

AI-Enabled Digital Twin for Enhanced Healthcare



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Declaration

Statement 1

This work has not been previously accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

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Date 30 September 2024

Statement 2

This thesis is the result of my own investigations, except where otherwise stated. Other sources are acknowledged by citations giving explicit references. A bibliography is appended.

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The University's ethical procedures have been followed and, where appropriate, ethical approval has been granted.

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Abstract

Transformative opportunities for both personalized patient care and operational efficiency are presented by the integration of Digital Twin (DT) technology within healthcare systems. In this dissertation, the application of Digital Twin technology is explored, particularly focusing on real-time location analytics and the integration of patient vital data to improve hospital management and personalized treatment plans. With the advancement of Internet of Things (IoT) sensors and artificial intelligence (AI), DT has been evolved from industrial use cases into healthcare, allowing for the creation of digital replicas of patients and healthcare environments. The benefits of combining real-time patient data—such as heart rate, temperature, and movement—with the digital twin of hospital environments are examined in this research. By utilizing AI-driven models, insights can be generated, health anomalies can be predicted, and early alerts can be provided to healthcare professionals in the system.

Existing digital twin visualization tools, such as the dSense platform, are also evaluated in the study, and enhancements are proposed through the integration of third-party vital data. A comparative analysis of machine learning algorithms, including Support Vector Machine (SVM) and Random Forest, is presented to predict patient health variations and improve critical response times. Results show that response times are significantly reduced, and predictive accuracy is enhanced by the integration of patient vitals into the DT system, demonstrating an 94 % success rate in identifying potential health issues. Moreover, real-time decision-making, resource optimization, and patient outcomes in a hospital setting are improved by the proposed system. This dissertation highlights the potential of AI-enabled digital twins in healthcare while addressing the technical and ethical challenges associated with data integration, accuracy, and security.

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1 Introduction

The digital twin (DT) is a digital avatar of any physical assets, be it movable or immovable, to generate real-time data and help to visualise the process and movements in the virtual world. The Digital twin has been practised since the 1960s by NASA during space programming (Karakra & Lamothe, 2019). However, it had gained popularity after the 2000s and has been on the rise since 2015. The advancement in IoT sensors influenced the development of digital twin technology, which was implemented in different domains. To overcome the technical difficulties associated with converting the physical space like a building into a digital twin is important for industries and stakeholders to adopt the technology to effectively digitalise the operations and create a digital twin using IoT sensors. Once the data is collected the system will then be analysed with advanced artificial intelligence methods and finally help to visualise to complete the digital twin

In recent years, especially after the COVID-19 pandemic, digitalisation of the healthcare sector has become essential. The digital twin technology has the capability to be the bridge between the physical and digital world by providing past, present and future predictive situations. (Erol, 2020) The digital twin technology has many branches in different industries and the implementation of the digital twin in the healthcare industry is gaining popularity. In healthcare, converting patients and the associated environment into a digital twin is important to obtain relevant data for further analysis to understand what each data represents to develop predictions for patients and hospital environments. A study by Han Yilong et al. [(Han, 2023)] explored the possibility of improving hospital operations through the use of advanced technology adoption, especially the digitalisation and automation of business processes through the intelligence gained via the digital twin implementation.

Furthermore, any unintentional errors in medical devices incorrect detection of medical findings, and misinterpretation of the findings can lead to misdiagnosis and untimely treatments. In addition, it is extremely important to find the right persons at the right time with right tools & equipment in an emergency in a hospital environment to save time. For this reason, it is empirical to adapt to new technologies to reduce errors and improve accuracy. From an application perspective, digital twins can treat patients as virtualised standalone assets that can be further used in environments and situations involving multiple related strategic assets of healthcare organisations [(Ricci, 2021)]

Additionally, the digital twin technology makes it easier to keep an eye on patient movements while they are on hospital grounds, which guarantees effective resource management and improves safety and security protocols. Patients may get fast and efficient attention, thanks to the real-time location service analytics and tracking of hospital equipment and related assets indoor, while the data analysis offers insightful information for optimising operational procedures and allocating resources.

The most potential use case for AI-enabled digital twins in healthcare is personalised treatment. Traditional personal care procedures and related methods are based on protocols that are too generic and most of the time fail to accommodate individual characteristics in genetics, lifestyle, and environmental factors that might impact a patient's treatment response. However, digital twins provide highly personalised treatment recommendations by using a diverse set of patient-specific data. The digital twin model may incorporate genetic information, lifestyle characteristics, and real-time physiological measures, allowing healthcare practitioners to simulate alternative treatment choices and forecast their effects for each patient [(Okegbile, 2023)][(Sun T. H., 2022)].

Digital twins can improve planning of various procedures as well as execution of those tasks by creating accurate digital replicas of patients in the virtual world, allowing healthcare staff to simulate the challenging procedures in a safe virtual setting. This helps them be more productive and confident. Efforts are made to improve surgical precision and minimise errors. Furthermore, digital twins and their visualisation can contribute significantly to post-surgery recovery plans and monitoring scenarios. The post-surgery care can be improved by monitoring patients' movements indoors and deploy the resources accordingly also all these can be monitored in real-time. For example, digital twins can replicate patient movements inside a hospital, predict resource requirements, and identify potential bottlenecks in patient care. By integrating digital twin models into the hospital record managing system, the hospitals can better allocate resources, optimise processes, and ensure that patients receive the care they need promptly [(Erol, 2020)][(Sun T. H., 2022)].

1.1 Motivation

The digital twin can help the healthcare industry to track and identify valuable assets (doctors, nurses, expensive life-saving types of equipment), receive data from patients and healthcare environments, and then visualise the data for a better experience. The absence of such a

framework to bridge the physical and digital world to help improve processes, save time during emergencies, and gain insights into the environment, find medical devices in real-time to save time and improve accuracy and quick and effective services to the patients.

The digital twin of the patient and healthcare environment will help to provide personalised and targeted treatment and diagnosis. It also helps to find the movement of the patients and healthcare professionals inside the hospital premises and the possibility of creating alerts based on different emergency scenarios for safety and security purposes.

1.2 Aims and objectives

The main aim and objective of this individual research is to improve and develop a better way to use the data for personalised treatment and improve hospital operations by integrating the digital twin, real-time location data and with the vital data from the patients. This framework focuses on addressing the current limitations in patient care, analyse the movement of patients, integrate the vital data for diagnostics through the use of real-time data integration and AI-driven models. Specifically, the study seeks to explore the following key objectives:

- To improve operational efficiency within healthcare facilities.
- Create a digital twin of the hospital environment and patients.
- Collect and analyse the digital twin of patients in real time.
- Monitor and understand the movement of patients inside any hospital spaces.
- Track the hospital equipment and related assets in real time.
- Analyse the data using artificial intelligence methods to find insights.
- Find the utilization and occupancy of the entire environment and improve the utilization.
- Create alerts based on the processes and activities to improve safety and security.
- Generate reports based on the activity of the assets.

1.3 Overview

The main objective is to create a framework to integrate the real-time location analytics system, enabling the digital twin with third-party vital data providers like smart watches or temperature monitoring systems. This can be used in various fields, especially in the healthcare environment, for personalised treatment and process optimisation. The visualisation tool to use

Bluetooth Low Energy (BLE) technology to monitor all kinds of assets (Movable and immovable). The methodology involves data collection, data integration, data visualisation, and data analysis. The expected outcome is to improve the existing system and provide ways to enhance patient care and increase operational efficiency.

To evaluate the effectiveness of the solution, we will compare the existing RFID-based solution to track and monitor indoor assets with a BLE-based real-time location digital twin system, constantly measure the vital data integration with the system, and measure whether the response time can be increased for better healthcare

2 Literature Review:

2.1 Evolution of Digital Twins in Healthcare

NASA first introduced the digital twin as a virtual, dynamic model of a physical entity-originated in the aerospace industry in the early 1960's [(Karakra A. a., 2019)], However, it was not until 2002 that the digital twin concept was formalized by Michael Grieves at the University of Michigan, where it was proposed as a key tool for product lifecycle management across industries [(Grieves, 2016)], Since then, the concept has evolved considerably, moving beyond industrial applications to sectors like healthcare, where the potential for personalized medicine, predictive diagnostics, and operational efficiency is unparalleled [(Erol, 2020)].

In healthcare, digital twins have undergone significant transformation. Initially, digital twins were utilized to model non-living physical entities, such as machines or mechanical parts. However, with advancements in computational power, sensor technology, and data analytics, digital twins began to be applied to biological systems. Today, healthcare digital twins have expanded to represent entire physiological systems, organs, tissues, and even individual cells. This shift has introduced groundbreaking opportunities for disease modelling, personalized treatment plans, and predictive analytics (" (Armeni, 2022)).

The digital twin's integration with the Internet of Things (IoT) was a pivotal moment in its evolution. IoT enables real-time data collection from connected devices, such as wearable health monitors, electronic health records (EHRs), and medical imaging systems, to be fed into digital twin models. This integration provides a continuous feedback loop between the digital

twin and its physical counterpart, allowing for ongoing updates and refinements to the virtual model based on new data inputs. The IoT backbone, combined with advances in big data analytics, has made it possible to create highly accurate, real-time digital replicas that can simulate complex physiological processes and predict future health outcomes.

These capabilities have profound implications for patient care. Digital twins can now be used to monitor the progression of chronic diseases, optimize treatment plans based on real-time patient data, and predict adverse health events before they occur. For instance, in managing diabetes, a digital twin can continuously monitor a patient's blood glucose levels and adjust insulin dosages in real-time, reducing the risk of complications and improving quality of life ("The Role of AI for Developing Digital Twins in Healthcare"). (JOUR, et al., 2022)

The introduction of artificial intelligence (AI) into digital twin technology further advanced its potential in healthcare. AI allows digital twins to not only replicate and monitor physical entities but also learn from the vast amounts of data collected, enabling predictive insights and dynamic decision-making. This marks a significant departure from the traditional, static use of digital twins, propelling them into intelligent systems capable of real-time adaptation and personalized care. In healthcare, AI-enabled digital twins have become powerful tools for clinicians, offering advanced diagnostics, tailored treatment plans, and optimized hospital operations ("Digital Twins in Healthcare: Recent Updates and Challenges") (Sun T. e., 2023).

2.2 The Role of AI in Healthcare Digital Twins

Alexandre Vallée, in his paper 'Digital twin for healthcare systems' [(Vallée, 2023)], discusses the possibility of gathering the data to analyse it and offer personalised treatment plans based on individual data, medical history and real-time data. Predictive analytics and preventive interventions are made possible by machine learning algorithms, allowing for early detection of health risks and proactive interventions. It also emphasises the point that the implementation of digital twin visualisation in healthcare has the potential to improve personalised patient supervision and increase patient safety. It also brings innovation to the healthcare industry. It also advocates for artificial intelligence to predict disease progression and identify high-risk individuals. In addition, the adaptation of digital twins can help in the efficiency of the health centres and improvement in the process adaptation.

This paper, however, opens a few challenges about the actual implementation strategies and the real difficulties in reconciling the data and presenting it in real-time, and a few of them are,

- Technical infrastructure: How to implement and maintain the technical aspect of digital twin and gather the data from different sources in real-time.
- Data integration – successful integration of the data from different sources is a challenge. However, if possible, it can help smooth operations.
- Adoption and training to healthcare professionals, as most of the health professionals will be new to the technology, pointed out the need for continuous training.

In conclusion, the study recognises that digital twin technology has applications in healthcare systems. Through real-time data integration, advanced analytics, and virtual simulations, it can enhance patient care, offer predictive analytics, and optimise operations. However, concerns regarding data privacy, data integration, data quality, and ethical considerations need to be addressed to ensure the successful acceptance and implementation of digital twin technologies in the healthcare sector. (Vallée, 2023)

The integration of AI into digital twin technology has been a game-changer, particularly in healthcare, where AI enhances the digital twin's ability to process large datasets, recognize patterns, and predict outcomes. By embedding AI algorithms into digital twin models, healthcare providers can make more informed decisions, tailoring medical interventions to each patient's unique physiological and genetic makeup. This section delves deeper into how AI is transforming digital twins and enabling more personalized, predictive, and efficient healthcare systems.

AI has revolutionized healthcare digital twins by enabling them to transition from static models to dynamic, learning systems. Through AI-driven data analysis, digital twins can now process vast amounts of patient data—ranging from genomic information to real-time vitals—and apply machine learning algorithms to uncover patterns and correlations that might otherwise go unnoticed by human clinicians. This ability to identify early warning signs, predict disease progression, and suggest personalized treatment plans is at the heart of AI's value in healthcare digital twins ("Exploring the Revolution in Healthcare Systems Through the Applications of Digital Twin Technology") (Abid, 2023).

One of the most impactful applications of AI-enabled digital twins is in personalized medicine. Traditional treatment approaches often follow a one-size-fits-all model, which may not account for individual differences in genetics, lifestyle, and physiological responses. AI-enhanced digital twins, however, can create highly personalized patient models by integrating data from wearable devices, EHRs, and other sources. These models can simulate different treatment scenarios, allowing clinicians to predict how a patient might respond to various therapies before administering them. For example, in oncology, AI-driven digital twins can simulate tumor growth and predict the effectiveness of chemotherapy or radiation treatment based on a patient's genetic makeup and tumour characteristics. This approach not only improves treatment efficacy but also minimizes adverse side effects, offering a more targeted and patient-centred approach to care.

Moreover, AI's role in healthcare digital twins extends beyond personalized medicine into clinical decision support. In complex clinical cases where multiple treatment options are available, AI-enabled digital twins can simulate each option and model potential outcomes, helping clinicians choose the most effective course of action. This capability is particularly valuable in fields like cardiology, where AI can simulate heart function, predict the impact of surgical interventions, and guide treatment decisions based on real-time patient data (Vallée, 2023).

The integration of AI also introduces a continuous learning loop into digital twin systems. As more data is collected from a patient, AI algorithms refine their predictions and adjust the virtual model, accordingly, ensuring that the digital twin remains accurate and relevant over time. This dynamic adaptability is crucial in healthcare, where patient conditions and treatment protocols are constantly evolving. AI enables the digital twin to stay up to date with the latest medical research, patient data, and treatment advancements, offering clinicians an invaluable tool for improving patient outcomes (" (Vallée, 2023)").

However, the integration of AI into healthcare digital twins also raises significant ethical and practical challenges. Ensuring the transparency and accountability of AI algorithms is paramount, particularly when these systems are used to make life-altering decisions for patients. Healthcare providers must develop explainable AI (XAI) algorithms that allow clinicians and patients to understand how decisions are made, rather than relying on "black box" models that are opaque and difficult to interpret. Additionally, AI systems must be rigorously tested and validated to ensure they are free from biases that could lead to unequal

treatment across different patient populations. Data privacy and security concerns are also heightened when dealing with sensitive health information. Robust encryption and cybersecurity measures are required to protect patient data from breaches and unauthorized access ("Exploring the Revolution in Healthcare Systems Through the Applications of Digital Twin Technology"). (Abid, 2023)

2.3 Applications of AI-Enabled Digital Twins in Healthcare

The practical applications of AI-enabled digital twins in healthcare are wide-ranging and span across various domains, from enhancing patient care to optimizing hospital operations. By leveraging AI's analytical capabilities and the real-time data integration provided by IoT, digital twins offer unprecedented opportunities for improving the efficiency and effectiveness of healthcare delivery.

Enhanced Patient Care: One of the primary benefits of AI-enabled digital twins in healthcare is their ability to enhance patient care by providing personalized, real-time insights into patient health. These digital twins create individualized models of patients by integrating data from multiple sources, including wearable devices, imaging systems, and genetic profiles. This enables healthcare providers to simulate various treatment options and predict disease progression based on a patient's unique characteristics. For instance, in the management of cardiovascular diseases, AI-enabled digital twins can monitor heart function in real-time, simulate different surgical or pharmaceutical interventions, and predict their outcomes. This allows clinicians to tailor treatments specifically to each patient's needs, resulting in improved outcomes and reduced complications ("The Role of AI for Developing Digital Twins in Healthcare") (JOUR, et al., 2022).

AI-enabled digital twins are also playing a key role in chronic disease management. For example, digital twins are used to monitor diabetes patients by continuously tracking their blood glucose levels through wearable devices and integrating that data into the digital twin model. AI algorithms then analyse the data to recommend real-time adjustments to insulin dosages, optimizing patient care and reducing the risk of complications. This approach exemplifies the power of AI to enhance digital twins and improve the quality of life for patients with chronic conditions ("Digital Twin in Healthcare: Recent Updates and Challenges") (Sun T. H., 2022).

Surgical Planning and Training: Another notable application of AI-enabled digital twins is in surgical planning and training. Digital twins allow surgeons to create precise virtual models of a patient's anatomy, enabling them to plan and rehearse complex procedures in a risk-free, virtual environment. By integrating real-time patient data with AI-powered simulations, surgeons can model different surgical approaches, anticipate potential complications, and refine their techniques before the actual procedure. This has proven particularly valuable in orthopaedic surgery, where AI-enabled digital twins can model bone structures and joint mechanics, allowing for optimal placement of implants and prosthetics ("The Digital Twin Revolution in Healthcare") (T. Erol, 2020).

Digital twins are also becoming valuable tools for training healthcare professionals. By simulating surgical procedures and medical scenarios in a virtual environment, digital twins offer surgeons and medical staff the opportunity to practice and hone their skills in a low risk setting. This type of immersive training experience not only improves technical proficiency but also enhances decision-making abilities in high-pressure situations, ultimately leading to better patient outcomes ("The Digital Twin Revolution in Healthcare"). (Erol, 2020)

Clinical Trials and Research: Digital twins are poised to revolutionize the clinical trial process by allowing researchers to simulate clinical trials in a virtual environment before enrolling human participants. This approach offers several advantages, including reduced trial costs, shorter timelines, and the ability to predict patient outcomes with greater accuracy. By creating virtual control groups, digital twins can simulate the effects of different treatments, reducing the need for large-scale participant recruitment and eliminating ethical concerns associated with placebo use ("Digital Twin for Healthcare Systems") (Vallée, 2023).

Moreover, digital twins enable researchers to test multiple treatment strategies in parallel, allowing them to identify the most promising options before moving forward with human trials. This approach accelerates the development of new therapies and improves the likelihood of trial success by identifying the optimal treatment pathways early in the research process. As clinical trials become more complex and personalized, the use of digital twins in research is expected to grow, providing a new paradigm for drug development and clinical experimentation ("The Role of AI for Developing Digital Twins in Healthcare") (JOUR, et al., 2022).

Manage Patient Care: The paper approaches a simulation of hospital services, especially the patient pathway especially to find the hidden opportunity. For that reason, the authors used a digital twin framework ('Flex Sim HC') using the event simulation systems and IoT devices. (Karakra, Lamine, Fontanili, & J. , 2018)

2.4 Improving 'Digital Twin' Platform by Integrating Patient Vital Data

Sun, Tianze, et al. in a recent study [(Sun T. e., 2023)] pointed out examples of digital twin applications like personalized medicines, disease monitoring and management, training, and education etc. The paper begins by emphasising the importance of simulation and personalised diagnosis and treatment in precision medicine. It presents the notion of a digital twin, a technology that allows for personalised treatment by producing a digital clone of a specific patient. The authors summarise instances of digital twin applications in medicine and analyse their prospective benefits, including precision diagnosis and personalised therapy. The article also highlights the importance of the relevance of digital twin technology and the use of artificial intelligence and machine learning applications in the data that is being gathered from different sources including the patient's wearable devices. However, there are a few drawbacks in this paper as it does not provide solid examples or details about the studies mentioned, also the paper failed to discuss in detail the challenges that are faced

An important part of the research is improving the existing real time location analytics and digital twin visualization tool called '**dSense**', designed and developed by Pinmicro, a Japanese technology company. It uses Bluetooth Low Energy (BLE) technology, receivers and broadcast the data to the cloud to create a real-time location system (RTLS) to track both movable and immovable assets within the specified area of hospital or indoor location. The system is capable of tracking doctors' nurses, patients and even various sized medical equipment based on the use cases of the healthcare facility. However, there is significant potential to enhance the dSense platform by integrating real-time physiological data from patients, such as temperature, heart rate, blood pressure, and oxygen levels, into the digital twin visualization tool.

With the completion of the integration of the patient vital data into the dSense platform, healthcare providers would be able to view the digital twin of the patients in his surrounding environment and the vital data associated with it in real-time. This further allow for a more comprehensive view of the patient health and enable the qualified persons to identify the co-relation. That is the changes to the vital data with respect to the environment changes. For example, if a patient equipped with proper devices and if the heart rate or temperature of the patient increases rapidly whenever they are in a specific area of the facility can trigger an alert to medical staff, prompting immediate intervention and the data can be used for future diagnosis and reference purposes. The integration of patient vitals with RTLS data could also improve diagnostic accuracy by providing clinicians with a continuous stream of data that reflects both the patient's physical condition and their real-time movements

This integration would also enhance the platform's predictive capabilities. In future by leveraging AI algorithms, the dSense platform can be equipped to analyse the combined data streams to predict potential health events, such as heart attacks or respiratory failure, before they occur. For example, if a patient's vitals show signs of deterioration, and they are in a remote area of the hospital, the system could alert the emergency medical team with the real-time location data and vital information of the resources and personnel to intervene before the situation escalates. This kind of real-time monitoring and predictive analysis would significantly improve patient care outcomes and reduce the burden on hospital staff and improve the resource utilisation.

This third-party data integration from different wearable devices, which follows the similar protocol to transfer the data will give a different potential enhancement to the dSense digital twin visualisation platform. These devices can collect the vital information and transfer, integrate in real-time would provide a complete view of a patient. Additionally, since this is remote based and cloud-based application, the information can be access anytime from outside the premises for ease of use and convenience especially for those vulnerable patients.

2.5 Technical Challenges and Ethical Considerations

There are significant technical challenges and ethical considerations that must be addressed while we do the technical implementation. One of the primary technical challenges is ensuring data accuracy & reliability. Especially in environments where multiple data reach from different sources, such as RTLS and wearable devices. Another challenge might be the signal

interference from external environments. All these noises can impact in the accuracy of the digital twin. Additionally, as the volume of data increases, the system must be capable of scaling efficiently while maintaining low latency in decision-making.

Another challenge involves the integration of disparate data sources, each of which may use different data formats and standards. Interoperability between different systems is crucial for ensuring that data can be shared seamlessly across platforms. The development of standardized protocols for data exchange is necessary to overcome these barriers and enable the full potential of digital twin systems.

From an ethical perspective, the integration of sensitive patient data into digital twin platforms raises concerns about privacy, security, and consent. Healthcare providers must implement robust cybersecurity measures to protect patient data from breaches and unauthorized access. Moreover, patients must be fully informed about how their data is being used, and consent processes should be transparent and accessible. AI algorithms used within digital twin systems must also be scrutinized for potential biases that could result in unequal treatment of patients based on factors such as race, gender, or socioeconomic status.

In conclusion, the evolution of digital twin technology from industrial applications to healthcare represents a significant leap forward in personalized medicine, predictive diagnostics, and operational efficiency. The integration of AI has enabled digital twins to transition from static models to dynamic systems that can learn, adapt, and provide real-time insights into patient health. The practical applications of AI-enabled digital twins, from personalized treatment plans to surgical planning and hospital operations, demonstrate the vast potential of this technology to improve healthcare outcomes.

3 Existing Digital Twin Visualisation Tool

In this paper, “Digital Twin for Intelligent Context-Aware IoT Healthcare Systems”, the authors analysed few digital twin systems and the comparison of those technologies. The author reiterated the point that even though the digital twin research proposing different theoretical frameworks and models, not many applicable solutions and applications exist. The below is the comparison used by the author. (Elayan, Aloqaily, & Guizani, 2021)

Table 1: Related Digital Twin - Model Comparison . (Elayan, Aloqaily, & Guizani, 2021)

Domain	Technology Used	Use Case Scenario	Real-time Data	Challenges
DT framework for healthcare	DT, IoT	-	No	Real-time Data Integration
Framework for a hospital DT	DT, IoT,DES, DSS, Simulation	Implementation of the framework in four scenarios 'Flex Sim' HC	Yes	Real-time problems, Data link between real life and virtual space
DT for personalised healthcare	DT, GAN, AI	-	-	-
DT framework for healthcare, personalised healthcare, and improve process	DT, IoT, Simulation, Third party vital data devices	DT enabled healthcare, Analysis of Vital data and anomaly prediction	Yes	Real-time data processing, Real-time anomaly prediction based on environmental data and vital data

An IoT based Real-time location analytics system designed to monitor the movement of people and assets in indoor environments. It used the Bluetooth Low Energy (BLE) beacon cards and receivers to capture and send back the data to the cloud for processing to complete the digital twin visualisation. The architecture of this system has many components.

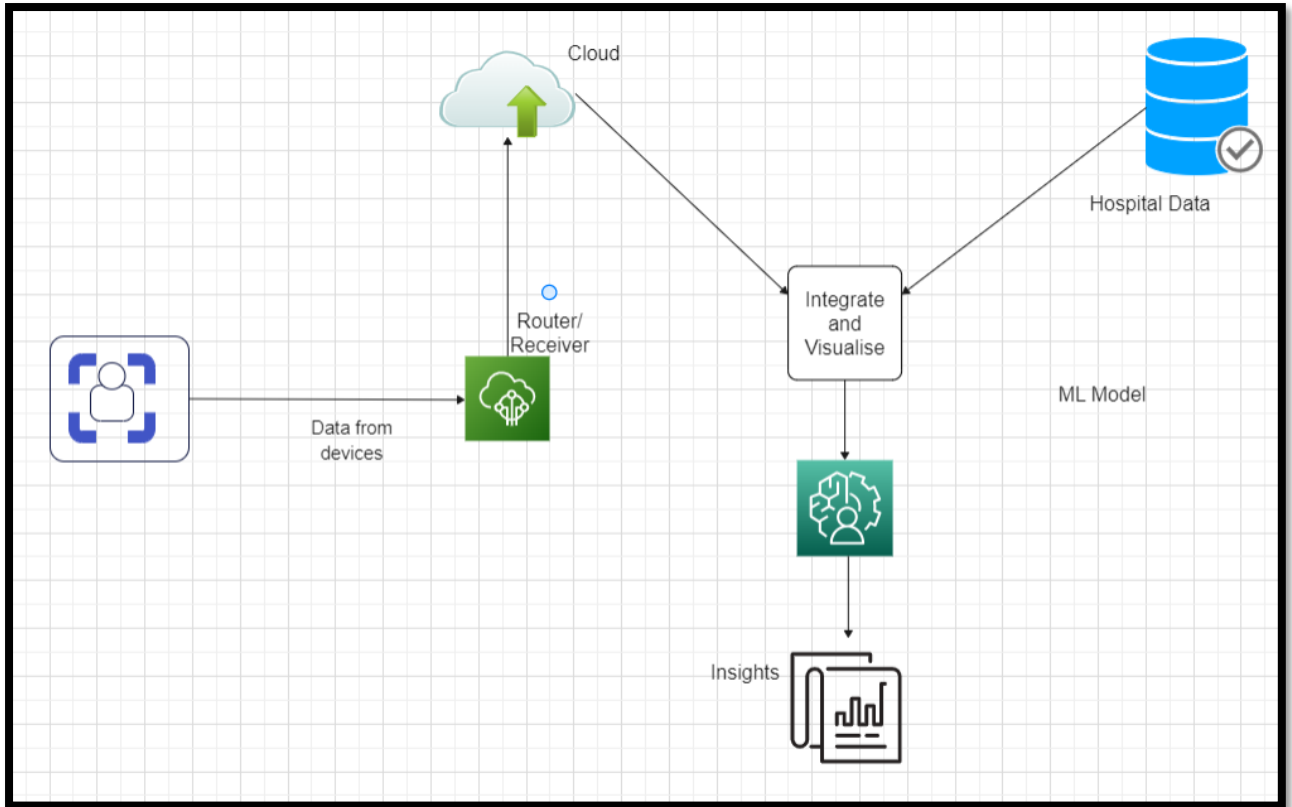


Figure 1: Proposed High Level Architectural Diagram

3.1 Hardware Layer

This is the foundation layer of the IoT enabled system and it consists of various sensors and BLE beacons.

3.1.1.1 The data structure of the beacon :

BLE Beacons: They are active (powered by battery) smart beacons which continuously transmit Bluetooth signals which will be captured by the sensors placed inside the premises at strategic places

- Universally unique identifier (UUID) – 128-bit value that is unique to every beacon.
- Major and Minor Values: This gives additional information about the location and function of the designated beacon
- Manufacturer Data : These are the custom fields that can be used to carry additional information if any as per the different need.

- Gateways: Gateways connected to 5V adaptor and powered externally. It then receives the signals from the BLE Beacons and send the data to the cloud. It has the capability built over WiFi 2.4GHz and Ethernet to establish a communication channel.

Hardware	Model	Specifications	Functionality
BLE Beacon	PM-iBeacon	BLE:5.0, Range:100m, Battery Life: 4 yrs, Operating Voltage: 3V	Send data continuously and used for proximity detection
Gateway	MCSG1	Input with DC 5.0V, 1A, Micro-USB, Supports: HTTP (SSL/TLS) / MQTT (SSL/TLS & Proxy) / TCP	Gateway to receive the BLE Beacons signals and send the data to the cloud servers.

Figure 2: Hardware Specification

3.2 Data Storage & Processing Layer

The collected data from the hardware layer is transmitted to the cloud for data reconciliation and processing. This can be done on cloud-based servers or on on-premises servers. This layer is responsible for aggregating, pre-processing, data cleaning and data generation.

There are multiple databases employed to manage the data that is been sent to the data processing layer. A combination of relational Structured Query Language and NoSQL is used for effective data processing. This allows to process both the structured and unstructured data in real time. There are pre-processing algorithms deployed to accept only the relevant data and to discard the redundant or meaningless data.

3.3 Data Analytics Engine

The dSense system uses the different algorithms to and leverages the cloud computing to process data and find the information relevant for the digital twin visualization. This layer also responsible for performing the data analysis and generate the insights.

- RSSI conversion Algorithm, it takes the RSSI values from the beacons and provide the exact location co-ordinates for the visualisation

$$d = 10^{\left((Tx \text{ Power} - RSSI) / (10 * n) \right)}$$

d – distance

Tx Power – Transmitted signal strength

n – loss exponent

3.4 Application Layer

The dSense system uses the different algorithms to and leverages the cloud computing to process data and find the information relevant for the digital twin visualization. This layer also responsible for performing the data analysis and generate the insights.

- **Software Architecture:** The web application request data from the server and after the authentication server provides the data and it relies of Client server model
- **RESTful API's:** Used for the communication between server and the front-end application
- **Real-time location visualisation dashboard:** Uses the data to complete the digital twin and map the movement of the assets based on the signals from the BLE beacons
- **Technologies Used:** Java, Python used in the backend development and HTML, CSS, JavaScript and Angular framework is used to build the front-end application. The database used are MySQL and Couchbase.

3.5 Security Layer

The dSense system used multiple security layers to protect the data and ensure the integrity.

- **Security and Privacy Measures**
 - Encryption mechanism used while sending and received the data to protect the integrity.
 - OAuth 2.0 Protocol for secure user authentication
 - Role based Access Control to manage the user permissions

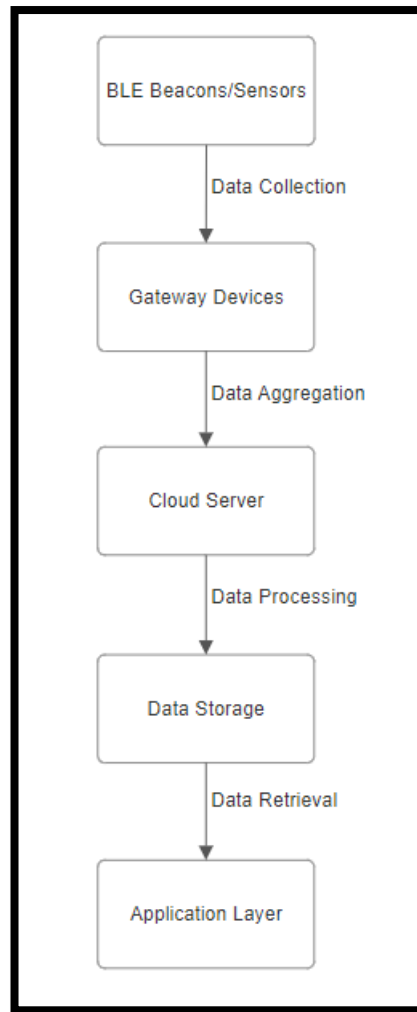


Figure 3: dSense Data Flow Diagram

4 Proposed System

The proposed change to improve the existing real-time location analytics and digital twin visualisation tool is to design and integrate the model to accept the third-party data like vital information which is not present at the moment with the system to improve the patient care and resource optimisation. By correlating the existing real time location data with the environmental data and the new vital data we shall attempt to derive the insights and try to measure it to finalise the improvements

In the new proposed system, the data will be generated from multiple sources in real time and all these data will be send to data analysis layer for the integration and reconciliation. Once

successful the data will form a new data frame with RTLS, & Environmental data from the digital twin system can coexist with Vital data from BLE enabled smart watches of patients.

This new data will then be used for the data analytics and machine learning algorithms to contribute to learning the current data pattern and predict the variation based on the external environments and notify right audience via alert.

Furthermore, data analysis and machine learning models and techniques can act as a crucial role in detecting the variation or anomaly. It also helps to predict the variations using the existing data. Techniques such as time-series analysis and pattern recognition can identify deviations from normal vital signs, enabling early warnings and prompt interventions (Chandola, Banerjee, & Kumar, 2009).

The high-level question to find the answers are,

- Improve the digital twin visualisation in real-time with the vital data to provide more holistic view of the patient and how the values are behaving with different environment parameters
- Anomaly/Variation Analysis and early prediction to alert the concerned people to make a swift decision on time

4.1 Methodology

4.1.1 Data Collection

- The system should have the capability to accept the new third party data that comes from the smart watches or health devices, used by Bluetooth low energy technology. The data should make it available and integrate with the existing data created by the digital twin platform.
- The digital twin data and the environment data collected by the dSense platform and its IoT devices
- Integrate successfully all the data to create a new dataset for further analysis.

4.1.2 Anomaly/Variation Prediction

1. Notification upon identifying a variation based on custom rule on the vital data to notify the patient and healthcare professionals to take immediate action. The rule will be flexible and can be decided based on the user input.
2. New data analysis using different machine learning methods to find the correlation between the vital data and the real time location data along with the environmental information. The following models are used and compared in the process
 - i. Support Vector Machine
 - ii. Random Forest Classification
 - iii. CNN Model
 - iv. LSTM Model

4.1.3 Scientific Questions

Question 1: How the integration of digital twin with real-time patient data helps the healthcare settings?

- The integration can improve clinical procedures by automating data gathering and minimising manual paperwork. This will certainly improve the efficiency by reducing the resource effort. . Effective change management methods, user-friendly interfaces, and clinical staff involvement in the design process may all help to increase adoption while minimising disturbance. However, the all the staff would require technology training and modifications to adopt to the new changes.

Question 5: How can the integration of machine learning algorithms with digital twin models improve the predictive alertness and personalized treatment plans in healthcare environment?

- By implementing the machine learning algorithms with digital twin models, the system can find start to look for the patterns and find the insights related with the health trends from both the real-time and historical patient data.

This allows for early diagnosis and can generate the alerts to proactive actions like personalised treatments and this will result in better patient outcomes through proactive care rather than reactive actions.

4.1.4 Tools Used

In this, several tools and libraries were used for data collection, data processing, machine learning and prediction.

For Data generation and processing, used '**Python**' programming language. For synthetic data generation, mainly used the libraries like 'Pandas' and 'NumPy'. The 'NumPy' used to generate random data generation especially for creating large datasets with realistic distributions. 'Pandas' was majorly used in data manipulation.

scikit-learn library used for the machine learning model development. It helps in implementing 'Random Forest Classifier' and 'Support Vector Machine (SVM)' machine learning predictive models.

To address the dataset's class imbalance, the imbalanced-learn package Synthetic Minority Over-sampling Technique (SMOTE) is used. SMOTE produced synthetic samples of the minority class ('Elevated' heart rate instances) which will balance the dataset from skewing and improved the models' capacity to learn better.

The scikit-learn library used to evaluate the metrics including precision, recall, F1-score and accuracy. These are the offered information to compare specific models's performance.

4.1.5 Use Case Analysis

Heart rate variation prediction based on environmental factors

Preconditions:

- The patient is equipped with wearable BLE enabled device.
- dSense, digital twin visualisation tool is implemented across the healthcare facility.

Main Flow:

- Wearable devices send real-time heart rate data.
- Gateways/routers detect occupancy levels, room temperatures and environmental factors.
- Patients' vitals are monitored.
- System generates alert, in case of variation detected or predicted variation based on machine learning models

Postconditions:

- The incident is logged for future analysis.
- Healthcare providers take appropriate action to mitigate the situation.

4.1.6 Testing and Evaluation**Proposed Metrics**

1. Response Time to Critical Events: Time taken from the occurrence of a critical health
2. Predictive Accuracy of Health Deterioration: Ability to predict potential health issues before they become critical.
 - Comparison of different models and its performance
3. Staff Efficiency: Time saved by healthcare staff in monitoring and responding to patient needs.

4.2 Proposed System Architecture

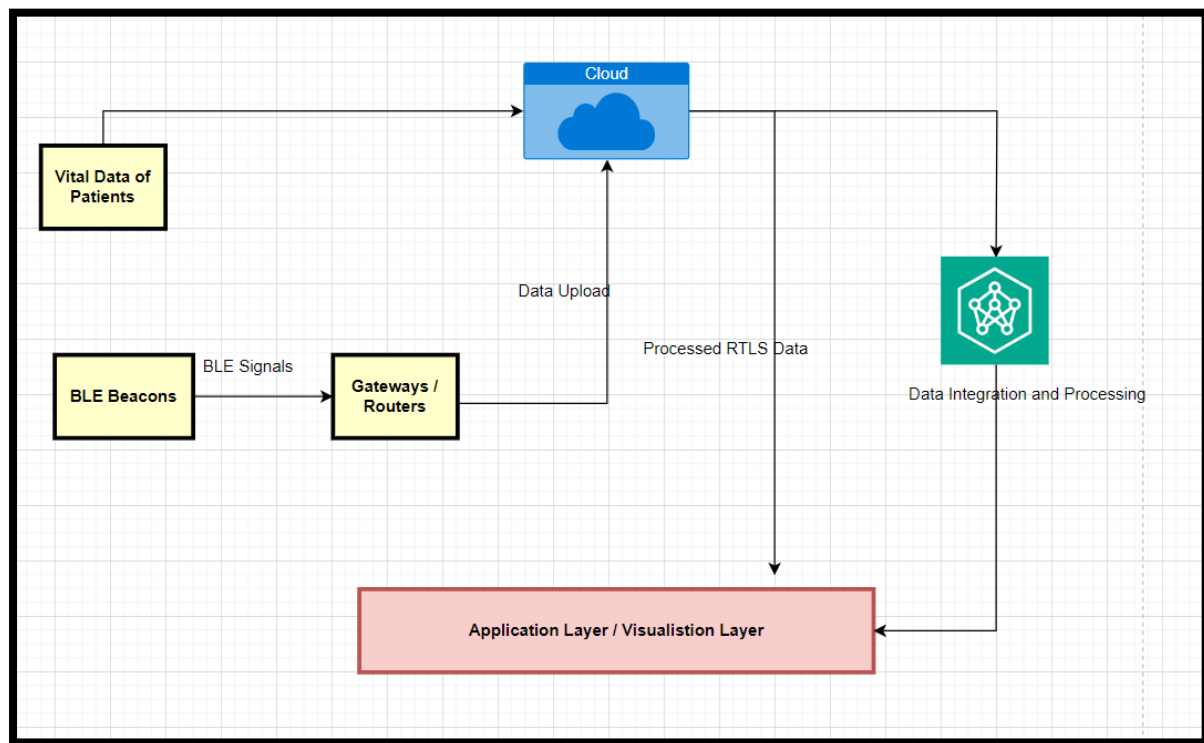


Figure 4 : Proposed System to accept Third party Data

4.2.1 Proposed System: Component Description:

1. **Data Collection Layer:** consists of BLE beacons, Gateway/Routers to generate RTLS and environmental data and Smart watches to generate patient data. The BLE beacons are low-power transmitter that use Bluetooth low energy technology to broadcast the signals at regular intervals. It has mainly two characteristics.
2. **Advertising Channels:** Uses 2.4Ghz Band to transmit the packets and the nearby gateway can detect this signature
3. **Transmission Power and Channels:** It defines the range to which it should transmit. The existing system used to be transmitted up to 100m
4. **Data Reconciliation Layer:** Integrates both the data into a single data frame to help with the analysis

5. Data Analytics Engine: Perform machine learning models on the generated data and predict the variation in future.
6. Visualisation and Alerts: The rule-based alerts and the visualisation of the movement can be done on the application layer.

4.2.2 Proposed System : Data Structure:

4.2.2.1 RTLS Data Structure :

- The ‘Asset’ uses string data type, and it can be used to identify the type of asset(Movable or Immovable) that as assigned to the beacon
- The ‘Group’ will be string data type and will be used to keep the group to identify.
- ‘In Time’ and ‘Exit Time’ to date stamp to calculate the first time the beacon is present in a particular position and when it is last detected.
- ‘Duration’ is to calculate the total time the asset spent in a particular spot
- ‘Detected place id’ and ‘sub place id’ , is to correctly identify the exact place in which the asset is detected.

No	Asset (String)	Group (String)	In Time (DateTime)	Exit Time (DateTime)	Duration (Float)	Detected Place ID (Integer)	Detected Sub Place ID (Integer)
1	Name	Patient	dd:mm:yy:hh:mm	dd:mm:yy:hh:mm	hh:mm	01	0101
2	Name	Nurses	dd:mm:yy:hh:mm	dd:mm:yy:hh:mm	hh:mm	02	0202
3	Name	Equipment	dd:mm:yy:hh:mm	dd:mm:yy:hh:mm	hh:mm	03	0303

Figure 5: RTLS Data Structure

The environmental data is also captured by the visualisation tool.

- The 'Location ID' corresponds to an exact place
- 'Temperature', 'Humidity', 'Occupancy', 'Noise Level', 'Air Quality' are the possible external environment values the sensors can detect and capture separately. All these data are optional
- 'Timestamp' is Date time datatype to capture the exact time at which the environmental data are captured

No	Location ID (Integer)	Temperature (Float)	Humidity (Float)	Occupancy (Integer)	Noise Level (Float)	Air Quality (Float)	Timestamp (DateTime)
1	0101	22.5	45.0	3	55.0	35.0	dd:mm:yy:hh:mm

Figure 6:RTLS Environmental Data Structure

4.2.2.2 The Vital Data Structure:

- The 'ID' uses Integer data type, and will be used as unique identifier
- 'Heart Rate', 'Temperature', 'Blood Pressure', 'Blood Oxygen' are the possible vital data values that can be captured and send to the digital twin visualisation tool in real time using the existing gateway or routers.

No	ID (Integer)	Heart Rate (Integer)	Temperature (Float)	Blood Pressure (String)	Blood Oxygen (Float)
1	1001	72	36.8	120/80	98.5

Figure 7: Patient Vital Data Structure

4.3 Data Generation

The data generation is a crucial part of the final output. The system will be collecting the data in two parts.

- The Real-time location data from dSense, visualisation tool. The data collected from the Bluetooth low energy beacons that is registered on the application. Each beacon will have an id associated with it to distinguish it from other beacons. This beacon signals will be detected by the routers / gateways placed in different places of the facility.
- Simulated Patients vital data, Will be using the python simulation code to generate the vital data of the patients.
- Setting up the seed for both NumPy and random modules to ensure reproducibility of the generated data

4.3.1 Machine Learning Model Development

Train to learn and evaluate the following three methods

4.3.1.1 Support Vector Machine (SVM):

Support vector machine is a supervised learning algorithm. It is commonly used for classification and regression tasks. The advantage of SVM is that it performs better with high dimensionality and effective in the situations where the number of

dimensions is higher. The basic concept is to find the hyper plane that is best in separating the different data points of multiple classes. This helps in forming a better decision boundary [(Bishop, 2006), (Vapnik, 1995)].

SVM operates by mapping the input data into a high-dimensional feature space and attempting to find a hyperplane that separates the data points into different classes. In two-dimensional space, this hyperplane is a line; in higher dimensions, it is referred to as a hyperplane. The goal of SVM is to find the optimal hyperplane that divides the data into two categories with the maximum margin. The margin refers to the distance between the hyperplane and the closest data points from each class. These closest points are called support vectors, and they are crucial in determining the position and orientation of the hyperplane [(Bishop, 2006), (Vapnik, 1995)].

For a linearly separable dataset, the SVM algorithm identifies the hyperplane by solving a convex optimization problem that maximizes the margin between the classes. The equation of a hyperplane in a d-dimensional space can be written as: [(Bishop, 2006), (Vapnik, 1995)]

$$w^T x + b = 0$$

Where, w is the weight, x is the input feature and b are the bias term. The challenge is to find the values of w and b that maximize the margin between the support vectors of the two classes. The margin is defined as the distance between the support vectors and the hyperplane, and SVM aims to maximize this distance. The support vectors are critical as they lie on the boundary of the margin and directly influence the final decision boundary [(Bishop, 2006), (Vapnik, 1995)].

Advantages of SVM

Effective in high-dimensional spaces: SVM works well when the number of dimensions is high, as it can handle the curse of dimensionality.

Robust against overfitting: Especially in cases where the data points are separated with a clear margin.

Versatile kernel functions: SVM's ability to use various kernel functions makes it adaptable to both linear and non-linear classification problems.

Limitations of SVM

Not suitable for large datasets: The computational cost of SVM increases with the size of the dataset.

Choice of kernel: The performance of SVM heavily depends on the choice of kernel function and its parameters, which may require tuning. [(Bishop, 2006), (Vapnik, 1995)].

4.3.1.2 Random Forest Classifier

The Random Forest Classifier is a popular ensemble learning algorithm used for both classification and regression tasks, and stability of predictions by aggregating the results of several trees, each trained on different data subsets. Due to its flexibility and ability to handle both structured and unstructured data, Random Forest is commonly applied in various fields, including finance and biology. (Hastie, Tibshirani, & Friedman, 2009)

The algorithm works by generating several decision trees during the training phase. It starts by selecting random samples from the dataset through a process called bootstrapping or bagging (Bootstrap Aggregating). For each tree, a random subset of features is chosen at each node, and the most informative features within that subset are used to create splits. This element of randomness is key to reducing overfitting and ensuring the trees remain uncorrelated, which results in more robust models. (Hastie, Tibshirani, & Friedman, 2009)

Once all the trees are trained independently, their predictions are combined. For classification problems, the final prediction is based on majority voting, where the class predicted by most trees is selected. In regression tasks, the result is determined by averaging the predictions from all the trees. (Hastie, Tibshirani, & Friedman, 2009)

Steps in the Random Forest Algorithm

- **Bootstrapping the data:** Randomly select samples from the training data with replacement. This means that some data points will be used multiple times, while others may not be used at all. .[(Hastie, Tibshirani, & Friedman, 2009) (BREIMAN, 2001)]
- **Random feature selection:** At each node in a tree, a random subset of features is selected. The best split among these randomly chosen features is used to split the node. .[(Hastie, Tibshirani, & Friedman, 2009) (BREIMAN, 2001)]
- **Building multiple decision trees:** Repeat the above steps to create several decision trees, where each tree is trained on a different bootstrapped dataset and different random feature subsets. .[(Hastie, Tibshirani, & Friedman, 2009) (BREIMAN, 2001)]
- **Aggregating predictions:** For classification, a majority vote is used to determine the final prediction. For regression, the average of the predictions from all trees is calculated. .[(Hastie, Tibshirani, & Friedman, 2009) (BREIMAN, 2001)]

Advantages of Random Forest

- **Reduced Overfitting:** One of the key benefits of Random Forest is its ability to prevent overfitting. Individual decision trees tend to overfit the training data, especially if they are allowed to grow very deep. However, by averaging the predictions of multiple trees, Random Forest reduces variance, leading to better performance on unseen data. .[(Hastie, Tibshirani, & Friedman, 2009) (BREIMAN, 2001)]
- **Robustness to Noise:** Since Random Forest takes into account multiple trees and samples from the data, it is less sensitive to noise. Even if some of the trees are poorly trained due to noise or randomness, the majority will still produce accurate predictions. .[(Hastie, Tibshirani, & Friedman, 2009) (BREIMAN, 2001)]
- **Feature Importance:** Random Forest also provides an intuitive measure of feature importance. By assessing how much each feature contributes to reducing the impurity in a tree, Random Forest can rank the importance of each feature in determining the final prediction. This can be particularly useful for feature selection

in data preprocessing. [(Hastie, Tibshirani, & Friedman, 2009) (BREIMAN, 2001)]

- **Handling Missing Data:** Random Forest can handle missing data quite well by utilizing surrogate splits in decision trees, which means that the classifier can use a similar feature when the primary feature is missing..[(Hastie, Tibshirani, & Friedman, 2009) (BREIMAN, 2001)]

Limitations of Random Forest

- **Computationally Expensive:** Training a Random Forest classifier can be computationally expensive, especially when dealing with large datasets and a large number of trees. As the number of trees increases, the computation time and memory requirements grow, although parallel processing can mitigate some of these concerns. [(Hastie, Tibshirani, & Friedman, 2009) (BREIMAN, 2001)]
- **Interpretability:** Although Random Forest tends to perform well in terms of prediction accuracy, it can be difficult to interpret the model compared to a single decision tree. The ensemble of trees makes it harder to understand the reasoning behind individual predictions. [(Hastie, Tibshirani, & Friedman, 2009) (BREIMAN, 2001)]
- **Not always the best choice for sparse data:** For high-dimensional, sparse datasets, Random Forest may not perform as well as algorithms specifically designed for such data, such as linear models or algorithms with L1 regularization. [(Hastie, Tibshirani, & Friedman, 2009) (BREIMAN, 2001)]

Tuning Random Forest Parameters

There are several hyperparameters in Random Forest that can be tuned to improve performance:

- **Number of Trees (n estimators):** Increasing the number of trees typically improves performance, though there are diminishing returns beyond a certain point. [(Hastie, Tibshirani, & Friedman, 2009) (BREIMAN, 2001)]

- **Max Features:** This defines the number of features to consider when looking for the best split. Smaller subsets lead to more randomness, reducing correlation between trees, but may also reduce accuracy if important features are consistently ignored. [(Hastie, Tibshirani, & Friedman, 2009) (BREIMAN, 2001)]
- **Max Depth:** Limiting the depth of each tree prevents overfitting but might reduce the model's ability to capture complex patterns[(Hastie, Tibshirani, & Friedman, 2009) (BREIMAN, 2001)]

4.4 Results and Discussions

4.4.1 Before and After Integration Performance Comparison

Performance Metric	Before Integration	After Integration
Response Time to Critical Events	--	0-5 Seconds
Predictive Accuracy of variation in heart rate	--	91%

Figure 8: : Before and After Integration Performance Comparison

The above table gives a high-level view of the result of before and after performance. The two criteria that are evaluated are : Response time to critical events and predictive accuracy of health issues.

Response Time to Critical Events:

The existing digital twin visualisation tool dSense, doesn't have the capability to read the vital information of the patients to create an alert. The existing system works on the occupancy of

affinity related alerts. This meaning in case of an urgent situation the system should need to reply on manual input to trigger the notification or alert. However, after the integration the new proposed system will have the ability to create an alert or notification when a custom rule is triggered. This can happen within 0 – 5 seconds, marking a huge improvement as it works in real time. The shorter response time will help the health facility to make a faster decision-making, enhancing the system's overall reliability and reducing risks associated with delays.

Predictive Accuracy of Health Issues:

The dSense digital twin visualisation system doesn't have any modules for predicting the health anomalies or variations in the vital data based on the external environmental data. However, after the integration, there has been a noticeable improvement in predictive accuracy, achieving an 80% accuracy rate. This improvement implies the implementation of predictive algorithms or machine learning models that evaluate data to foresee possible health-related occurrences. An accuracy rate of 80% represents a significant advancement, facilitating more proactive strategies in managing health concerns and thereby improving the system's preventive care functions.

Overall, the improvements in both response time and predictive accuracy reflect a significant enhancement in the system's performance, particularly in its ability to handle urgent events efficiently and to foresee potential health risks with a high degree of accuracy.

4.4.2 Machine Learning: Models Comparison

Correlation Between Occupancy and Heart Rate

The Pearson correlation coefficient between occupancy levels and heart rate was calculated to assess the linear relationship between these variables. The result against the generated data set is **0.0022**, indicating an almost weak positive linear correlation. Find below the screenshot obtained on the distribution of the data.

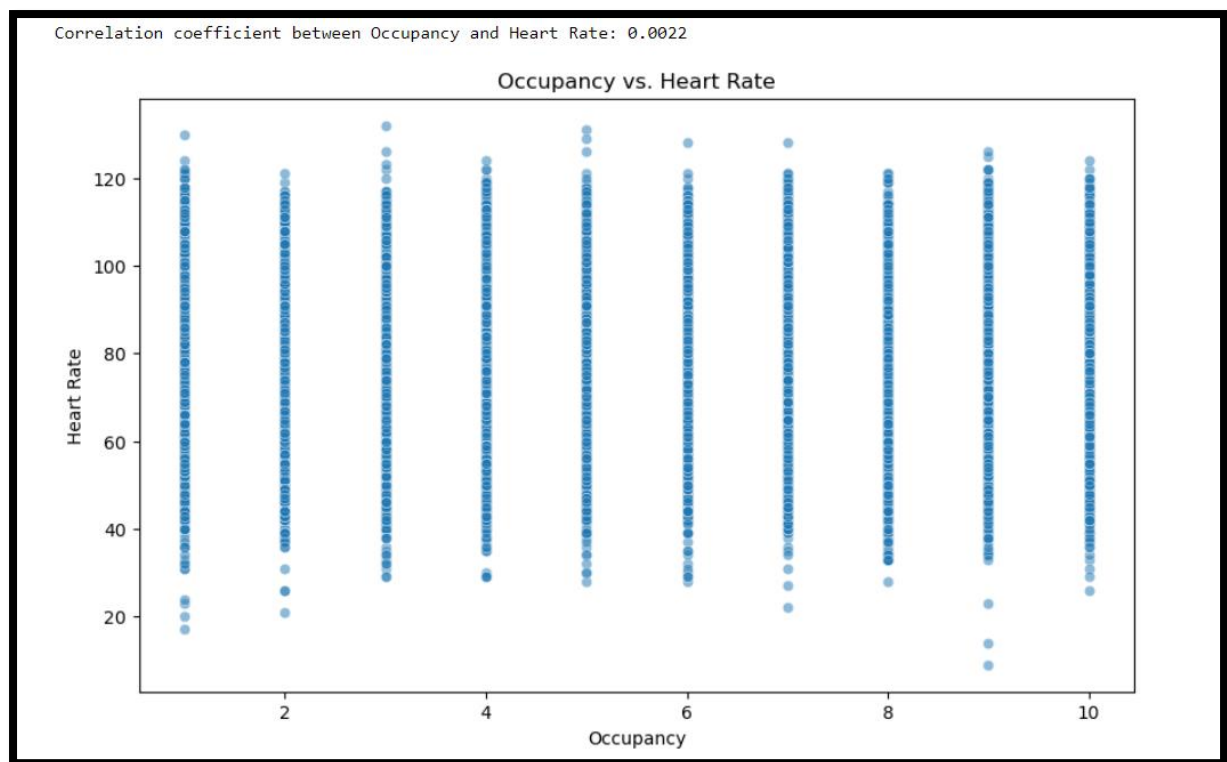


Figure 9: Occupancy vs Heart rate

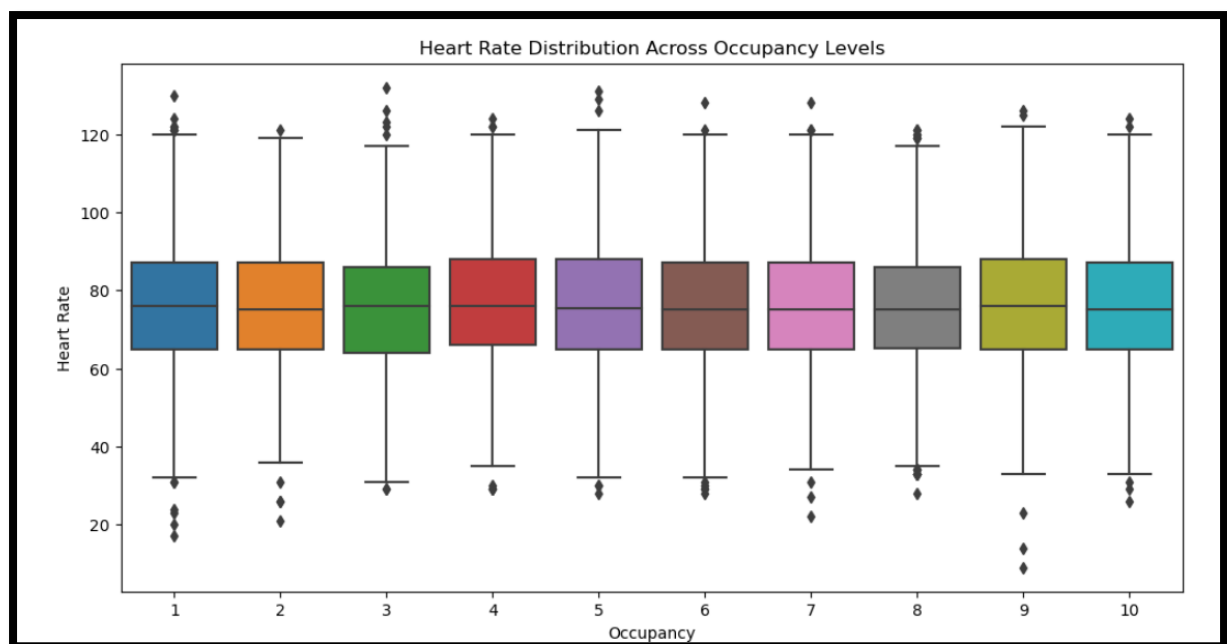


Figure 10 : Heart rate across occupancy levels

Machine Learning Model Performance

Despite the weak correlation coefficient, the machine learning models are capable of capturing complex, non-linear relationships that are not evident through simple statistical measures. Therefore, the study proceeded to train and evaluate models with and without occupancy data to explore its impact on predictive performance.

4.4.2.1 Class Distribution Before and After Resampling:

Before resampling, Normal has 2,958 instances and Elevated has 463 instances. This shows an imbalance between classes. So had applied the SMOTE (Synthetic Minority Over-sampling Technique).

After the resampling, both classes now have 2,958 instances each and the classes are perfectly balanced.

4.4.2.2 Classification Report for Support Vector Machine:

Accuracy with Occupancy : 61.59 %

Precision and Recall with Occupancy:

Table 2 :SVM Model with Occupancy

Class	Precision	Recall	F1-Score	Support
Elevated	0.58	0.76	0.66	3009
Normal	0.67	0.48	0.56	3104

Accuracy without Occupancy : 58.63 %

Precision and Recall without Occupancy:

Table 3: SVM without Occupancy

Class	Precision	Recall	F1-Score	Support
Elevated	0.56	0.74	0.64	3009
Normal	0.64	0.43	0.52	3104

The inclusion of occupancy data, which is generated from the real time location data shows a marginal improvement in accuracy. The SVM model with occupancy data showed better precision and recall for both classes, indicating enhanced predictive performance. This suggests that occupancy data contributes valuable information that helps the SVM model in distinguishing between 'Elevated' and 'Normal' heart rate categories.

Observations

- **Higher Recall for 'Elevated' Class:**
 - The SVM model with occupancy data demonstrates a higher recall for the 'Elevated' class (76%) compared to the 'Normal' class (48%).
- **Lower Precision for 'Elevated' Class:**
 - Precision for the 'Elevated' class is lower (58%) than for the 'Normal' class (67%)
 - Indicates that there are more false positives for 'Elevated' predictions.
- **Imbalanced Performance:**
 - The model exhibits different performance metrics for each class, with higher recall but lower precision for the 'Elevated' class and the reverse for the 'Normal' class.

- **Overall Moderate Performance:**

- The accuracy of the SVM model with occupancy is 61.59%, showing a modest improvement over the model without occupancy, which has an accuracy of 58.63%.

4.4.2.3 Classification Report for Random Forest:

Accuracy with Occupancy : 94.34 %

Precision and Recall with Occupancy:

Table 4: RF Model with Occupancy

Class	Precision	Recall	F1-Score	Support
Elevated	0.95	0.93	0.94	3009
Normal	0.93	0.96	0.94	3104

Accuracy without Occupancy : 89.45%

Precision and Recall without Occupancy:

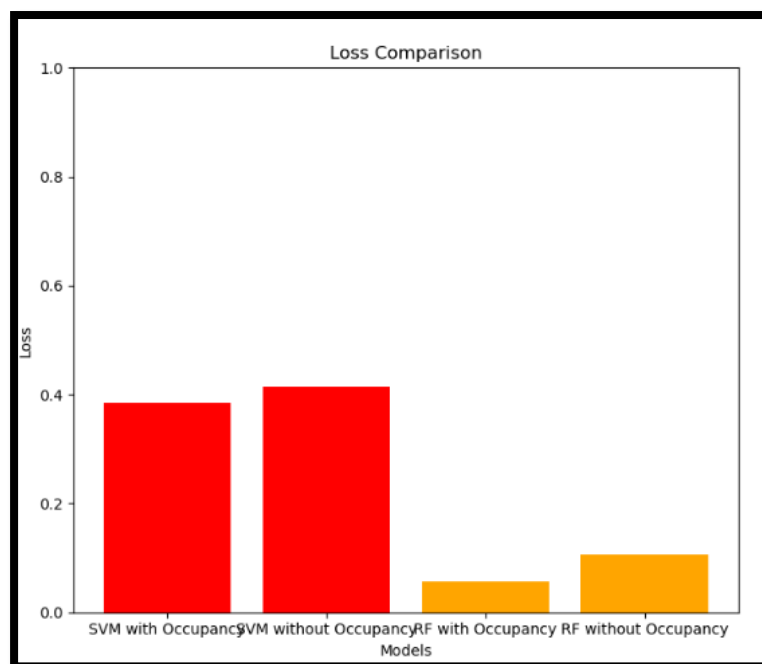
Table 5: : RF Model without Occupancy

Class	Precision	Recall	F1-Score	Support
Elevated	0.88	0.92	0.90	3009
Normal	0.91	0.87	0.89	3104

The Random Forest model demonstrated a significant improvement in accuracy (approximately 5%) when occupancy data was included. Precision and recall metrics were higher across both classes with occupancy data, suggesting that occupancy is a critical feature in enhancing model performance. The model's ability to capture complex interactions among features likely contributes to this improvement.

Observations

- **High Precision and Recall for Both Classes:**
 - The model performs well in both identifying and correctly predicting both classes.
- **Balanced Performance:**
 - The metrics are similar across both classes, indicating good generalization.
- **High Overall Performance:**
 - An accuracy of 94% is indicative of a strong model.



- *Figure 11: SVM & RF Change in Loss with occupancy and without occupancy*

Conclusion is that ‘Random Forest’ gives better accuracy and precision and a reliable in predicting the heart anomaly based on the environmental values such as temperature of the room and the number of people in the surrounding. ‘Random Forest’ provides a reliable model for predicting elevated heart rates based on environmental and location data and it can be used to identify patients at risk and enable proactive interventions.

4.4.2.4 Classification Report for CNN:

With Occupancy:

- Training Accuracy: 57.00%
- Validation Accuracy: 56.18%

Without Occupancy:

- Training Accuracy: 55.54%
- Validation Accuracy: 54.08%

4.4.2.5 Classification Report for LSTM:

With Occupancy:

- Training Accuracy: 62.27.00%
- Validation Accuracy: 60.10%

Without Occupancy:

- Training Accuracy: 59.07%
- Validation Accuracy: 58.09%

Like the CNN, the LSTM model exhibited improved performance with the inclusion of occupancy data. The LSTM's ability to capture temporal dependencies may have been enhanced by the additional information provided by occupancy levels.

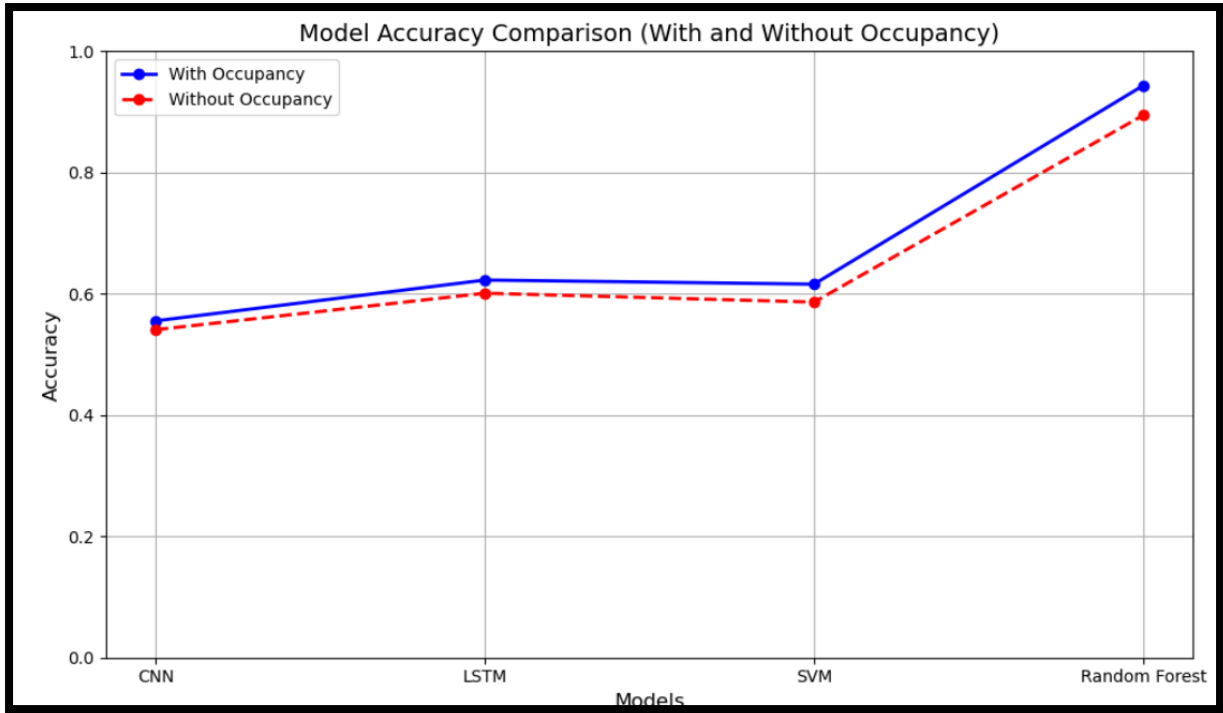
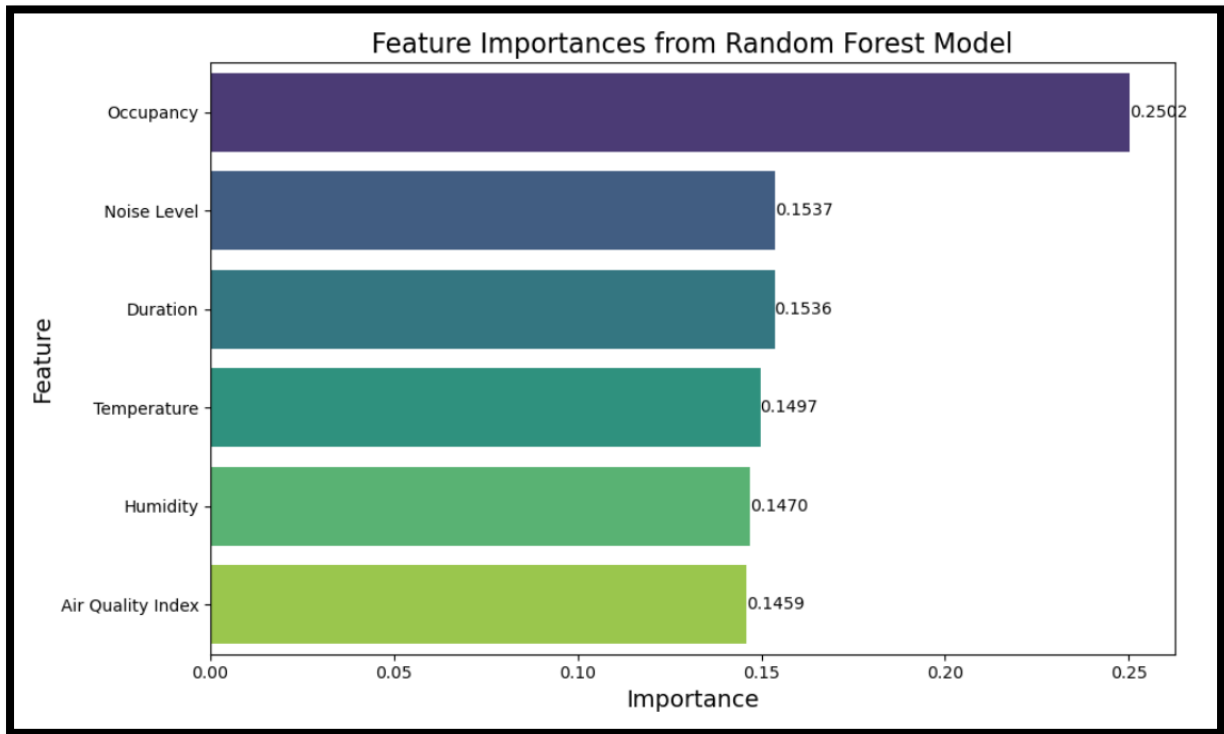


Figure 12 : Comparison of results with occupancy and without occupancy

4.4.2.6 Most Significant Predictor Analysis:

The Real-time location data, Occupancy (the number of people present in a location at any given time) is the most important feature, accounting for approximately 25% of the model's predictive power. This underscores the significant role that occupancy data plays in predicting heart rate status. The importance of other environmental factors, such as noise level and air quality, further highlights the influence of environmental conditions. This further is a significant step to showcase that the real time location analysis can contribute to the healthcare sector.

Table 6 : Most Significant Feature



In conclusion, occupancy does influence heart rate variation prediction and hence the real time location system and its integration with the third-party data like the smart watch to get the patients vital data will be helpful in predicting the change in heart rate based on the external factors. but its effects are intertwined with other real-time location and environmental data like temperature, air quality, and noise levels. The Random Forest model was the most effective at detecting these interactions and predicting heart rate anomalies. It outperformed SVM, CNN, and LSTM, particularly in handling complex feature interactions.

4.4.3 Discussions

The results of the machine learning model, including Support Vector Machines (SVM), Random Forest, CNN, and LSTM, demonstrated varying performance in predicting heart rate variations using the real-time location data. The inclusion of occupancy in the models had a significant impact on their performance, as occupancy data provided additional context for understanding environmental factors that might influence heart rate fluctuations.

The results strongly suggest that occupancy plays a crucial role in predicting heart rate anomalies. Both SVM and Random Forest models performed significantly better when occupancy data were included. The occupancy data provides additional context about how crowded or isolated a patient's environment is, which can influence stress levels, movement patterns, and thus, heart rate variations. In contrast, models like CNN and LSTM, which are traditionally stronger in handling time-series or spatial data, performed less optimally without the occupancy feature.

In particular, Random Forest with occupancy demonstrated the highest overall accuracy (0.9434), suggesting that it effectively captures complex relationships between various features, such as temperature, noise, air quality, and occupancy, to predict heart rate variations. The importance of occupancy in understanding real-time location data and its effects on physiological responses indicates that future implementations of RTLS systems should consider integrating environmental factors like occupancy to enhance prediction models for patient monitoring

There are many challenges faced during the research process. These challenges that faced are from every aspect starting with understanding the existing dSense platform, integrating third party new data with the RTLS system, and mitigating data imbalances in machine learning models. Addressing these obstacles required further study and research, collaboration, and the better utilization of specific technical tools to progress.

The 'dSense' platform that used as a digital twin visualisation tool using the real-time location services is new and understanding the working is the first challenge that faced. The absence of user manual made it difficult to learn the working initially. However, with the help of the development team, was able to understand its architecture and the methods used for visualisation of asset movement. Further on using the system learned the data flow and the components that are used helped in designing the proposed system with the patient data for improving the capability of the system.

During the development phase, another challenge that was faced is with now to merge the real time location data with the patient's vital data in real time. The existing system is not designed to accommodate the new data and hence had propose for a new data structure to combine both the data into a single database. The creation of this new data

structure required making assumptions based on the RTLS data framework, ultimately resulting in a unified model capable of capturing both patient movement data from beacons and physiological data from wearable devices or sensors. This new change is not supported with the system at present; however, this can be added in later versions to make it open for third party data.

A significant limitation is on accessing the patients real vital data due to privacy regulations, such as HIPAA and GDPR. Hence to test the theory, in the absence of live health records, used python programming language to generate synthetic data similar to the live data to validate the assumptions and to prove that the integration is technically possible. However, the data generation faced many challenges. In which the significant challenge is the imbalance in the generated data. This imbalance affected the efficiency of the machine learning models especially when finding the elevated heart rate based on external factors. To mitigate this challenge Minority Over-Sampling Technique (SMOTE) was used. As a part of that process, it artificially balances the dataset for the underrepresented classes. After the step the data set was better balanced, and which led to a better prediction of heart rate anomaly prediction.

4.5 Testing Approaches

1. Simulation Testing: Used system generated synthetic vital data to simulate patient scenarios and measure system performance.
2. Algorithm Evaluation: Assess the performance of machine learning models in detecting anomalies and predicting health issues.

5 Suggestions for Future Works

In this study, there are several challenges faced during the development stage. Even though the study shows an improvement in the existing system there are several opportunities that identified during this phase to make it better. These suggestions for future work focus on addressing the limitations and optimizing the digital-twin framework to enhance its functionality, scalability, and applicability in healthcare environments.

The primary limitation during this research is the availability of real patient vital data along with the real time location enabled environment. The study identified and proposed the new data structure for the seamless integration however it would be a great opportunity to implement the same with real patient data to advance further. Also advanced technology can be used to make the integration quick to support high volume of data. In future access to real-world hospital data (while maintaining compliance with HIPAA, GDPR, and other privacy laws), it would be beneficial to explore more real time machine learning algorithms that can operate in real-time to alert and to refine the predictive algorithms to extend the scope to multiple environmental variables.

6 Conclusions

The integration of digital twin technology with real-time data analytics, particularly in the healthcare field, is regarded as a significant advancement in operational efficiency and patient care quality. In this study, a framework was established to enhance personalized treatment and optimize hospital operations by employing advanced AI-driven models and integrating real-time data. Comprehensive digital twins of both the hospital environment and individual patients were created using the functionalities of Bluetooth Low Energy (BLE) beacons, gateways, and Internet of Things (IoT)-based real-time location systems (RTLS). The capacity to monitor the location of assets—including medical devices and healthcare personnel—while integrating patient-specific vital signs data from third-party smart devices is anticipated to transform how healthcare institutions oversee and manage their resources.

A marked decrease in response times to critical incidents was observed as a primary outcome of this research. Before the adoption of this sophisticated digital twin system, healthcare facilities were hindered by inadequate infrastructure for tracking real-time patient vitals and movements. Delays in recognizing and responding to patient emergencies were caused by the previous system, which depended on manual data entry and lacked predictive capabilities. With the implementation of this advanced system, response times have been significantly reduced to between 0–5 seconds, allowing prompt and effective action in critical scenarios. This

enhancement directly addresses a fundamental inefficiency in hospital operations: the lag in interventions during life-threatening situations. Real-time data collection is facilitated, and alerts are generated based on established criteria by the new system, promoting quicker, data-informed decision-making, thereby mitigating the risks associated with delayed treatment and enhancing overall patient outcomes.

Additionally, a considerable enhancement in predictive accuracy for potential health issues has been achieved.

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A. Implementation of main algorithm

```
import numpy as np

import random

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.metrics import classification_report,
accuracy_score


# Set random seeds for reproducibility

np.random.seed(40)

random.seed(40)


# Features including occupancy

features_with_occupancy = ['Occupancy', 'Temperature',
'Humidity', 'Noise Level', 'Air Quality Index', 'Duration']

# Features excluding occupancy

features_without_occupancy = ['Temperature', 'Humidity', 'Noise
Level', 'Air Quality Index', 'Duration']


# Load and preprocess data with occupancy

X_with_occ, y_with_occ, label_encoder =
load_and_preprocess_data(data_path, features_with_occupancy)


# Load and preprocess data without occupancy

X_without_occ, y_without_occ, _ =
load_and_preprocess_data(data_path,
features_without_occupancy)


# Split data
```

```

X_train_occ, X_test_occ, y_train_occ, y_test_occ =
train_test_split(X_with_occ, y_with_occ, test_size=0.2,
random_state=42)

X_train_no_occ, X_test_no_occ, y_train_no_occ, y_test_no_occ =
train_test_split(X_without_occ, y_without_occ, test_size=0.2,
random_state=42)

# Initialize models

from sklearn.svm import SVC

from sklearn.ensemble import RandomForestClassifier

svm_model_occ = SVC(kernel='rbf', random_state=42)
svm_model_no_occ = SVC(kernel='rbf', random_state=42)

rf_model_occ = RandomForestClassifier(n_estimators=100,
random_state=42)

rf_model_no_occ = RandomForestClassifier(n_estimators=100,
random_state=42)

# Train models with occupancy

svm_model_occ.fit(X_train_occ, y_train_occ)
rf_model_occ.fit(X_train_occ, y_train_occ)

# Train models without occupancy

svm_model_no_occ.fit(X_train_no_occ, y_train_no_occ)
rf_model_no_occ.fit(X_train_no_occ, y_train_no_occ)

# Evaluate models

def evaluate_model(model, X_test, y_test, model_name):
    y_pred = model.predict(X_test)
    acc = accuracy_score(y_test, y_pred)

```

```

    loss = 1 - acc    # Treat 1 - accuracy as a proxy for
classification error (loss)

    print(f"{model_name} Accuracy: {acc:.4f}")

    print(classification_report(y_test,                y_pred,
target_names=label_encoder.classes_))

    return acc, loss

print("SVM Model with Occupancy:")

acc_svm_occ,    loss_svm_occ    =    evaluate_model(svm_model_occ,
X_test_occ, y_test_occ, "SVM with Occupancy")


print("SVM Model without Occupancy:")

acc_svm_no_occ,                loss_svm_no_occ                =
evaluate_model(svm_model_no_occ, X_test_no_occ, y_test_no_occ,
"SVM without Occupancy")


print("Random Forest Model with Occupancy:")

acc_rf_occ,    loss_rf_occ    =    evaluate_model(rf_model_occ,
X_test_occ, y_test_occ, "Random Forest with Occupancy")


print("Random Forest Model without Occupancy:")

acc_rf_no_occ, loss_rf_no_occ = evaluate_model(rf_model_no_occ,
X_test_no_occ,    y_test_no_occ,    "Random    Forest    without
Occupancy")


# Compare accuracies and losses

accuracy_values = [acc_svm_occ,  acc_svm_no_occ,  acc_rf_occ,
acc_rf_no_occ]

loss_values = [loss_svm_occ,  loss_svm_no_occ,  loss_rf_occ,
loss_rf_no_occ]

models = ['SVM with Occupancy', 'SVM without Occupancy', 'RF
with Occupancy', 'RF without Occupancy']

```

```

# Visualize accuracy and loss

fig, ax = plt.subplots(1, 2, figsize=(14, 6))

# Plot accuracy

ax[0].bar(models, accuracy_values, color=['blue', 'blue',
'green', 'green'])

ax[0].set_title('Accuracy Comparison')

ax[0].set_xlabel('Models')

ax[0].set_ylabel('Accuracy')

ax[0].set_ylim(0, 1)

# Plot loss

ax[1].bar(models, loss_values, color=['red', 'red', 'orange',
'orange'])

ax[1].set_title('Loss Comparison')

ax[1].set_xlabel('Models')

ax[1].set_ylabel('Loss')

ax[1].set_ylim(0, 1)

plt.tight_layout()

plt.show()

```