in ambulances And Testing was performed with normal individuals in private cars instead of real-time ambulance data. However, the alternative approach using this secondary data and private car testing has proven effective. The Isolation Forest Algorithm was employed for anomaly detection, and the system provides real-time alerts via buzzer, and on-screen notifications. Patient data is transmitted from sensors to a server and displayed on dashboards developed with Python's framework Flask and SQL Server Database. The system successfully demonstrated its ability to track ambulances and monitor patient conditions. The prototype and dashboards confirmed the system's effectiveness in enhancing emergency care through real-time in-ambulance patient health monitoring.

Keywords: Patient Real-time Health Monitoring, IoT-enabled System, Machine learning in healthcare, Ambulance tracking system

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List of Acronyms

ACEIoT: African Center of Excellence in Internet of Things

CSS: Cascading Stylesheet

CSV: Comma-Separated Values

EMS: Emergency Medical Service

ETA: Estimated Time of Arrival

GPS: Global Positioning System

HTML: Hypertext Markup Language

IoT: Internet of Things

LCD: Liquid Crystal Display

MCU: Microcontroller Unit

ML: Machine Learning

SPO2: Peripheral Capillary Oxygen Saturation

SVM (One-Class SVM): Support Vector Machine (One-Class Support Vector Machine)

UR: University of Rwanda

Wi-Fi: Wireless Fidelity

CHAPTER I. INTRODUCTION

1.1 Introduction

Ambulances are an important part of emergency medical services (EMS) around the world, providing essential care and transportation for patients in need[1]. These specialized vehicles are outfitted with medical equipment and staffed by skilled healthcare professionals, allowing them to respond quickly to medical emergencies and provide emergency care while transporting patients to hospitals or healthcare institutions. Ambulances are critical in saving lives, lowering death rates, and providing quick access to healthcare services. [2] Today's technology is evolving and improving in every sectors' corner, the IoT is becoming ubiquitous and is capable for connecting different gadgets together over the internet and this leads to the improvement of innovation [3] as the technology increased, the hospitals and people are concerned with the status of ambulance knowing the location, tracking accidents and monitoring every status of it and also the health condition of the patient by knowing the health parameters of the patients[4].

The integration of IoT and machine learning technologies has revolutionized various industries, including healthcare [5]. One critical application of this combination is the development of advanced ambulance tracking and real-time patient health monitoring systems, which have the potential to significantly enhance emergency care. This research aimed to develop an IoT and machine learning-based solution specifically tailored for Rwanda, a country with unique healthcare challenges and a growing need for improved emergency medical services.

Rwanda is a landlocked country in East Africa with a population of approximately 13,246,394 people [6]. The healthcare system faces numerous challenges, including limited resources, inadequate infrastructure, and a high burden of disease, often leading to patients being referred to district hospitals and referral hospitals for advanced medical care. However, Rwanda is actively addressing these challenges by investing in technology and innovation across all sectors. In healthcare, this commitment to technological advancement is driving improvements in access, infrastructure, and resource management, with the aim of enhancing the overall quality of care and better meeting the needs of patients.[7].

In emergency situations, timely response and accurate medical interventions are critical for saving lives. Traditional ambulance dispatch systems often lack the capability to efficiently track ambulance locations, and monitoring patient in transit leading to inefficient emergency care. Additionally, monitoring the vital signs and health status of patients during transit is crucial for making informed medical decisions. By integrating IoT and machine learning technologies, it is possible to develop a comprehensive system that addresses these challenges, ultimately improving emergency care outcomes [8].

The IoT provides a framework for interconnecting various devices and sensors to collect and transmit real-time data. In the context of ambulance tracking, IoT can enable the monitoring of ambulance location, speed, and route in real-time as well health parameters of patient in the ambulance. This information can be shared with hospitals, emergency responders, and traffic management systems, enabling better coordination and faster response times [9].

Machine learning algorithms can analyze the data collected from patients' vital signs and health parameters during transit. The integration of ML with IoT-based patient monitoring in ambulances enhances the system's ability to analyze data, make predictions, and provide intelligent decision support. ML empowers healthcare providers with real-time insights, enables personalized care, optimizes resource allocation, and facilitates continuous learning to improve emergency response and patient outcomes[8].

In light of the healthcare challenges faced in Rwanda, this research proposed a customized IoT and machine learning-based ambulance tracking and patient health monitoring system.

The system was designed to monitor and collect essential health parameters, including heart rate, body temperature and oxygen pulse in real-time from patients during emergency transportation. To ensure the security and privacy of patient data, the system employs end-to-end data encryption. Moreover, the system was engineered to be cost-effective, scalable, and readily accessible, ensuring that even remote regions can benefit from improved emergency healthcare services.

1.2 Background and Motivation

Access to quality healthcare services, especially during emergencies, is a critical aspect of health sector. In many regions, including Rwanda, the effectiveness of emergency healthcare delivery relies on efficient patient transportation, real-time monitoring, and effective communication between healthcare providers. However, there are significant challenges in ensuring timely and high-quality emergency care, particularly in low-resource settings.

Throughout Rwanda's healthcare system, emergency medical services are provided at various levels of care. From the most basic to the most specialized care, these levels of care are offered by district hospitals, provincial hospitals, community health workers, health posts, health clinics, and referral hospitals. When a patient is in an emergency, an ambulance is called in to transport them to a higher institution through Rwanda's referral system if the current facility is unable to offer the necessary level of care [10].

Rwanda, like many developing countries, faces unique healthcare infrastructure and resource limitations [11]. The process of transporting patients from lower-level health facilities, such as Health Centers, to higher-level facilities, including Hospitals, often involves manual data recording and limited means of communication between healthcare providers. In such situations, critical patient information may not reach healthcare professionals in a timely manner, potentially leading to suboptimal care and compromised patient outcomes.

The healthcare system in Rwanda has made remarkable progress over the years. The government has prioritized healthcare accessibility, resulting in increased life expectancy and a reduction in maternal and child mortality rates [12]. Despite these achievements, the nation still faces challenges in providing efficient emergency healthcare services.

Traditionally, ambulance services in Rwanda relies primarily on phone calls and manual record-keeping during patient transit. This lack of technological integration limits the ability to collect and share vital patient data effectively [13]. The absence of real-time data collection and communication between ambulance personnel and receiving healthcare providers can result in information gaps, delayed diagnosis, and inadequate preparation for incoming patients. Patients in critical condition may not receive the prompt care they require [14].

This project " An Intelligent IoT-Enabled System for Real-Time Ambulance-Based Patient Health Monitoring" is driven by the need to improve emergency healthcare services in Rwanda. By addressing the limitations of the current healthcare system, the project aimed to enhance patient care and outcomes during transit and upon arrival at the hospital.

The utilization of Internet of Things (IoT) emerging technology enables real-time monitoring of patient health parameters, including heart rate, oxygen levels, and temperature. The data collected during ambulance transport is transmitted to a central server for immediate analysis. To ensure patient safety, the project incorporates machine learning techniques, specifically isolation forest, to detect anomalies in patient data.

1.3 Problem Statement

Advancements in healthcare technology have significantly improved service delivery. However, critical gaps persist in the implementation of integrated IoT and machine learning-based solutions for ambulance tracking and real-time patient health monitoring, the pressing challenge lies in ensuring data security and confidentiality. Many current systems do not incorporate robust measures to protect sensitive health information, leaving patient data vulnerable to breaches and compromising privacy standards.

This project seeks to address these challenges by:

1. Enhancing real-time health monitoring in ambulances through the integration of IoT and machine learning techniques for accurate anomaly detection in patient health data.
2. Implementing end-to-end encryption and other robust data security measures to ensure the confidentiality and integrity of patient information.

By addressing these gaps, this project aims to contribute to the advancement of emergency healthcare systems, enabling timely interventions, improving patient outcomes, and safeguarding sensitive health data.

1.4 Study Objectives

This project aimed to create a cutting-edge IoT and machine learning-driven solution that enables the tracking of ambulance location while simultaneously monitoring vital health parameters of patients during transit. The system was designed to capture and analyze real-time data, including temperature, heart rate, and oxygen saturation (SpO2).

The developed system enables healthcare providers in the ambulance to monitor the patient's health data in real-time and provide appropriate care. Additionally, healthcare providers at the hospital level are able to monitor the locations of different ambulances approaching their facility, along with the health parameters of patients in transit. The project seeks to enhance emergency healthcare services by enabling proactive and efficient patient care planning and coordination between ambulances and hospitals.

1.4.1 General Objective

This project aimed to develop an IoT and Machine Learning enabled system to track Ambulance location and monitor in ambulance Patient Real-Time Health parameters.

1.4.2 Specific Objectives

1. Develop a machine learning model for anomaly detection in patient data
2. Create a prototype to showcase core functionalities
3. Implement end-to-end encryption for secure data transmission
4. Develop a web-based system for data storage and visualization

1.5 Hypotheses

Implementing an IoT-enabled machine learning system for ambulance tracking and real-time patient health monitoring in Rwanda will significantly enhance the efficiency and effectiveness of emergency healthcare services. This system will provide real-time tracking of ambulances, continuous monitoring of patient conditions, and data visualization through dashboards. Additionally, it will improve emergency planning by predicting ambulance arrival times as they move between health facilities.

1.6 Study Scope

This research focused on developing and implementing an IoT-enabled machine learning system for monitoring patients transferred from low-level to high-level health facilities while in the ambulance in transit, and ambulance location tracking.

The key components of the scope include:

Ambulance Location Tracking: Development of a GPS-enabled tracking system for ambulances to ensure real-time monitoring of their locations to enhance the efficiency of emergency response.

Real-Time Patient Health Monitoring: Implementation of wearable IoT devices for continuous monitoring of health parameters during ambulance transportation and Utilization of machine learning algorithms to analyze and interpret real-time patient data for immediate medical interventions.

Communication Infrastructure: Establishment of a robust communication network to facilitate seamless data exchange between healthcare providers, hospitals and the central monitoring system and Integration of secure and reliable data transmission to ensure the privacy and integrity of patient information.

User Interface and Experience: Development of user-friendly interfaces or interactive dashboard for healthcare professionals, and central monitoring staff for data visualization and alerts system for quick decision-making based on real-time data.

Data Collection, Model Training and Prototype Testing: Due to ethical constraints related to collecting real-time patient data, this study utilized secondary data registered in openMRS for patients arriving by ambulance and these were used for model training. Additionally, the prototype was tested on normal individuals moving in private cars. This approach allowed for testing the model's capabilities while maintaining ethical standards, tailored for the improvement of emergency healthcare services in Rwanda.

1.7 Significance of the Study

The significance of this study lies in its potential to bring about transformative improvements in the emergency healthcare landscape. The key aspects of its significance include:

Enhanced Patient Outcomes: Real-time patient health monitoring during ambulance transport enables healthcare providers to receive immediate data on vital signs and health parameters. This timely information facilitates quick decision-making, allowing for more effective treatment strategies and potentially improving patient outcomes.

Optimized Resource Allocation: The system's ability to track ambulance locations and monitor patient conditions in real time allows for better allocation of healthcare by ensuring that medical staff and equipment are prepared for incoming patients.

Infrastructure Development: Implementing an IoT-enabled healthcare system requires the development of robust communication infrastructure, contributing to advancements in technology and connectivity within the healthcare sector. This infrastructure can serve as a foundation for future innovations and improvements in healthcare services.

Potential for Replication and Scalability: Findings from this study in Rwanda could serve as a model for other regions facing similar challenges in emergency healthcare. The scalable nature of IoT solutions allows for the potential replication of successful implementations in diverse geographical and healthcare settings.

Socio-Economic Impact: Improving emergency healthcare services has broader socio-economic implications. Timely and effective emergency medical care can lead to reduced mortality rates, decreased healthcare costs associated with prolonged treatments, and an overall improvement in the health and well-being of the population.

Contribution to Global Health Technology: The study contributes to the growing field of health technology, showcasing the potential of integrating IoT and machine learning in emergency healthcare. Lessons learned from this research can inform the development of similar systems worldwide, advancing the global landscape of healthcare innovation.

In summary, the study holds significance by addressing critical aspects of emergency healthcare, from response times to patient monitoring, and has the potential to positively impact not only Rwanda but also serve as a valuable reference for advancements in healthcare technology globally.

1.7.1 Survey Overview

In addition to the technical development of the IoT-enabled health monitoring system, a survey was conducted to gather feedback from healthcare providers and health informaticians. The healthcare providers included nurses primarily involved in emergency care, particularly those accompanying patients in ambulances. These nurses were drawn from the catchment area of Muhima District

Hospital, located in Gasabo District. The health informaticians surveyed were graduates from the Health Informatics Department at the University of Rwanda.

This survey aimed to align the system's functionalities with the needs and preferences of its end-users. The insights gained were instrumental in understanding the practical implications of the system and refining its design to meet user requirements effectively.

For a comprehensive overview of the survey findings and methodology, please refer to Appendix A

1.8 Organization of the Study

Apart from the chapter one which describes the introduction, general background and motivation of the research, problem statement, study objectives, hypothesis, study scope and significance of the study. The rest of this document is organized as follows: The next chapter gives a review of related literature on use of IoT and machine learning for enhancing emergency healthcare, tracking ambulance and real-time patient health monitoring system; Chapter 3 describes the methodology used in the study, the research process is outlined, the ML model development, the system design methodology and materials also presented; Chapter 4 presents the system design and analysis, the system architecture of the prediction model, the system-level design; Chapter 5 presents System Results and analysis of the trained model and developed prototype; Chapter 6 Conclusion, Recommendations and Future work.

1.9 Conclusion

This chapter delves into the fundamental aspects of the research, providing a comprehensive overview of the problem statement, objectives, and the motivation driving this study. The critical role of ambulances in emergency medical services globally was highlighted, emphasizing the need for innovative solutions to enhance their efficiency. The integration of Internet of Things (IoT) and machine learning technologies was introduced as a potential game-changer for improving emergency care, especially in regions facing healthcare challenges such as Rwanda. As the chapter unfolds, it sets the stage for a focused exploration of the new IoT and machine learning-based Ambulance Tracking and Real-Time Patient Health Monitoring System, with a particular emphasis on addressing the identified gaps in existing emergency healthcare systems.

CHAPTER 2: LITERATURE REVIEW

2.1 Related Works

The rationale behind this project was to address the challenges in emergency healthcare services, specifically in the context of ambulance location tracking and real-time patient health monitoring. Currently, there is a need for innovative solutions that can enhance the coordination and efficiency of emergency care, both within ambulances and between ambulances and hospitals in Rwanda. By leveraging IoT and machine learning technologies, this project aimed to provide a comprehensive secure system that enables healthcare providers to track ambulances, monitor patient health parameters, and facilitate proactive care planning.
Several studies and research papers have explored the integration of emerging technologies (Internet of Things IoT and Machine Learning ML) in healthcare, highlighting their potential to improve emergency care services.

A study by [15] developed an IoT-based ambulance tracking system utilizing GPS technology to monitor ambulance locations in real-time. This system demonstrated effectiveness in improving emergency response times and reducing ambulance idle time, showcasing the importance of real-time location tracking for efficient emergency management. However, it did not integrate patient health monitoring or address data security concerns, which are critical for a comprehensive emergency healthcare solution.

Study [16] conducted research on real-time patient health monitoring using wearable IoT devices. The focus was on collecting and analyzing vital signs data, such as heart rate and blood pressure, to detect anomalies and provide timely alerts to healthcare providers. The study highlighted the potential of IoT in enabling remote monitoring and early intervention for patients in critical conditions. Despite these benefits, the study did not combine this monitoring with ambulance tracking or address the security of patient data during transmission.

The application of machine learning algorithms in healthcare data analysis was explored by [17]. This study showcased the capability of ML models to identify patterns and predict health outcomes based on large datasets, emphasizing ML's potential in assisting healthcare providers with decision-making and personalized patient care. However, it did not focus on the specific context of emergency healthcare or the integration with IoT for real-time applications.

[18] examined diverse applications, innovative technologies, and challenges within the healthcare system, focusing on the integration of IoT with smart technologies. The goal was to improve computational efficiency and ensure the pervasive, profitable, and accessible use of IoT from any location and at any time. While this highlights the broader implications of IoT in enhancing healthcare delivery, it does not specifically address the challenges of emergency healthcare, such as ambulance tracking and patient monitoring.

The work of [19] explored how AI and sensor-equipped smart devices contribute to continuous patient condition monitoring and orchestrated services, ultimately benefiting patients. This study proposed literature-based hypotheses for future empirical validation, pointing towards a need for further research in this area. However, it did not focus on the integration of these technologies for emergency healthcare services or address data security issues.

Authors [20] introduced an intelligent healthcare monitoring system using wireless sensors on patients to collect vital physiological information such as heart rate, blood pressure, body temperature, and glucose levels. These sensors, controlled by IoT devices, transmit health information via 5G services to a monitoring station, enabling immediate intervention for critically ill patients. The incorporation of ML models enhanced the accuracy of detecting critical conditions, improving the timeliness and effectiveness of predictions. Despite these advancements, the study did not address the integration with ambulance tracking or the security of transmitted data.

Authors [21] highlighted the role of IoT technology in achieving automation. Their research suggested exploring a cloud-integrated automated system for supervising hospitals and patients to improve accessibility for medical practitioners and patients by tracking critical health data in real-time. They introduced an IoT-enabled ambulance with ML algorithms to identify the nearest hospital for critical patient care, emphasizing the importance of real-time data for emergency responses. However, the study did not integrate real-time patient health monitoring with ambulance tracking or address data security concerns.

Studies by [22] and [23] focused on enhancing patient survival rates by establishing effective communication between ambulances and hospitals, along with intelligent routing at signal posts. They proposed a distributed architecture to facilitate efficient communication and enable ambulances to communicate with nearby traffic posts for priority passage, optimizing travel time. While this addresses the issue of communication and routing, it does not integrate real-time patient health monitoring or ensure data security during transmission.

Authors [24] investigated the importance of swift transfer of critical patients to well-equipped hospitals during the crucial "Golden Hour" in road accidents. Their study proposed a system to identify the nearest hospital, determine the shortest route, transmit vital parameters to the hospital in advance, and control traffic signals to ensure the smooth passage of ambulances. While this study addresses several critical aspects of emergency healthcare, it does not focus on the comprehensive integration of IoT and ML for real-time monitoring and data security.

The research by [25] aimed to improve traffic control by utilizing data from highway movement through IR sensors. It prioritized emergency vehicles like ambulances and fire engines, enhancing the system's efficiency with advanced sensors and cloud services to manage traffic based on sensor density. However, it did not address the integration of real-time patient health monitoring or the security of transmitted data.

Authors [26] developed a patient monitoring and ambulance tracking system using 5G communication and IoT technologies. This system delivers a rapid thirty-second diagnosis using sensors for heartbeat, temperature, and breath rate, transmitting crucial patient parameters wirelessly to the hospital before ambulance dispatch. This approach is vital for critically ill patients, allowing for timely medical intervention. However, the study did not ensure robust data security during the transmission of patient data.

Authors [27] proposed a Fast Response system for preserving lives in disasters or accidents where prompt healthcare is critical. This smart ambulatory approach oversees victims, offering live tracking for a swift response, conducting non-invasive monitoring of patients' heart rate and body temperature, and integrating emergency notifications and distant communication capabilities for hospitals and paramedics. While this solution integrates several key technologies, it does not comprehensively address the security of patient data during transmission.

2.2 Conclusion

Existing literature, exemplified by [21], highlights IoT's role in healthcare automation. However, a gap persists in studies focusing on the combined use of IoT and machine learning for ambulance tracking, real-time patient health monitoring, and care coordination. [21] concentrated on IoT-enabled ambulances for critical patient care but did not explore the broader potential of IoT and machine learning in emergency healthcare specifically patient health parameters, instead finding the nearest hospital. Additionally, the literature lacks emphasis on robust data security during patient data transfer, overlooking potential risks. Addressing this gap, our project integrated IoT and machine learning while prioritizing end-to-end encryption for data security. By filling this literature gap and enhancing data security, our system tracks ambulance location, monitors real-time patient data, and aimed to revolutionize emergency healthcare for better patient outcomes.

CHAPTER 3: METHODOLOGY

3.1 Introduction

In this chapter, we present the methodology employed in the development of "An Intelligent IoT-Enabled System for Real-Time Ambulance-Based Patient Health Monitoring" in Rwanda. The methodology encompasses the process of data collection, model development, system architecture, and implementation of key functionalities aimed at improving ambulance tracking and real-time patient health monitoring.

3.1.1 Preliminary Survey

In addition to the technical and data-driven aspects of this study, a preliminary survey was conducted to capture the perspectives of healthcare providers regarding the proposed system. This survey provided valuable input on the desired functionalities and critical features from the end-users' perspective, thereby guiding the development process to better meet practical needs.

3.2 Secondary Data Acquisition and Description

To develop the machine learning (ML) model and other components of the intelligent IoT-enabled system for monitoring patients in ambulances, we obtained secondary health data from Muhima District Hospital. Due to ethical constraints, acquiring real-time data from ambulances was not feasible for this study. Collecting real-time patient data during emergency transport could have posed risks to patient privacy and safety, and the necessary ethical approvals and coordination with medical personnel were beyond the scope of this research. Therefore, secondary data that were allowed to be shared were used to train the model.

The data collection process involved a formal request to the hospital, accompanied by a supporting letter from the Director of the Center of Excellence in Internet of Things at the University of Rwanda.

[28]Muhima District Hospital is a public institution located in Nyarugenge District, City of Kigali, and began operations in 2001 as an extension of the Muhima Health Center, which was built in 1988. The hospital was constructed with financing from the World Bank's "Santé Population" project and was officially assigned to the Ministry of Health in July 2001. Muhima Hospital serves as a referral center for four health centers—Muhima, Rwampara, COR UNUM, and Kanyinya—and oversees ten functional health centers and one prison clinic in Kigali.

The provided dataset included records from February 2019 to August 25, 2024, consisting of 11,228 records and containing critical patient information recorded upon arrival at the hospital, specifically for patients transported by ambulance. The dataset includes the following key parameters:

- DateTaken: The date the data was recorded.
- PatientID: A unique identifier for each patient.
- PatientNames: The name of the patient.
- Distance: The distance traveled from the originating health center to Muhima Hospital.
- SPO2: Oxygen saturation level in the blood, measured in percentage.
- Temperature: The patient’s body temperature, recorded in degrees Celsius.
- Heart Rate: The patient’s heart rate, measured in beats per minute (BPM).
- Weight: The patient’s weight, recorded in kilograms.
- Age: The patient’s age at the time of arrival.
- Gender: The patient's gender.

The dataset provides a rich source of secondary data necessary for developing and training the machine learning model. The recorded parameters represent crucial physiological data that can be used to predict the health status of patients during emergency transport and aid in making timely decisions.

This dataset forms the backbone of the project, supporting the development of the intelligent system for real-time monitoring, tracking, and analysis within ambulance-based emergency scenarios while adhering to ethical research standards.

3.3 Data Utilization

The development of a machine learning model for assessing patient status during emergency transport relies on the availability of accurate and relevant data. For this purpose, we utilized secondary health data from patients who arrived by ambulance, which includes key physiological variables such as SPO2, Heart Rate, and Temperature. By leveraging this real-world data, we ensured that the model was trained on scenarios directly relevant to the project, enhancing its ability to make informed predictions and recommendations based on authentic patient information.

The secondary data was collected from medical records and emergency response logs of patients transported by ambulance. The data was sourced from hospital records and ambulance service databases, ensuring it reflects a range of real-world scenarios encountered during emergency transport. The data was organized into structured datasets, including variables such as SPO2, Heart Rate, and Body Temperature. The datasets were cleaned to remove inconsistencies and ensure completeness. Missing or erroneous entries were managed appropriately through interpolation or exclusion.

In addition to using secondary data, the prototype was tested on normal individuals traveling in private cars to evaluate the system in non-emergency scenarios. This allowed us to verify the functionality of the real-time health monitoring system outside of emergency transport contexts, ensuring that the developed system can adapt to a wider range of situations while still adhering to ethical standards.

To validate the accuracy and relevance of the data, we referenced established medical literature and guidelines. Normal ranges for physiological variables were established as follows: SPO2 (95 to 100%), Body Temperature (36.5 to 37.5°C), and Heart Rate (60 to 100 beats per minute) [30]. This ensured that the data adhered to clinically relevant boundaries.

For the machine learning model, the target variable "Patient Status" was derived from the physiological data, categorizing patient conditions into "Critical" or "Normal" based on predefined thresholds for key physiological parameters: Temperature, Heart Rate, and SPO2.

1. **Temperature:**
    - Normal Range: 36.5°C to 37.5°C
    - Abnormal Limits:
        - Low: Below 36.5°C
        - High: Above 37.5°C
2. **Heart Rate:**
    - Normal Range: 60 to 100 beats per minute (bpm)
    - Abnormal Limits:
        - Bradycardia: Below 60 bpm
        - Tachycardia: Above 100 bpm
3. **SPO2 (Blood Oxygen Saturation):**
    - Normal Range: 95% to 100%

- Abnormal Limits:
  - Hypoxemia: Below 95%

These limits and terms are based on established medical guidelines for assessing patient health status. This categorical variable served as the ground truth for model training and evaluation.

3.3.1 Dataset Splitting for Training and Testing

The real-world dataset was split into training and testing sets to facilitate model development and evaluation. We used an 80-20 split ratio, which divides the data into 80% for training and 20% for testing, ensuring a robust evaluation of the model’s performance.

Splitting was performed using the train_test_split function from the sklearn.model_selection module, with random stratification applied to maintain the distribution of the target classes in both sets. This approach ensures that the training and testing datasets accurately represent the overall data distribution.

The resulting datasets were organized into four distinct files: x_train, y_train, x_test, and y_test. These files contain the features and labels for training and testing, respectively, supporting effective model training and performance evaluation.

3.4 Model Development

3.4.1 Model Selection: Isolation Forest Algorithm

To detect anomalies within vital signs data, we evaluated various anomaly detection algorithms and selected the Isolation Forest algorithm due to its efficiency in identifying outliers in high-dimensional datasets. This algorithm excels in medical domains where abnormal patterns often appear as sparse outliers distinct from normal observations. Isolation Forest's ability to handle high-dimensional data effectively made it the optimal choice for our anomaly detection needs [18].

3.4.2 Isolation Forest Algorithm

The **Isolation Forest (iForest)** algorithm is an efficient anomaly detection method introduced by Liu, Ting, and Zhou. It isolates anomalies through recursive partitioning, leveraging binary search trees and data sampling, with linear time and space complexity.

The algorithm builds an "isolation forest" using random subsamples, where anomalies are easier to isolate due to their distinctiveness, resulting in shorter average path lengths in the trees. Each data point receives an anomaly score (0 to 1), with higher scores indicating anomalies. Data with scores above a set threshold are classified as anomalies. Its scalability and efficiency make it ideal for detecting anomalies in large datasets[29].

These evaluation methods (precision, recall, and F1-score) provided a comprehensive assessment of the Isolation Forest algorithm's ability to accurately identify anomalies in vital signs data. The high-performance metrics and effective handling of high-dimensional data reinforced our decision to use Isolation Forest for this anomaly detection task.

3.4.3 Model Training

The training of the Isolation Forest model was carried out using the scikit-learn library in Python. The process involved several key steps and configurations:

1. **Data Preparation:** Training and testing datasets were prepared by reading data from CSV files, which included features related to vital signs. The datasets were split into training and testing subsets to ensure robust model evaluation.
2. **Model Configuration:** The Isolation Forest algorithm was initialized with 100 decision trees (n_estimators=100). The contamination parameter was set to 0.1, reflecting the expected proportion of anomalies in the dataset. This configuration is crucial for the algorithm to effectively identify anomalies within the high-dimensional data.
3. **Model Training:** The model was trained on the training dataset using the fit method. During training, the Isolation Forest algorithm learned to distinguish between normal and anomalous patterns by isolating data points in the feature space.
4. **Model Saving:** After training, the model was saved to a file using joblib. This allows for later reuse and deployment without the need to retrain the model.
5. **Anomaly Prediction:** Predictions were made on the testing dataset to evaluate the model's performance. The predicted anomalies were saved to a CSV file for further analysis.

This approach ensured that the Isolation Forest model was trained effectively on the vital signs data, leveraging the algorithm's capabilities to identify anomalies. The choice of parameters and the use of scikit-learn facilitated a structured and efficient training process.

3.4.4 Interpretation of Anomaly Predictions

Anomaly predictions from the Isolation Forest model are binary, classifying instances as either normal (1) or anomalous (-1). We analyzed these predictions by examining the distribution of predicted labels, which indicated that the majority of instances were classified as normal, with a smaller proportion identified as anomalous. This classification reflects the model's capability to distinguish between typical physiological patterns and outlier anomalies.

We also visualized the distribution of vital signs (body temperature, heart rate, and SpO2) for both normal and anomalous instances to gain insights into the characteristics of detected anomalies. For visualizing the data and presenting the results, we utilized the matplotlib library, a comprehensive library in Python for creating static, animated, and interactive visualizations. Matplotlib offers extensive capabilities for plotting various types of graphs and charts.

These visualizations help in understanding how different vital signs vary between normal and anomalous instances and support the interpretation of the model's predictions.

3.4.5 Model Evaluation

To evaluate the performance of the Isolation Forest model, several methods and techniques were employed:

1. **Model Loading:**
   - The trained Isolation Forest model was loaded using the joblib library. This step enabled the application of the pre-trained model to new test data for evaluation purposes.
2. **Data Loading:**
   - Test data, including features and corresponding labels, were imported from CSV files using the pandas, library. This data was crucial for assessing the model's performance by comparing its predictions with the actual labels.
3. **Anomaly Prediction:**
   - The Isolation Forest model was applied to the test dataset to predict anomalies. Each instance in the test set was classified as either normal or anomalous, based on the model's predictions.
4. **Performance Metrics:**

- **Classification Report:** A detailed classification report was generated, providing metrics such as precision, recall, and F1-score for both normal and anomalous instances. This report offered a comprehensive assessment of the model’s performance, highlighting its accuracy in identifying both classes.

The evaluation results indicated that the Isolation Forest model correctly classified 85% of the instances. The performance metrics, including precision, recall, and F1-score, demonstrated the model’s effectiveness in detecting anomalies. These insights are valuable for understanding the model’s capability in real-time anomaly detection, particularly in emergency healthcare scenarios.

3.5 System Architecture and Prototype Development

The system architecture integrates a blend of hardware and software components designed to enable efficient ambulance location tracking and real-time patient health monitoring. This integration encompasses IoT devices, machine learning algorithms, and robust communication protocols to ensure seamless operation and accurate data processing.

The system architecture and prototype were developed with considerations drawn from the survey feedback. Key findings from the survey, such as the need for intuitive user interfaces and efficient alert mechanisms, were integrated into the prototype to ensure it aligns with the practical requirements of healthcare providers. This iterative approach helped refine the system's functionalities and improve its overall effectiveness.

3.5.1 Components

3.5.1.1 Hardware Components:

- **ESp8266:** A compact microcontroller platform used for acquiring and processing sensor data. Its role is crucial for handling input from various sensors and controlling other hardware components.
- **GPS Module:** Facilitates accurate location tracking and navigation for ambulances, enhancing situational awareness during emergency responses.
- **Lithium Battery:** Provides a reliable power source for mobile IoT devices, ensuring continuous operation without interruptions.

- **LCD Display:** Enables real-time visualization of patient health parameters, allowing immediate assessment by healthcare professionals.
- **MAX30102 Sensor:** Measures critical health metrics such as heart rate, oxygen saturation, and pulse rate, essential for monitoring patient conditions.
- **Human Body Temperature Sensor**: For measuring the patient's body temperature.
- **WiFi:** Supports communication with a central server for data transmission, enabling remote monitoring and data analysis.

3.5.1.2 Software Components:

- **Front-End Technologies (HTML, CSS, JavaScript):** Used to develop a user-friendly web interface that displays real-time patient health data and system status.
- **Back-End Technologies (Python with Flask Framework, MS SQL Server):** Facilitates server-side scripting, data management, and interaction with the database, ensuring efficient data processing and storage.

3.5.2 Prototype Development

3.5.2.1 Hardware Implementation:

- **Sensor Integration:** Involves the connection and configuration of the MAX30102, temperature and GPS sensors to accurately capture and transmit vital signs from patients.
- **Microcontroller Programming:** Programming the **ESp8266to** handle sensor data, interface with the GPS module, and manage data transmission through the WiFi module. This step ensures that the microcontroller can perform all necessary functions to support the system.
- **Power Management:** Involves integrating the lithium battery and power management circuitry to provide a stable and continuous power supply for the mobile IoT devices.

3.5.2.2 Software Development:

- **Web Interface:** Created using HTML, CSS, and JavaScript to offer a real-time, intuitive user interface for monitoring patient health data. The design focuses on usability and accessibility for emergency response teams.
- **Server-Side Scripting:** Utilizes Python with the Flask framework to handle data processing, storage, and retrieval from the SQL Server database. This setup supports efficient and secure backend operations.

- **Data Encryption:** Implements end-to-end encryption protocols to ensure the confidentiality and security of patient data during transmission over the network.

3.5.2.3 Integration and Testing:

- **System Integration:** Combines hardware and software components to create a fully functional prototype. This phase ensures that all parts of the system work together seamlessly to achieve the desired outcomes.
- **Testing:** Conducts simulations of emergency care scenarios to evaluate the prototype's performance, reliability, and usability. Testing helps identify any issues or areas for improvement, ensuring the system meets its objectives effectively.

Conclusion

In this chapter, we detailed the methodology employed in developing "An Intelligent IoT-Enabled System for Real-Time Ambulance-Based Patient Health Monitoring" in Rwanda. The methodology encompassed secondary data collection for model training, Isolation Forest algorithm selection for anomaly detection, and rigorous system architecture and prototype development.

CHAPTER 4. SYSTEM ANALYSIS AND DESIGN

This chapter provides a detailed analysis and design of the developed healthcare system, which integrates machine learning, real-time tracking, and multi-channel alerting functionalities. The primary aim of this chapter is to present the system models, simulation methodologies, and evaluation parameters used to assess the system's effectiveness in emergency care scenario

4.1 Embedded system block diagram

The embedded system block diagram for an Intelligent IoT-Enabled System for Real-Time Ambulance-Based Patient Health Monitoring incorporates essential components to ensure accurate data collection, processing, and communication.

At its core of the system, there is ESp8266 microcontroller, serving as the main microcontroller responsible for managing data from interconnected modules. The GPS module provides location tracking, crucial for real-time ambulance monitoring.

The GY-MAX30100 sensor captures vital signs like heart rate and oxygen saturation levels and MAX30205captures temperature. A lithium battery for portability powers these components.

The LCD display enables real-time visualization of patient health metrics. Finally, wi-fi technology facilitates wireless communication, transmitting patient data securely to remote servers.

This integrated setup enables efficient health monitoring during ambulance transport, aiding healthcare providers in delivering timely and informed care.

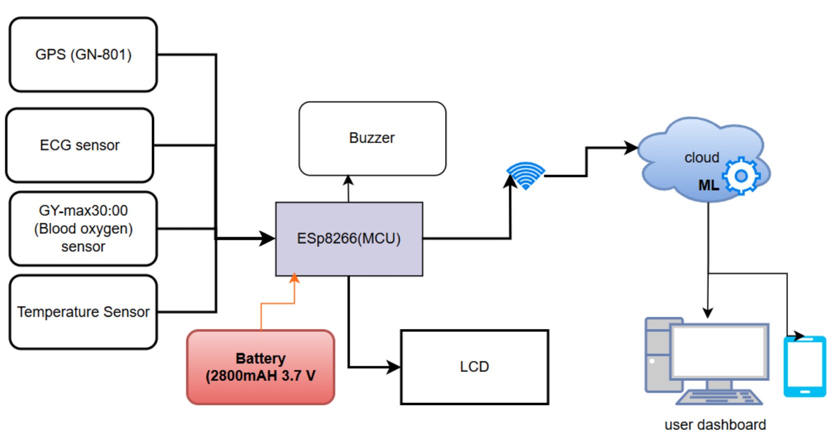


Figure 1: Block Diagram

4.1.1 Working principles of embedded block diagram

The working principles of an embedded system was illustrated using a block diagram that highlights its fundamental components and their interactions.

Below are the descriptions of each component in the system:

1. ESp8266(MCU)

It is microcontroller unit manufactured by Espressif Systems, which has Wi-Fi connectivity capability, it is suited for IoT applications. It has digital and analog I/O pins; therefore, it can interface with other devices and sensors. It can also work in various projects because it operates to 3. 0 V to 3.6 V power supply source[30].

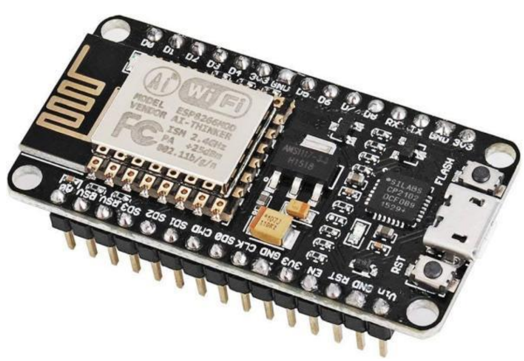


Figure 2: Microcontroller

2. GY-MAX30100 Heart Rate Oxygen Pulse Sensor

The GY-MAX30100 is a small board sensor module for measuring blood oxygen rate (SpO2) and the pulse rate without contact. It employs Red & Infrared LEDs & Photodetector for detecting amount of light obtained by blood flow to produce right SpO2 & pulse rate. The sensor can offer its service with the electricity supply of 1. 8 V to 5. 5 V and operates through I2C with SCL (clock) and SDA (data) pins and INT pin coming in for interrupts [31].

Figure 3: Heart Rate Oxygen Pulse Sensor

3. MAX30205 Temperature Sensor

The **MAX30205** is a highly accurate temperature sensor specifically designed for medical and wearable applications. It provides clinical-grade temperature measurements that comply with the ASTM E1112 standards when properly soldered onto the final PCB. The sensor features a high-resolution sigma-delta analog-to-digital converter (ADC) that converts temperature readings into digital data. It communicates through an I2C-compatible two-wire serial interface, allowing for easy configuration and data retrieval.

The sensor includes an overtemperature alarm, interrupt, and shutdown functionality to enhance system safety. With a supply voltage range of 2.7V to 3.3V and a low power consumption of just 600 µA, it is highly efficient and well-suited for portable devices. The MAX30205 supports up to 32 device addresses using three address-select lines and comes in a compact 8-pin TDFN package. Operating within a temperature range of 0°C to +50°C, it is an excellent choice for applications such as wearable fitness devices and medical monitoring systems[32].

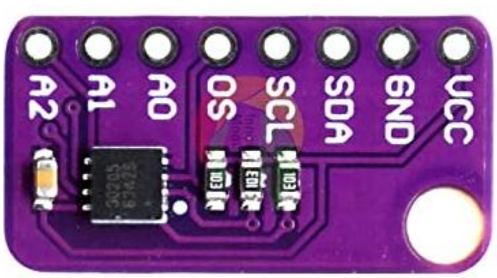


Figure 4: Human Body Temperature Sensor

5. LCD

The LCD, or Liquid Crystal Display, was used to display the measured patient date. It requires a minimum logic voltage of 4.5 V and operates with a supply current of 2 mA.

Figure 5: LCD

6. Buzzer

The buzzer was employed to provide sound notifications. In this system, it is for alerting users to changes in patient information, specifically for anomalous detected data. The buzzer operates at a rated voltage of 6 V DC, with an operating voltage range of 4 to 8 V DC, and a rated current of less than 30 mA.


Figure 6: Buzzer

6. AD8232 Heart Rate Monitor

The AD8232 Heart Rate Monitor is a cost-effective ECG measurement board designed to detect and amplify heart activity for clear ECG signal readings. It features a signal conditioning block to extract, amplify, and filter biopotential signals in noisy conditions. The board provides essential pins for Arduino integration, connections for custom sensors (RA, LA, RL), and a pulsating LED indicator to reflect heartbeats. Biomedical sensor pads and cables are required for operation.

Figure 7: ECG Sensor

7. NEO-6M GPS Module with Antenna

The NEO-6M GPS module was used to offer positioning information through GPS technology, for the ambulance location. It communicates with the microcontroller (ESP32) through serial communication using UART. The module features a voltage regulator, a default baud rate of 9600, and dimensions of 23 mm by 30 mm, with an antenna size of 25 mm by 25 mm and a cable length of 50 mm. It also includes an LED signal indicator and is compatible with Arduino, Raspberry Pi, and computers [33].

Figure 8: GPS Module

8. Power Supply (2800mAh 3.7V Li-ion Battery)

This lithium-ion battery was used for supplying power to the system while transporting a patient in ambulance. It has a capacity of 2800mAh, making it suitable for a variety of portable electronics and embedded systems and operates at a nominal voltage of 3.7V, providing a reliable power source with a compact form factor. It was used because it is suitable to devices requiring long-lasting energy and stability[34].

Figure 9: Lithium battery

4.1.2 Power and Energy Calculations for the Embedded System Prototype Components

1. Components Data

Component	**Voltage (V)**	**Current (mA)**	**Power (mW)**
ESP8266 (MCU)	3.3	80 (typical)	80×3.3=264
GY-MAX30100 (Heart Sensor)	3.3	1.6	1.6×3.3=5.28
MAX30205(Temp Sensor)	3.3	1.0	1.0×3.3=3.3
LCD (Logic Voltage)	4.5	2	2×4.5=9
Buzzer	6.0	30	6.0×30=180
AD8232 (Heart Rate Monitor)	3.3	0.17	0.17×3.3=0.561
NEO-6M GPS Module	3.3	45 (typical)	45×3.3=148.5
WiFi Module (e.g., ESP32)	3.3	120	120 × 3.3 = 396
Total		**280.77 mA**	**1,006.641 mW**

2. Battery Runtime

The lithium-ion battery has a capacity of **2800 mAh** at **3.7 V**.

Runtime in Hours:

Runtime (hours)=Total Current Draw (mA) / Battery Capacity (mAh)

Runtime (hours)=2800 mAh/ 280.77 mA=**9.9 hours.**

3. Energy Consumption Calculation for 9.9 Active Hours

Energy in mAh:

$$\text{Energy (mAh)} = I_{\text{average, total}} * \text{Active Hours}$$

Energy (mAh)=280.77 mA×9.9 hours=**2779.6 mAh**

Energy in mWh:

$$\text{Energy (mWh)} = P_{\text{average, total}} * \text{Active Hours}$$

Energy (mWh)=1006.641 mW×9.9 hours=**9965.7 mWh**

Battery Suitability: The battery capacity (2800 mAh) is adequate for the required operation time, as 9.9 hours are enough to move from one health facility to another in Rwanda.

4.2 System Flowchart

The system is focusing on ambulance tracking and real-time patient health monitoring. "An Intelligent IoT-Enabled System for Real-Time Ambulance-Based Patient Health Monitoring" involves a coordinated integration of various sensors and modules to enable efficient emergency healthcare response. The system incorporates sensors like the MAX30205 Human Body Temperature Sensor for monitoring body temperature and the GY-MAX30100 Heart Rate Oxygen Pulse Sensor for tracking heart rate and oxygen saturation.

Additionally, the wi-fi facilitates communication capabilities and internet connectivity, while the NEO-6M GPS Module accurately tracks the ambulance's location via serial communication with the microcontroller ESp8266.

In this flow chart, data acquisition from the sensors is followed by processing and decision-making stages within the microcontroller. Real-time data fusion and analysis enable the extraction of meaningful health parameters which are then displayed on an LCD for healthcare providers. The system utilizes a buzzer for immediate notification of critical patient information changes and leverages wi-fi communication to send patient data, GPS coordinates, and alerts to healthcare providers and central monitoring systems.

Machine learning algorithms are integrated into the system to analyze patient data for early detection of critical conditions, continuously improving response and anomalies detection among collected data. Overall, this system aims to optimize emergency healthcare by enabling proactive monitoring, timely interventions, and enhanced decision-making support for healthcare providers through predictive analytics based on real-time data.

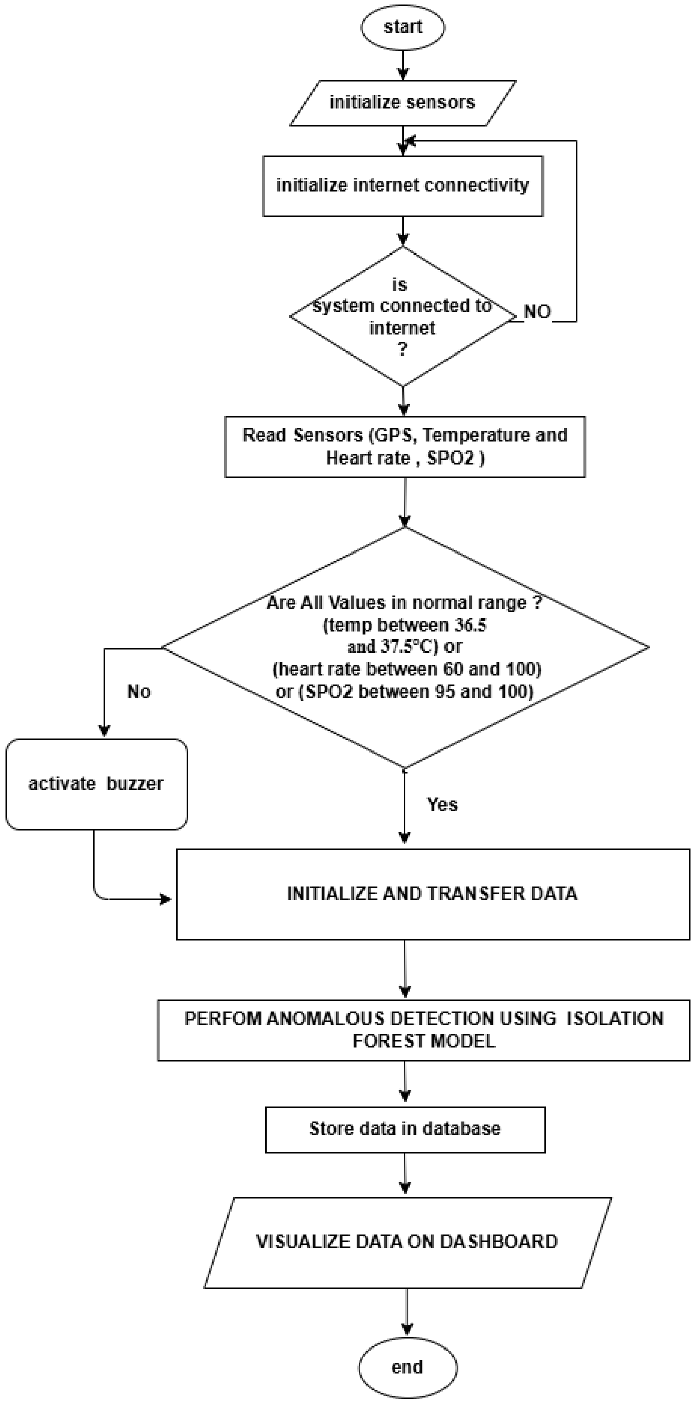


Figure 10: System's Flowchart

4. 3 Embedded Device Set Up

The prototype system described for "IoT-Enabled Machine Learning integrates several sensors and components to enable effective ambulance tracking and real-time patient health monitoring.

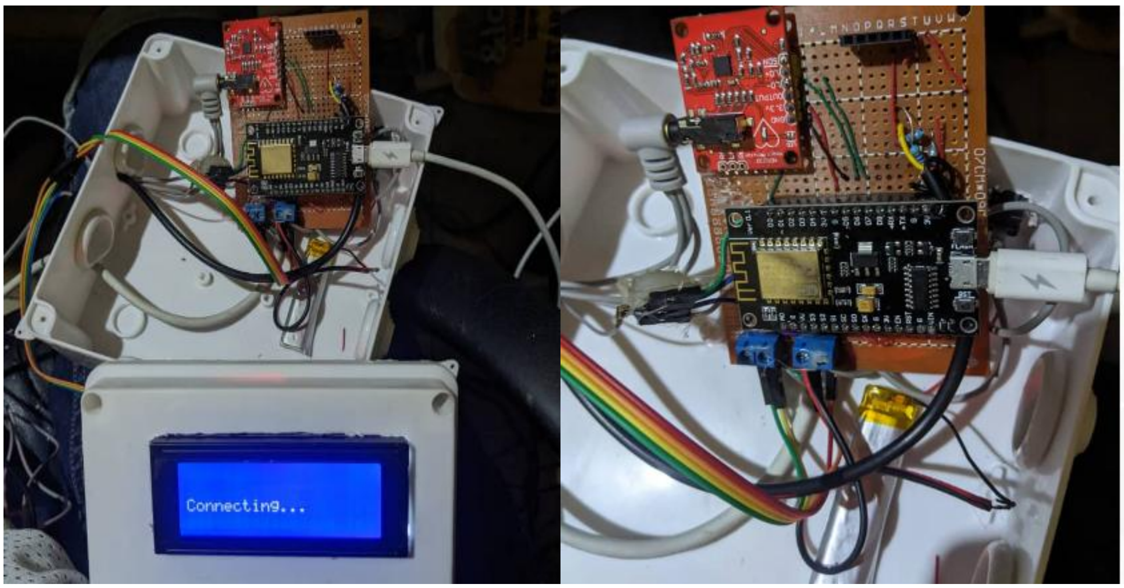


Figure 11: Prototype

This setup includes specialized sensors such as the MAX30205Human Body Temperature Sensor for precise body temperature measurements and the MAX30102 Heart Rate Oxygen Pulse Sensor, which integrates heart rate monitoring, pulse oximetry, and ambient light sensing for comprehensive physiological data collection.

Additionally, the NEO-6M GPS Module with Antenna is employed to provide accurate positioning information through GPS technology, enabling real-time ambulance tracking. A Liquid Crystal Display (LCD) is used to visually present patient vitals and GPS coordinates, ensuring healthcare providers have immediate access to critical information. The inclusion of a buzzer enhances the system's effectiveness by providing audible notifications for important patient updates or emergency alerts.

Briefly, this integrated prototype system utilizes the ESp8266 microcontroller to manage sensor data collection, communication with external networks (via Wi-Fi), GPS location tracking, and display of patient data on the LCD. The system can track ambulances in real-time, monitor patient vitals remotely, and enable timely emergency response with notifications. Machine learning algorithms can be applied to analyze the collected data for predictive and diagnostic purposes, enhancing emergency healthcare delivery in Rwanda.

4.4 System Database Design

4.4.1 Description and Overview

The database for the in-ambulance patient monitoring and tracking system is designed to efficiently store, manage, and provide access to critical data related to patient transfers and real-time health monitoring during transit. Built using Microsoft SQL Server, the database serves as the backbone of the system, enabling healthcare providers to track patient status, ambulance locations, and sensor data throughout the journey.

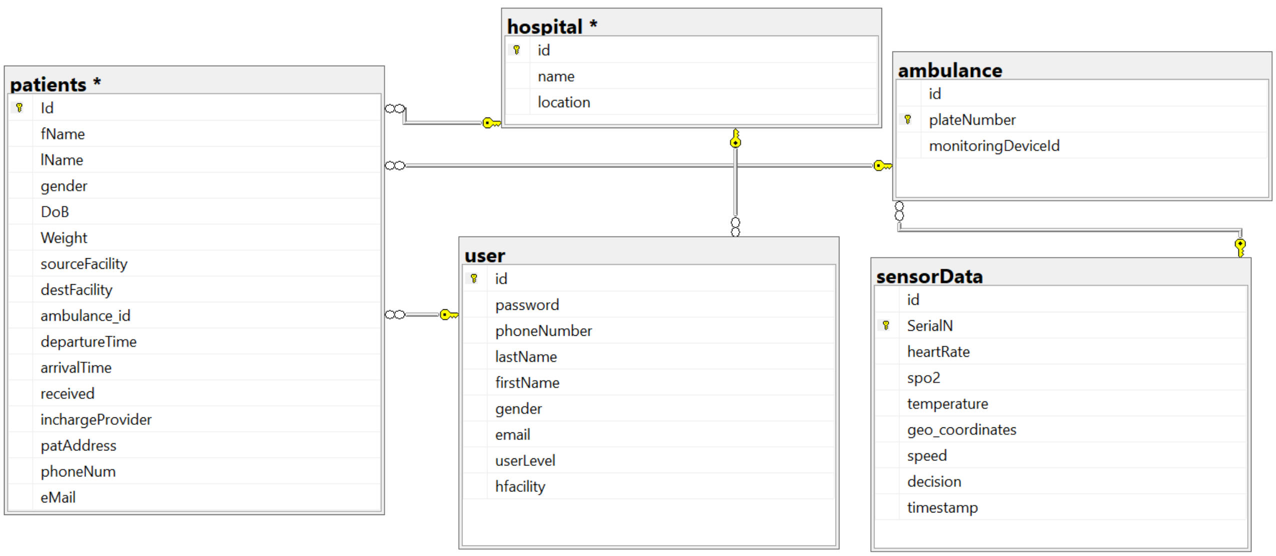
The database includes different key entities:

- **Hospitals**: This table stores details of hospitals, including their names and locations, which are important for identifying the source and destination of patient transfers.
- **Users (Healthcare Providers)**: This table holds information about the healthcare providers responsible for patient care during ambulance transfers. Each provider is associated with a specific hospital.
- **Ambulances**: Each ambulance is uniquely identified by its plate number and equipped with a monitoring device that tracks the patient's condition during transport. The table stores information related to the ambulance and the device.
- **Patients**: This table records detailed information about patients being transported, including their personal details, the ambulance used, and the healthcare provider in charge.
- **Sensor Data**: This table stores real-time health metrics such as heart rate, oxygen saturation, body temperature, and geographical coordinates from the monitoring devices installed in ambulances. The sensor data is crucial for monitoring patients' vital signs during transport.

Together, these tables form a relational model that ensures data consistency and integrity across the system.

4.4.2 Entity-Relationship Diagram (ERD)

The Entity-Relationship Diagram (ERD) visually represents the structure of the database and the relationships between its entities. Below is the ERD that illustrates how the main entities—Hospitals, Users, Ambulances, Patients, and Sensor Data—are connected, ensuring seamless data flow and integrity within the system.



4.5 System Requirements

- **Functional Requirements:**
  - Machine learning model development for anomaly detection.
  - Real-time ambulance tracking.
  - Patient health monitoring.
  - Data visualization dashboard.
- **Non-Functional Requirements:**
  - System performance (speed, accuracy).
  - Security and privacy.
  - Usability and user experience.

CHAPTER V: RESULTS AND ANALYSIS

This chapter delves into the findings from the developed system and provides a detailed analysis of the results. It presents an evaluation of the machine learning model, prototype functionality, secure intelligent system, and alerting mechanisms, supported by relevant graphs and data visualizations. Each section includes a discussion on how the results align with the project's objectives and what they reveal about the system's performance.

Graphs and visual representations are used to illustrate key metrics and outcomes, offering a clear view of the system's effectiveness. The chapter aims to provide an in-depth explanation of these results, interpreting the data to highlight significant trends, performance indicators, and areas for potential improvement.

5.1 Performance Metrics of Anomaly Detection Algorithms

This section presents the results of applying different anomaly detection algorithms and evaluates their performance based on the metrics described in Chapter 4. The performance metrics of the anomaly detection algorithms were evaluated not only against technical benchmarks but also in light of feedback obtained from healthcare providers. This feedback highlighted the importance of accurate and timely anomaly detection, which influenced the performance criteria used in evaluating the system.

Summary of Findings:

- **Isolation Forest** excels with high precision for normal instances (0.84) and an impressive F1-score for normal instances (0.91). Despite having a lower recall for anomalies (0.41), its overall accuracy of 0.85 indicates that it performs well in distinguishing between normal and anomalous data, making it a strong candidate for our needs. The high precision for normal instances ensures that normal data is classified with high confidence, which is crucial for minimizing false positives in practical applications.
- **Local Outlier Factor** shows lower precision and recall for anomalies (0.42 and 0.17, respectively), indicating it may not be as effective at detecting anomalies. However, it performs reasonably well in identifying normal instances (recall of 0.92) and has an overall

accuracy of 0.74. While it can be useful for identifying normal data, its lower performance in anomaly detection makes it less suitable for our primary objective.

- **One-Class SVM** provides a balanced performance with decent precision (0.78) and recall (0.32) for anomalies. It achieves a good F1-score for normal instances (0.89) and an overall accuracy of 0.81. Although it offers a compromise between detecting anomalies and classifying normal instances, it does not outperform Isolation Forest in our specific context.

Algorithm	**Precision (Anomaly)**	**Recall (Anomaly)**	**F1-score (Anomaly)**	**Precision (Normal)**	**Recall (Normal)**	**F1-score (Normal)**	**Accuracy**
Isolation Forest	0.91	0.41	0.57	0.84	0.99	0.91	0.85
Local Outlier Factor	0.42	0.17	0.24	0.77	0.92	0.84	0.74
One-Class SVM	0.78	0.32	0.45	0.81	0.97	0.89	0.81

Table 1:Performance Metrics of Anomaly Detection Algorithms

The performance analysis of the anomaly detection algorithms reveals that Isolation Forest stands out as the most effective solution for our application. Each algorithm has its strengths, but Isolation Forest demonstrates notable advantages that align well with our system's requirements.

Given the analysis, **Isolation Forest** was recommended as the primary algorithm for our anomaly detection system. Its high precision for normal instances and overall accuracy makes it a robust choice, particularly where accurate identification of normal data is critical. Despite its lower recall for anomalies, its performance aligns well with our system's needs, providing reliable results for distinguishing between normal and anomalous instances.

While **One-Class SVM** offers a good alternative with balanced performance metrics, Isolation Forest's superior precision and accuracy make it the preferred choice for achieving our objectives.

5.2 Analysis of Vital Signs Data for Model Training

To gain a deeper understanding of the anomalies detected by the model, we analyzed the distribution of vital signs used during model training. This analysis helps illustrate the specific physiological characteristics associated with both normal and anomalous instances.

Visualization and Analysis:

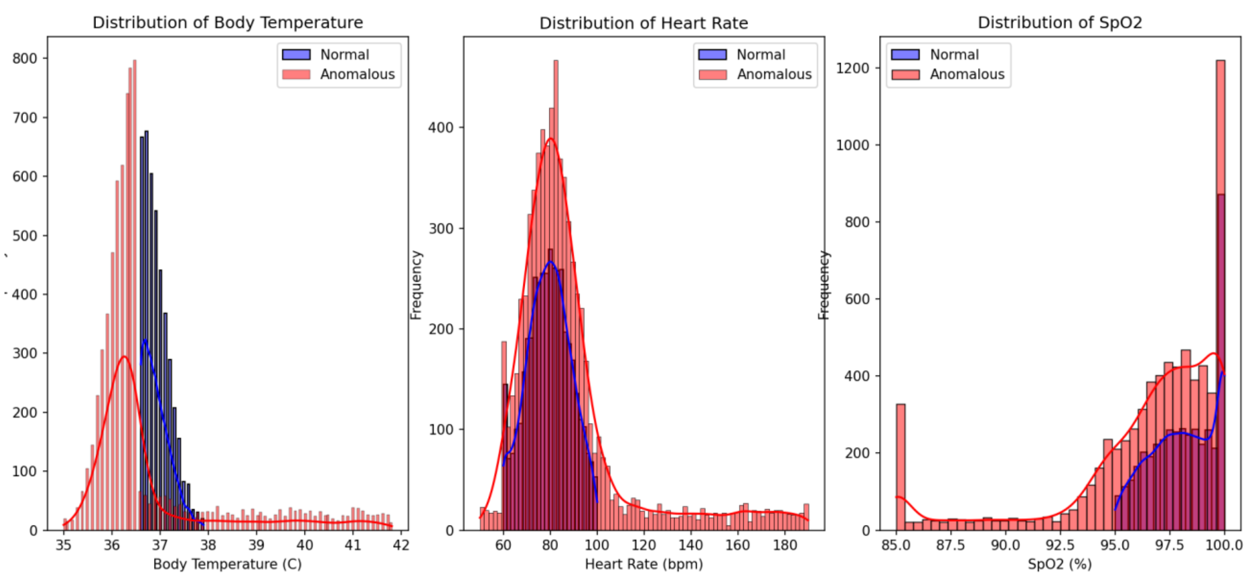


Figure 12: Distribution of Vital Signs

- **Body Temperature:** The distribution of body temperature values for normal and anomalous instances was plotted to compare the typical range of temperatures for healthy individuals against those flagged as anomalies. The plot reveals that anomalous instances often exhibit temperature values that deviate significantly from the normal range, highlighting the algorithm's ability to detect these deviations effectively.
- **Heart Rate:** A similar plot for heart rate values illustrates how the detected anomalies relate to unusually high or low heart rates compared to the normal range. The graphical representation shows distinct patterns where anomalous heart rates fall outside the typical range, aiding in the identification of abnormal physiological states.

- **SpO2 Levels:** The distribution of oxygen saturation levels (SpO2) was visualized to show the variation between normal and anomalous instances. The plot indicates that anomalies are often associated with lower SpO2 levels, which could signify critical health issues.

The visualizations of vital signs provide valuable insights into the nature of anomalies detected by the Isolation Forest algorithm. By comparing the distributions of body temperature, heart rate, and SpO2 levels between normal and anomalous instances, we can see clear patterns that support the model's effectiveness in identifying physiological deviations. These graphical representations not only validate the performance of the anomaly detection system but also offer a practical understanding of the types of anomalies that are most effectively detected.

5.3 Prototype and System Testing and Results

5.3.1 The Prototype

The prototype was designed to showcase the system's core functionalities, including real-time patient monitoring and data collection using sensors. It simulates emergency care scenarios by gathering data from attached sensors and displaying the information on a user-friendly dashboard.

Due to ethical and logistical constraints, testing on real patients in emergency situations was not feasible. Engaging patients during critical medical events could have compromised their privacy and safety, and the required ethical approvals and medical personnel coordination were beyond the scope of this study.

Instead, the prototype was tested in non-emergency scenarios using normal individuals traveling in private cars. This alternative testing approach provided a safe environment to evaluate the system's adaptability in real-time health monitoring while ensuring that no risk was imposed on patients in distress.

The results demonstrated the system's ability to effectively monitor vital signs in various contexts, reinforcing its potential to improve emergency healthcare services when deployed in real-world ambulance settings.

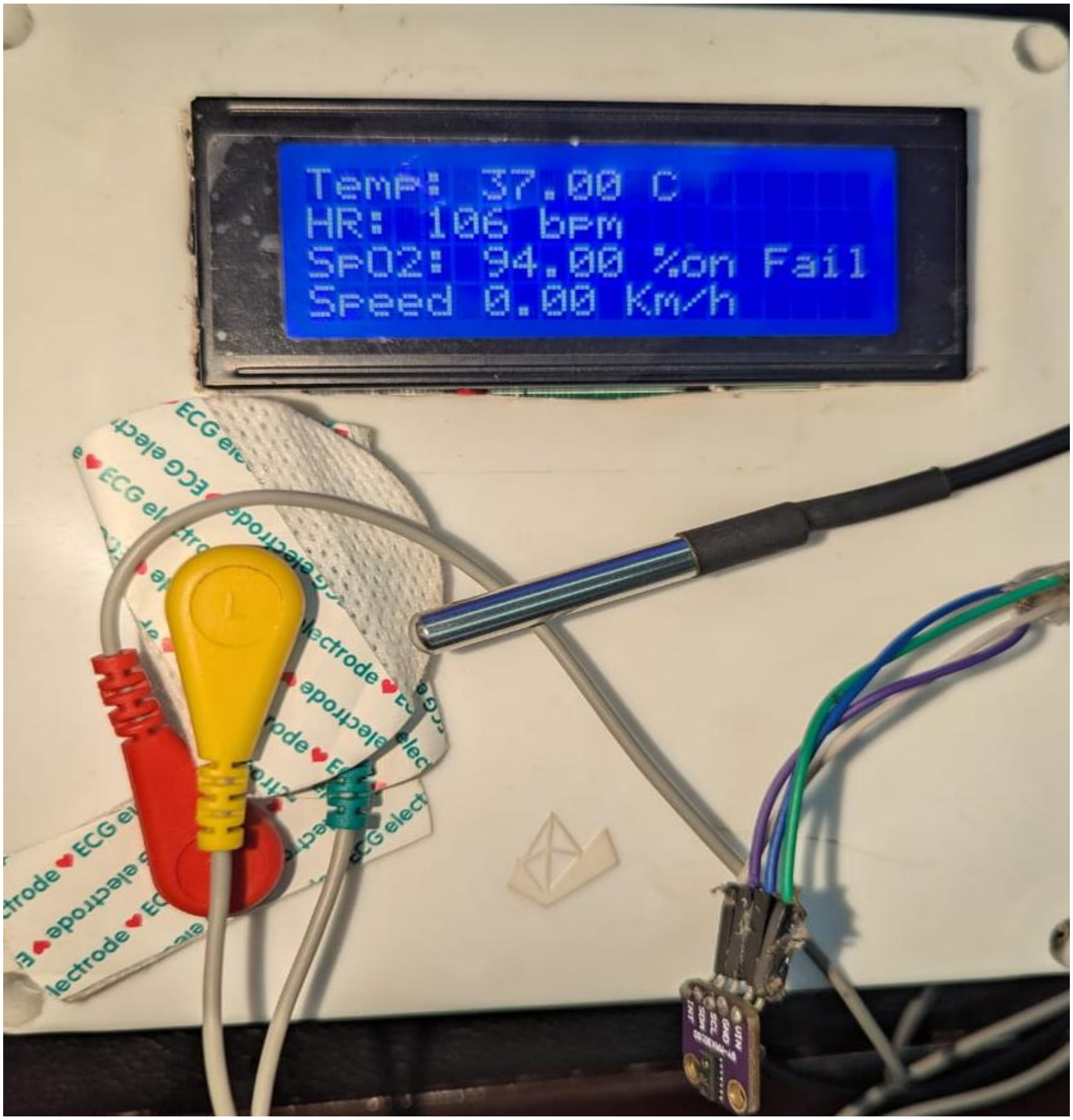


Figure 13: Prototype of the System

The image above shows the prototype used in this project. It was designed to simulate a real-world emergency care scenario, capturing patient vitals through sensors and transmitting the data to a centralized system for monitoring and analysis.

5.3.2 User Web Interfaces

Survey respondents indicated that clear and concise visualization of vital signs is crucial for effective monitoring in emergency situations. The design of the visualizations incorporated into the system was adjusted based on this feedback to ensure that they meet the users' needs for quick and accurate assessment of patient conditions.

The system features two main dashboards: one for users in the ambulance and another for hospital staff.

User Login Page

The User Login Form provides a secure interface for users to access the system. It includes fields for entering a email and password. The form ensures authentication and protects sensitive data through secure validation protocols.

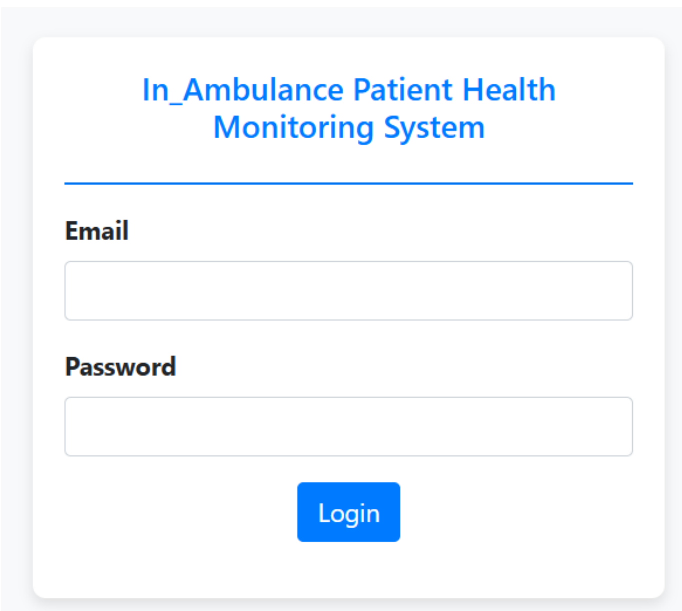


Figure 14: User Login Form

User in Ambulance Dashboard:

The ambulance dashboard allows healthcare providers, such as nurses, midwives, to monitor patient conditions in real-time during transport. The dashboard is designed to be intuitive, displaying vital signs, alerts, and estimated time of arrival (ETA) of the ambulance.

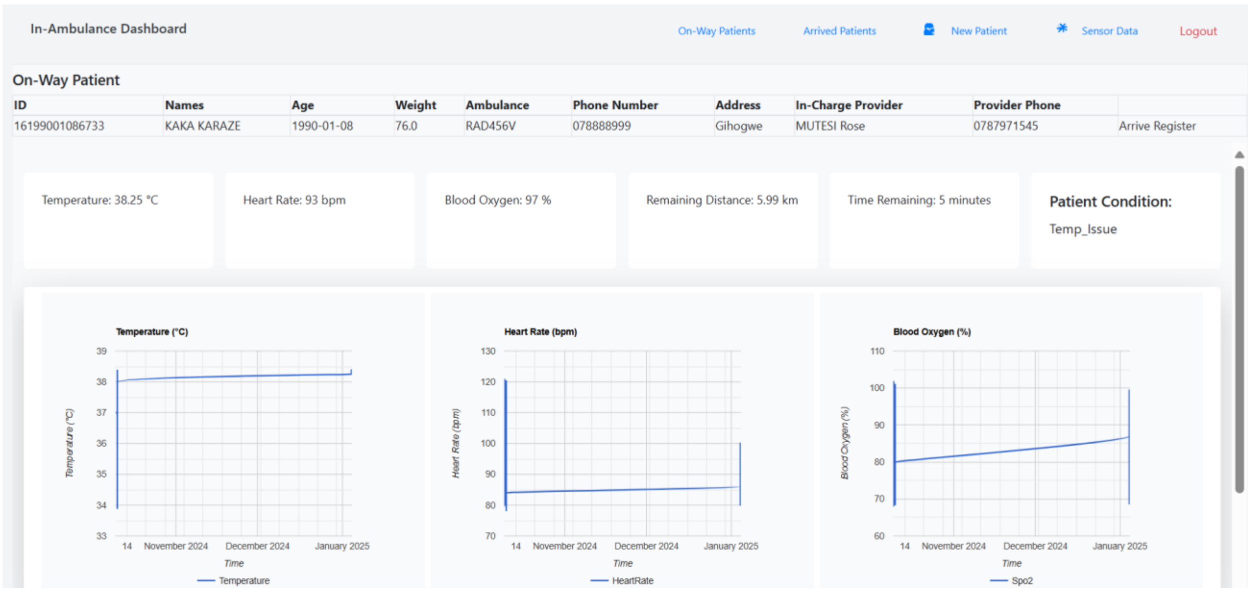


Figure 15: In-Ambulance Dashboard

The screenshot above demonstrates the user interface of the ambulance dashboard. It provides real-time updates on the patient's condition, helping the nurse to take timely actions.

Hospital Dashboard for Incoming Patients:

The hospital dashboard is used by healthcare staff at the destination hospital to monitor incoming patients. It displays patient data as transmitted from the ambulance, allowing the hospital to prepare in advance for the patient's arrival.

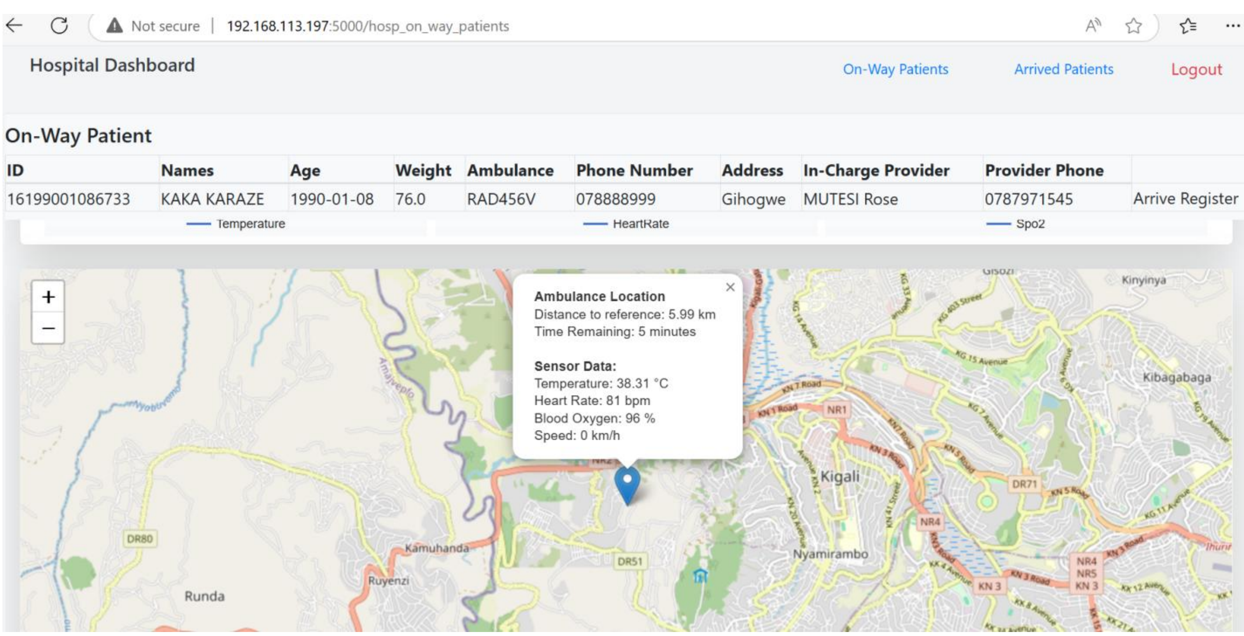


Figure 16: Hospital Dashboard

The image above illustrates the hospital dashboard, which shows incoming patient data, including vital signs and ETA. This information is crucial for preparing the emergency room and informing the medical team.

Patient Registration Form

The Patient Registration Form is designed to collect detailed patient information where a healthcare provider in the ambulance with a patient firstly records patient data, including personal details, contact information, and assigned ambulance. It ensures accurate and organized data entry for efficient patient management and care coordination.

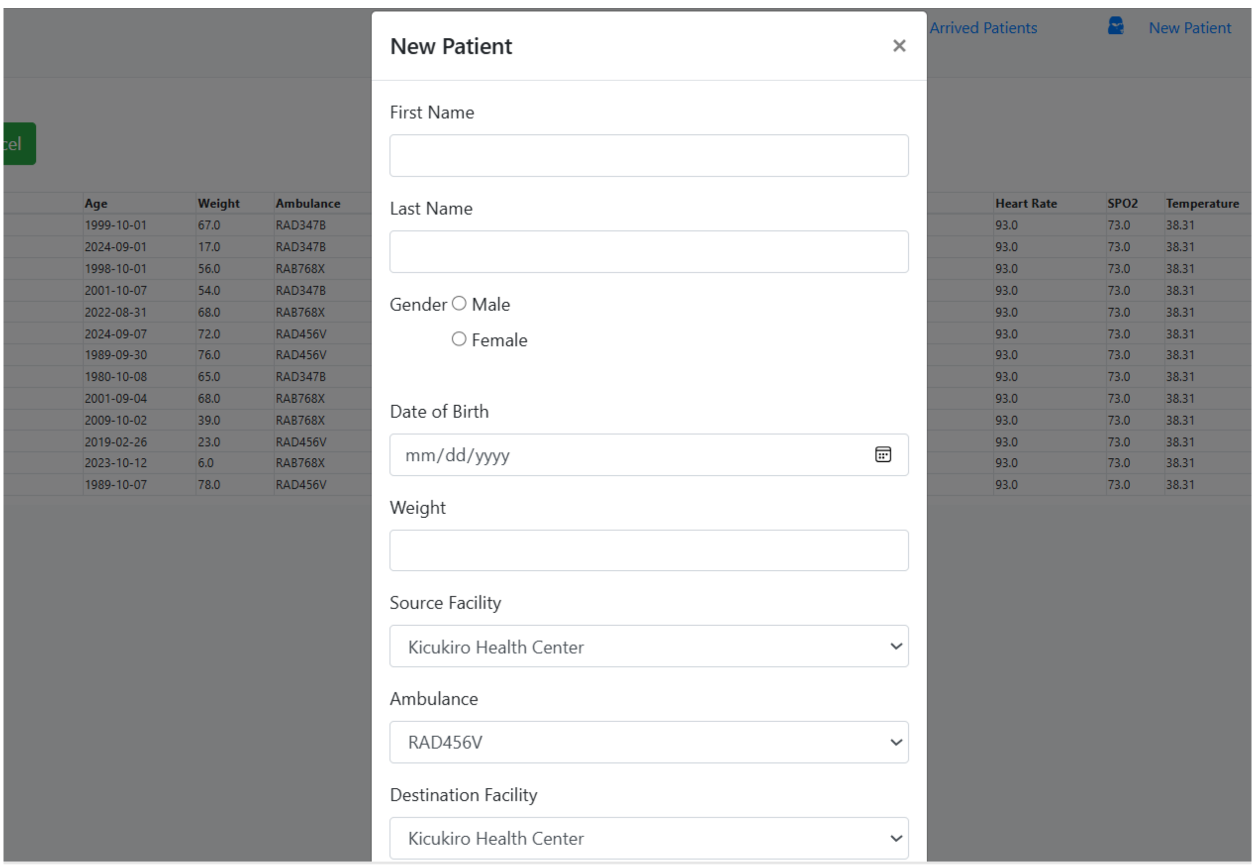
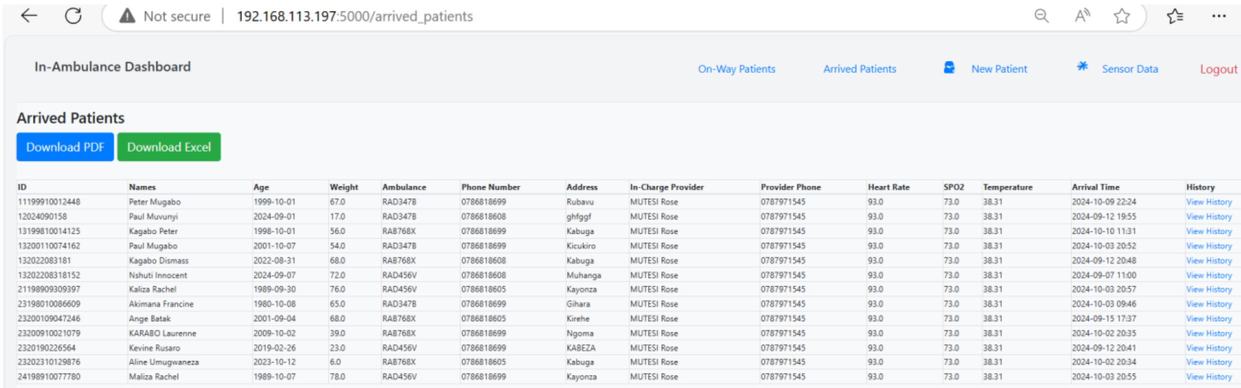


Figure 17: Patient Registration Form

Arrived Patients List

The Arrived Patients List provides a comprehensive view of all patients who have been received at the facility, including their personal details, contact information, and assigned ambulance. Users can view each patient's history for detailed records of past visits and treatments. Additionally, the list offers the option to download the data in Excel or PDF format for easy sharing and reporting.



ID	Names	Age	Weight	Ambulance	Phone Number	Address	In-Charge Provider	Provider Phone	Heart Rate	SPO2	Temperature	Arrival Time	History
11199910012448	Peter Mugabo	1999-10-01	67.0	RAD347B	0786818699	Rubavu	MUTESI Rose	0787971545	93.0	73.0	38.31	2024-10-09 22:24	View History
12024090158	Paul Muvunyi	2024-09-01	17.0	RAD347B	0786818608	ghfggf	MUTESI Rose	0787971545	93.0	73.0	38.31	2024-09-12 19:55	View History
13199810014125	Kagabo Peter	1998-10-01	56.0	RAB768X	0786818699	Kabuga	MUTESI Rose	0787971545	93.0	73.0	38.31	2024-10-10 11:31	View History
13200110074162	Paul Mugabo	2001-10-07	54.0	RAD347B	0786818699	Kicukiro	MUTESI Rose	0787971545	93.0	73.0	38.31	2024-10-03 20:52	View History
132022083181	Kagabo Dismass	2022-08-31	68.0	RAB768X	0786818608	Kabuga	MUTESI Rose	0787971545	93.0	73.0	38.31	2024-09-12 20:48	View History
13202208318152	Nshuti Innocent	2024-09-07	72.0	RAD456V	0786818608	Muhanga	MUTESI Rose	0787971545	93.0	73.0	38.31	2024-09-07 11:00	View History
21198909309397	Kaliza Rachel	1989-09-30	76.0	RAD456V	0786818605	Kayonza	MUTESI Rose	0787971545	93.0	73.0	38.31	2024-10-03 20:57	View History
23198010086609	Akimana Francine	1980-10-08	65.0	RAD347B	0786818699	Gihara	MUTESI Rose	0787971545	93.0	73.0	38.31	2024-10-03 09:46	View History
23200109047246	Ange Batak	2001-09-04	68.0	RAB768X	0786818605	Kirehe	MUTESI Rose	0787971545	93.0	73.0	38.31	2024-09-15 17:37	View History
23200910021079	KARABO Laurenne	2009-10-02	39.0	RAB768X	0786818699	Ngoma	MUTESI Rose	0787971545	93.0	73.0	38.31	2024-10-02 20:35	View History
2320190226564	Kevine Rusaro	2019-02-26	23.0	RAD456V	0786818699	KABEZA	MUTESI Rose	0787971545	93.0	73.0	38.31	2024-09-12 20:41	View History
23202310129876	Aline Umugwaneza	2023-10-12	6.0	RAB768X	0786818605	Kabuga	MUTESI Rose	0787971545	93.0	73.0	38.31	2024-10-02 20:34	View History
24198910077780	Maliza Rachel	1989-10-07	78.0	RAD456V	0786818699	Kayonza	MUTESI Rose	0787971545	93.0	73.0	38.31	2024-10-03 20:55	View History

Figure 18: List of Arrived Patients

5.3.3 Feedback Integration:

The prototype testing phase incorporated feedback from the initial survey among healthcare providers to address any discrepancies between the system's design and user expectations. For example, adjustments were made to the alerting system based on provider feedback to enhance its responsiveness and reliability during emergency scenarios.

Conclusion

This chapter analyzed the intelligent system developed for emergency care, focusing on the machine learning model, real-time tracking, and patient monitoring. The results show that the system effectively meets the requirements for emergency care, providing timely and secure data transmission and communication. These findings support the system's feasibility and its potential to enhance emergency care outcomes.

CHAPTER VI. CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

This thesis aimed to develop an intelligent system to enhance emergency care through real-time ambulance tracking, and patient monitoring. The project successfully achieved its objectives by developing a machine learning model to predict patient conditions, creating a prototype to showcase the system's core functionalities, and integrating secure communication features.

The analysis demonstrated that the system could significantly improve the efficiency and effectiveness of emergency care. The real-time data provided by the system allows healthcare providers to make informed decisions quickly, potentially leading to better patient outcomes.

In summary, the project has laid a solid foundation for the development of intelligent systems in emergency care, highlighting the importance of integrating advanced technologies like machine learning and real-time monitoring in healthcare.

6.2 Recommendations

To ensure the successful implementation and impact of the developed system, the following recommendations are proposed:

Firstly, real-world testing in actual emergency scenarios is crucial. Conducting such tests will provide deeper insights into the system's performance under genuine conditions and reveal any potential areas for improvement. This step is vital to ensure that the system operates effectively and reliably in real-world emergency situations.

Finally, consider integrating the system with existing hospital information systems. Seamless data flow and coordination between different healthcare systems can improve overall efficiency and facilitate better emergency response. Ensuring that the system can work in harmony with other tools and platforms will maximize its utility and impact in emergency care settings.

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APPENDICES

Appendix A: Survey Design and Analysis

A.1 Survey Design and Distribution

To enhance the IoT-enabled system for real-time ambulance-based patient health monitoring, a survey was created to gather healthcare providers' input on essential features and functionalities. Distributed via Google Forms, the survey included a range of questions targeting nurses, midwives, and health informaticians. The responses, collected and organized by Google Forms, were crucial for refining the system's design.

A.1.1 Population Sampling

Target Population: Healthcare providers and health informaticians engaged in emergency care and health information systems.

Sampling Frame: Health facilities and professional associations.

Inclusion Criteria: Relevant experience, willingness to participate, and fluency in the questionnaire language.

Exclusion Criteria: Lack of relevant experience, unwillingness, and incomplete responses.

Sample Size Calculation:

- **Initial Sample Size:** Based on proportions and finite population correction.
- **Stratified Sampling Results:**
    - **Health Informaticians:** 15
    - **Healthcare Providers:** 198

A.1.2 Analysis

Data were analyzed using Python:

- **Descriptive Statistics:** Frequencies and measures of central tendency.
- **Inferential Statistics:** Chi-square test for associations between variables.
- **Visualization:** Charts and diagrams (Radar, Grouped Bar, Pie, Horizontal Bar, Venn).

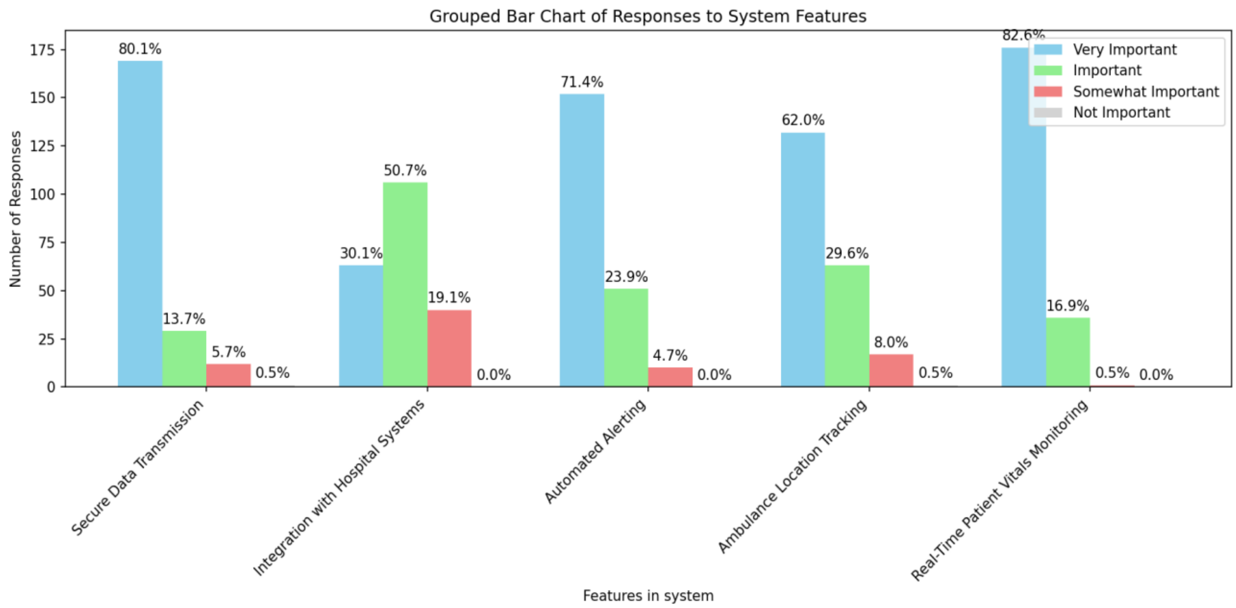
A.1.3 Ethical Considerations

Participants were informed about the study's purpose, consented to participate, and assured of confidentiality.

A.2 Healthcare Providers' Requirements and Preferences

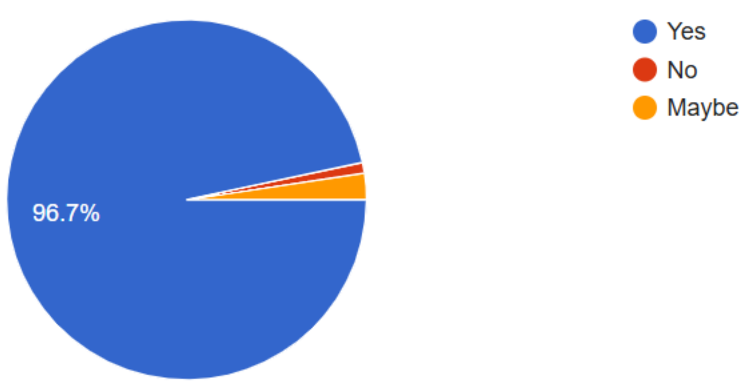
A.2.1 Importance of Key System Features

- **Real-Time Patient Vitals Monitoring:** 83% rated as "Very Important."
- **Secure Data Transmission and Storage:** 80% rated as "Very Important."
- **Integration with Hospital Systems and Automated Alerting:** High importance indicated.



A.2.2 Willingness to Recommend the System

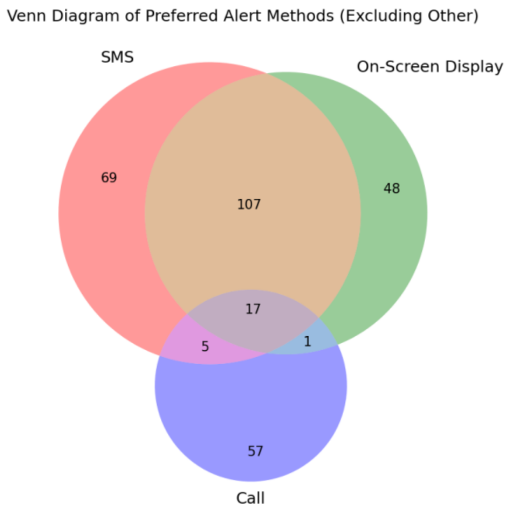
- **Yes:** 96.7% (203 respondents)
- **Maybe:** 2.4% (5 respondents)
- **No:** 1% (2 respondents)



A.2.3 Preferred Alert Methods

- **SMS:** 84.6%
- **On-Screen Display:** 72.9%

- **Telephone Call:** 21.5%



A.2.4 Chi-Square Analysis

Chi-square statistic: 24.163, p-value: 0.673. No significant association found between healthcare roles, gender, experience, and willingness to adopt the technology.

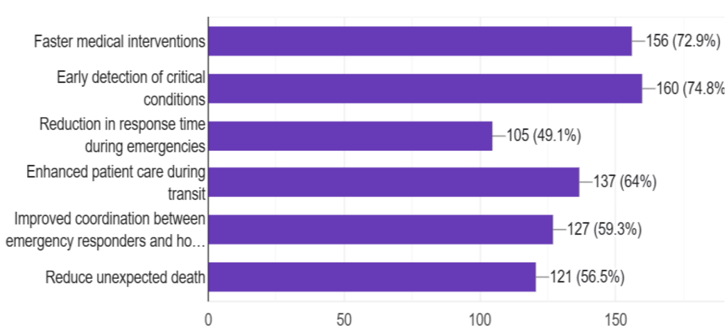
A.2.5 Comprehensive Assessment

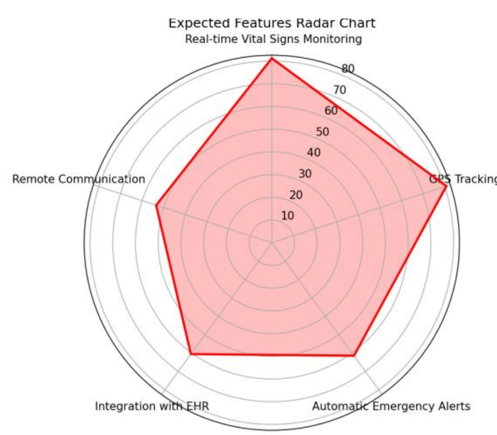
Identified Needs:

- **Early Detection of Critical Conditions:** 74.8%
- **Faster Medical Interventions:** 72.9%

Expected Features:

- **Real-Time Vital Signs Monitoring:** 81.2%
- **GPS Tracking of Ambulance Location:** 80.8%





Interpretation: The findings underscore the need for real-time monitoring and secure data handling, aligning with healthcare providers' priorities.

Appendix B: Questionnaire

Questionnaire for Healthcare Providers

Introduction: This questionnaire is designed to gather feedback from healthcare providers to understand their needs and expectations for an intelligent IoT-enabled system for real-time ambulance-based patient health monitoring.

Project Title: An Intelligent IoT-Enabled System for Real-Time Ambulance-Based Patient Health Monitoring

DESCRIPTION OF THE RESEARCH AND YOUR PARTICIPATION

You are invited to participate in a research study conducted by Jean Claude HABIMANA

This research is one of the requirements I have to fulfill in order to obtain the Master of Science degree in Internet of Things (IoT) at the UNIVERSITY OF RWANDA, COLLEGE OF SCIENCE AND TECHNOLOGY.

Your feedback is invaluable for our research project aimed at developing an intelligent IoT-enabled system for real-time ambulance-based patient health monitoring that will help to monitor the patient in transit in ambulance transferred from a health facility to another. Please take a few minutes to share your views and insights on the proposed system.

Risks and discomforts

There are no risks associated with this research.

Potential benefits

There are no known benefits to you that would result from your participation in this research. This research may help us to come up with the feasibility of the development and implementation of this system.

Protection of confidentiality

We will do everything we can to protect your privacy: Your identity will not be revealed in any publication resulting from this study.

Voluntary participation

Your participation in this research study is voluntary. You may choose to participate or not and you will not be penalized in any way.

Contact information.

If you have any questions or concerns about this study, please contact HABIMANA Jean Claude on Mobile phone at **0786818607** or on **claudeacademic@gmail.com**

If you have any questions or concerns about your rights as a research participant, please contact The University of Rwanda, College of Science and Technology; Kigali, Nyarugenge.

Section 1: Demographics

1. What is your role in healthcare?

- Nurse
- Midwife
- Health Informatician
- Other

2. **How many years of experience do you have in your role?**
    - Less than 1 year
    - 1 to 3 years
    - More than 3 years

Section 2: System Features

3. **How important are the following features for an intelligent IoT-enabled system?**

- Secure Data Transmission and Storage
  - Very Important
  - Important
  - Somewhat Important
  - Not Important
- Integration with Hospital Systems
  - Very Important
  - Important
  - Somewhat Important
  - Not Important
- Automated Alerting for Critical Conditions
  - Very Important
  - Important
  - Somewhat Important
  - Not Important
- Ambulance Location Tracking
  - Very Important
  - Important
  - Somewhat Important
  - Not Important
- Real-Time Patient Vitals Monitoring
  - Very Important
  - Important
  - Somewhat Important

        ▪ Not Important

4. **Would you recommend the development of this system in emergency care settings?**

- Yes
- Maybe
- No

5. **What are your preferred methods for receiving alerts or notifications about patient status during ambulance transit?**

- SMS
- On-Screen Display
- Telephone Call
- Other (please specify)

Appendix C: Data Collection Request and Acceptance Letters

To: The Director General of MUHIMA District Hospital **November 9th, 2023**

Dear Sir/Madam

Subject: Introductory letter for data collection,

for ACEIoT Master's students**, Mr. Jean Claude Habimana**

This is to introduce **Mr. Jean Claude Habimana** with reference number **221031800**, a master student who is doing his research thesis under the Africa Center of Excellence in Internet of Things (ACEIoT) established at the **University of Rwanda** (UR), College of Science and Technology (CST) in the program of Wireless Intelligent Sensor Network (WSN).

His research title is **". IoT-Enabled Machine Learning for Enhanced Emergency Healthcare in Rwanda: Ambulance Tracking and Real-Time Patient Health Monitoring System**" The student needs to collect data related to his thesis research from the Institution under your responsibility.

Your support with the needed information will be highly appreciated.

Dr Damien HANYURWIMFURA

Associate professor and Ag. Director, ACEIoT

College of Science and Technology

University of Rwanda

Tel: 0787394447

AFRICAN CENTRE OF EXCELLENCE IN INTERNET OF THINGS
ACEIoT
UNIVERSITY OF RWANDA

ql

HABIMANA Jean Claude
African Center of Excellence in Internet of Things, University of Rwanda eMail: claudeacademic@gmail.com
Phone Number: 0786818607
13th November 2023

Pour Réception
Hôpital Muhima
Date: 14/11/2023
Signature:

Dear Director General, Muhima Hospital,

Subject: Request for Permission to Collect Patient Data for Research Project

I humbly address this letter to your exalted personality, requesting permission to collect data for my thesis research project.

My name is HABIMANA Jean Claude, a Master's Student in University of Rwanda, and I am currently pursuing a research project titled "IoT-Enabled Machine Learning for Enhanced Emergency Healthcare in Rwanda: Ambulance Tracking and Real-Time Patient Health Monitoring System." The purpose of my research is to contribute to the advancement of emergency healthcare through the use of new emerging technologies.

The objectives of my project include:

- Developing a machine learning (ML) model based on secondary data collected and analyzed from patients transported in ambulances.
- Developing a prototype to showcase the core functionalities and technical capabilities of the system within the context of emergency care scenarios.
- Developing a secure intelligent system for real-time ambulance tracking, patient monitoring, and a data analytics dashboard to enhance emergency care.
- Developing an alerting system using SMS, Voice, and on-screen notifications to convey ambulance estimated time of arrival (ETA) and patient condition.

To achieve the first objective, I am seeking permission to access secondary data collected on patients transported in ambulances at Muhima Hospital. The specific data points of interest are patient vital signs such as temperature, heart rate, oxygen level (SPO2), and blood pressure. This secondary data will be used to train and validate the machine learning model, contributing to the development of a system that can enhance emergency healthcare services.

Upon successful development of the system, I anticipate the need for primary data collection during the testing phase. I want to assure you that I will work closely with the hospital staff to ensure minimal disruption to daily operations and patient care.

I assure you that all data collected will be treated with the utmost confidentiality, and no personally identifiable information will be disclosed in any reports or publications resulting from this research.

I kindly request your permission to proceed with the data collection process. I believe that this research has the potential to make a positive impact on emergency healthcare services, and I am committed to adhering to all ethical standards and guidelines. Enclosed, please find the ACEIoT Director's clearance letter and the project proposal.

Thank you for considering my request. I look forward to the possibility of collaborating with Muhima Hospital on this important initiative.

Sincerely,

HABIMANA Jean Claude

REPUBLIC OF RWANDA

Kigali, 16th May 2024

KIGALI CITY
NYARUGENGE DISTRICT
MUHIMA HOSPITAL
P.O. BOX 2456 KIGALI
Tél. /Fax : +252 50 37 7
E-mail : muhima.hospital@moh.gov.rw

Re: An intelligent IoT-Enabled System for real-time Ambulance Based Patient Health Monitoring at Muhima District Hospital.

Dear **Jean Claude HABIMANA;** Student of UR, Center of Excellence in Internet of things (IoT)

Reference is made to your letter received on 10th February 2024 requesting for 'permission to conduct data collection for your research "**An intelligent IoT-Enabled System for real-time Ambulance Based Patient Health Monitoring at Muhima District Hospital.**"

I would like to inform you that Muhima Hospital Ethics, Education and Research Committee has granted you the authorization to conduct this data collection according to approved study protocol.

You are requested to share with the Hospital the results from the study; also you are requested to comply with the accreditation policies and procedures within Muhima hospital.

Yours sincerely,

MUHIMA HOSPITAL ETHIC COMMITTEE

Marie Goretti Hategekimana

Chairperson Ethic, Education and Research Committee

Cc:
- Human Resource officer
- Director of Medical and Allied Health Sciences Service