Self-Aware AI-Enabled Medical System

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***Abstract*—The medical field is crucial for saving lives, promoting public health, improving life quality, advancing scientific knowledge, and driving economic growth. Health monitoring devices are vital in providing timely and accurate data to healthcare providers for early diagnosis and intervention. However, wireless medical devices can be susceptible to data anomalies due to internal faults or external interference. These devices lack self-awareness, leading to inaccurate readings being communicated to users without their knowledge, potentially jeopardizing their health. To address this issue, our research focuses on developing a Self-Aware AI-Enabled Medical System. The proposed system employs machine learning and deep learning algorithms to make electronic health monitoring devices self-aware, with a specific focus on detecting interference and abnormalities. Furthermore, users are often unaware of the potential implications of inaccurate readings on their health, including symptoms of emergency medical conditions. To address this, our framework incorporates an Early Warning Score (EWS) system that infers if a user's vitals suggest any emergency medical condition and alerts them for immediate medical assistance. In evaluating our framework, we considered two models: Kalman Filter and Long short-term memory (LSTM). Overall, our framework, utilizing LSTM as the initial model, Random Forest Classifier for the EWS model, and Support Vector Classifier (SVC) for abnormality detection, achieved an impressive overall accuracy rate of 94%. By making health monitoring devices self-aware, our system enables users to receive timely notifications of potential medical conditions before severe symptoms arise, thus improving the effectiveness of electronic health monitoring devices in preventing and managing medical conditions. This advancement contributes to the well-being of individuals and society by enhancing healthcare outcomes and promoting proactive health management.**

***Index Terms*—Self Awareness, Artificial Intelligence, Health, Long Short-Term Memory (LSTM), Kalman Filter, Early Warning Score (EWS), Support Vector Classifier (SVC)**

I. Introduction

The field of medicine holds immense significance as it not only promotes the overall public health but also responds effectively to global health crises, and continuously expands scientific knowledge through collaboration. The findings highlighted in [1] underscore the indispensable role played by medical professionals in improving the quality of life and well-being of individuals and society as a whole.

Moreover, advancements in technology have improved ability of diagnosing, treating, and preventing various diseases and medical conditions. Medical imaging techniques such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT) Scans, and X-rays have revolutionized and challenged the traditional methods of diagnosing diseases and treating patients [2]. In addition, real-time patient monitoring is now possible with the growing use of portable medical devices [3]. These devices provides healthcare providers with continuous data on vital signs such as blood pressure, heart rate and oxygen levels. They are particularly useful for patients suffering from chronic diseases as it allows doctors to monitor their health and make prompt decisions.

Health monitoring devices can be connected to a network through either wired or wireless means. Wired connections involve physical cables connecting the device to the network, while wireless connections use radio waves to transmit data. Both methods have their own limitations and benefits. Wired connections are generally more reliable and secure, but can be more expensive to install and maintain. On the other hand, wireless connections are more flexible and cost-effective, but can be susceptible to interference and security breaches [4].

Currently, wireless health monitoring devices are not smart enough to detect any malfunctioning or external interference such as some entity trying to alter the data of these devices [5–7] i.e they do not exhibit Self-Awareness (SA) property. As the use of these wireless health monitoring devices increases, so does the risk of anomalies in the data measured by these devices [8]. The reasons for these incorrect measurements include technical faults and malicious attacks by external entities [5].

Our proposed solution is to make these electronic health monitoring devices Self-Aware by implementing a Self-Aware AI-Enabled framework which will be capable of detecting anomalous data in the vital (temperature, blood pressure, heart rate) readings. Our framework consist of multiple deep learning models to take in account the effect of external and internal environment on vitals and make prediction with high accuracy. The Self-Aware model will continue to update with each subsequent data to identify patterns and classify anomalous data with improved accuracy.

Moreover, the normal user is not aware of the possible implications of these vital measurements on his health such as he might have symptoms of medical conditions that could occur such as heart attack, stroke, fatigue, etc. The early diagnosis of such conditions and diseases helps in preventing progression of the disease [9]. Hence, our framework consists of an Early Warning Score (EWS) system to analyze the readings of vitals and infer if the user requires any immediate medical assistance. If this is the case, an alert is generated so the user can contact his nearest healthcare professional.

The following are the major contributions of this paper:

- To design a Self-Aware AI-enabled Medical System capable of detecting abnormality in the data of vitals it receives from different medical devices.This can be achieved by integrating health monitoring devices, training an AI model on user's dataset, and continuously analyzing the received data evolving with the time.
- To develop a system that can detect symptoms of medical emergencies through analysis of vital measurements. This can be accomplished by identifying the relevant vital signs and physiological parameters that are indicative of emergency conditions.
- To create a sustainable system that can perform with high accuracy over the long term. To achieve this, we focus on designing the system with scalability and modularity, allowing for easy integration of data from new medical devices and AI models as they become available.

This paper includes the design and results of our proposed framework which aims to enhance the accuracy of data measured by medical devices and provide appropriate alerts to lay users about any underlying medical conditions. This solution can improve the overall effectiveness of medical devices and ultimately enhance public health.

This paper contains six sections including the introduction. The second section outlines literature review and relevant work done in the field of healthcare. Third section defines Self-Awareness and emphasizes its need in health monitoring devices. Fourth section includes the design, methodology for this research and details of the deep learning models used. In fifth section we outline and discuss the results while the last section concludes the paper with future direction of the work.

II. Literature Review

The use of Internet of Things (IoT) applications, such as digital healthcare, is rapidly increasing worldwide due to the development of significant IoT technologies [10]. Medical Internet of Things (MIoT) aims to improve the health and well-being of individuals by providing seamless medical facilities, transparency, and improved services across various healthcare stakeholders [11]. With the rise of chronic diseases, an aging population, and emergencies like the recent COVID-19 pandemic, MIoT has gained attention for its potential to reduce the burden on global healthcare resources. MIoT enables remote healthcare services, real-time monitoring of patients, and efficient management of healthcare resources. Healthcare providers are utilizing various MIoT-based applications and services for patient treatment, disease management, and medical diagnosis, leading to improved patient care and reduced costs [5, 12–15]. Medical sensors, whether implanted or worn by patients, provide continuous monitoring of vital body parameters and pathological details, enabling remote and real-time monitoring of a patient's condition [16–23]. The collected data is analyzed and sent to cloud storage or medical data centers for further processing, enabling stakeholders such as doctors, caregivers, and insurance service providers to access relevant information [23, 24]. Artificial Intelligence (AI) and machine learning (ML) techniques, such as deep learning, have shown promise in the medical field. They are used to interpret and analyze large and complex datasets, diagnose medical conditions, and predict patient outcomes [25, 26]. AI's potential in healthcare extends beyond high-income economies, where it can address medical skills and staffing shortages and provide access to specialists [27]. Examples include AI's ability to diagnose chest X-ray-based pneumonia and tuberculosis, identify signs of severe malaria in retinal images, and classify skin cancer using photos with accuracy comparable to dermatologists [28, 29]. AI can also predict the progression of type 2 diabetes from pre-diabetes using electronic health records [30]. These advancements in AI and ML techniques have the potential to significantly improve the quality of care and early detection of medical conditions. However, the integration and connectivity of smart medical devices in the MIoT environment introduce vulnerabilities that can compromise privacy, security, and data accuracy. Technical faults, security breaches, and external interference can result in inaccurate readings and jeopardize patient safety [5–7, 31]. Electromagnetic interference (EMI) and jamming are particular threats to wireless medical devices' reliable and safe operation [32]. Therefore, detecting and mitigating EMI and other security threats are essential to ensure the proper functioning of these devices [33]. To address the challenges associated with digital medical devices, the development of a self-aware system is proposed. This system continuously monitors and classifies abnormalities in the data collected by medical devices, improving reliability, accuracy, and early detection of medical emergency conditions. By learning and adapting to patterns in the data, the self-aware system can differentiate and identify the cause of anomalous readings, ensuring accurate classification and reducing the risk of misinterpretation. Furthermore, the system can infer underlying medical conditions based on vital readings and provide appropriate alerts to users, potentially enabling early intervention and improved patient outcomes. In conclusion, the increasing adoption of MIoT applications and the advancements in AI and ML techniques offer significant opportunities to enhance healthcare services. However, it is crucial to address the associated risks and vulnerabilities to ensure patient safety, data accuracy, and device reliability. By detecting and mitigating threats like EMI and improving the self-awareness of digital medical devices, the quality of care can be improved, leading to better patient outcomes.

III. Self-Awareness in Health Monitoring Devices

The importance of portable and smart health monitoring devices like wristbands and smartwatches has been highlighted due to the aging population and recent pandemic [34]. With a projected increase in the elderly population, there's a growing need for healthcare services for age-related illnesses. The Internet of Things (IoT) offers a solution by enabling continuous monitoring through wearables and IoT technology. These devices can monitor activities without disruption, while AI techniques provide insights for better care [35, 36].

Integrating self-awareness in medical devices reduces caregiver burden and ensures measurement reliability [37]. Self-awareness involves understanding a system's condition and adapting to new situations. It's explored in various domains, including health monitoring [38]. Focusing on remote health monitoring, research underscores the benefits of self-aware design [39].

Friston's model of self-awareness presents a promising approach to making machines self-aware. This model incorporates conscious processing with a temporal depth that enables inferences about the consequences of action [40]. By employing Bayesian dynamical systems, Friston's model can describe and simulate human brain findings through neuron firings, providing an indeterminate and hierarchical self-coherent representation. For health devices, it detects errors by comparing observations and predictions, updating the model. Integrating self-awareness in vital monitoring improves patient care and device capabilities

IV. Methodology

A. Data Set

The data generated by medical devices is a collection of various vitals, such as heart rate, oxygen level, blood pressure, and body temperature. Therefore, choosing the appropriate vitals to work with is a critical task in any research project. Due to the sensitive nature of medical data, obtaining a sufficient amount of real-world medical data can be challenging. Therefore, we have decided to generate synthetic data sets to ensure that we have enough data to train and test our models. Although the generated data may not fully represent real-world data, we are confident that our models will provide accurate results as we have carefully selected the appropriate vitals and external factors to be considered. The use of synthetic data sets will also allow us to experiment with different scenarios and conditions that may not have been possible with real-world data sets.

After conducting thorough research and careful consideration, we decided to focus on three vitals: body temperature, heart rate, and blood pressure. We determined that these vitals are the most affected by diseases, changes in activity, and environment. To ensure the accuracy of our model, we defined several external factors, including age, gender, weather conditions, and activities of the person, and set them as constants. Table i outlines the details of these constants.

TABLE i: Values of constants

Constants	**Values**
Age Group	25 - 30
Gender	Male
Weather	Climate conditions of Karachi, Pakistan
Activities	Sleeping, Sitting, Walking, Running

We have established the average value ranges of our test subjects and the initial seed value to synthetically generate the data set. It is crucial to define these controls before generating the data set to ensure that extreme variations in data do not affect our system's performance. The values of these constants are defined in Tables ii.

TABLE ii: Average range of vital values

Vitals	**Average range**
Body Temperature	35.28 - 37.26 °C
Systolic Blood Pressure	90 - 120
Diastolic Blood Pressure	60 - 80
Heart rate	60 - 100

Since our system is personalized, we need to train and test it on individual data. Therefore, we must define the controls of our subjects. Additionally, we considered the effects of weather and different activities on a person's vitals. We have outlined the effects of weather on the vitals in table iii, and the effects of different activities on the vitals in table iv.

TABLE iii: Effect of weather on body temperature

Weather Conditions	**Effect on body temperature**
Greater than 35°C	Increase by 0.2°C
Between 30 and 35 °C	Increase by 0.1°C
Between 25 and 30 °C	Decrease by 0.1°C
Less than 25°C	Decrease by 0.2°C

The Early Warning Score (EWS) system is a crucial component of our proposed framework, designed to monitor vital measurements like temperature, blood pressure, and heart rate. It generates a score based on these measurements and continuously tracks any deviations from the normal range. If the score exceeds a predefined threshold, an alert is triggered, notifying the user or healthcare provider of the need for immediate medical attention. Our EWS system acts as a safety net for individuals managing their health at home, providing early warnings and enabling proactive intervention.

To train our Early Warning Score (EWS) system, we created a dataset to study the impact of mild medical conditions, such as the common cold or flu, on vital signs. Table v provides details of the vital signs and their corresponding values. The dataset used for training and testing the EWS model consisted of 19,500 records, which were split in a 70-30 ratio, with an equal number of records for each EWS score ranging from 0 to 12. Figure 1 presents the kernel density distribution graph depicting the dataset used for training the Early Warning System (EWS) model for each vital sign. This graph serves as a visual representation of the data's probability density function, enabling a deeper understanding of its distribution and characteristics. In each graph, the x-axis represents the vital sign range, while the y-axis indicates the density of the data at any given point. The utilization of different colors helps distinguish between various EWS scores. Upon examining each graph, we can observe that EWS scores ranging from 0 to 5 exhibit a unimodal shape, characterized by a single peak. Conversely, scores ranging from 6 to 12 display a bimodal shape, with two distinct peaks. Furthermore, a comparison between the two score ranges reveals that EWS scores ranging

TABLE iv: Effect of different user activities on vitals

Activities	Body temperature	Systolic Blood Pressure	Diastolic Blood Pressure	Heart Rate
Sleeping	Decrease by 0.5°C	Decrease by 10 %	Decrease by 10 %	Decrease by 20 %
Sitting	No effect	Decrease by 5 %	Decrease by 5 %	Decrease by 7 %
Walking	Increase by 0.25°C	Increase by 12 %	Increase by 12 %	Increase by 10 %
Running	Increase by 1°C	Increase by 20 %	Increase by 15 %	Increase by 25 %

from 0 to 5 exhibit a narrower spread in comparison to scores ranging from 6 to 12, indicating lower variability among the vital sign measurements within the former range.

TABLE v: Effect of mild fever on vitals

Vitals	Effect
Body Temperature	Increase by 0.5 to 1.0°C
Systolic Blood Pressure	Decrease upto 10 mmHg
Diastolic Blood Pressure	Decrease upto 10 mmHg
Heart Rate	Increase up to 20 bpm

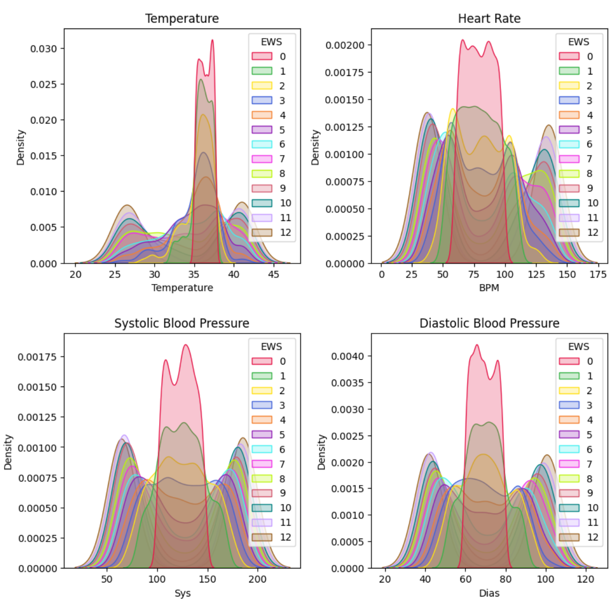


Fig. 1: Distribution of vitals in EWS training/testing dataset

The interference and abnormality detection model plays a vital role in our research. It is aimed at detecting abnormalities in sensor data caused by an external intruder. To train our abnormality detection system, we considered the effects of intruders, which can cause abnormal effects on sensor readings. Our dataset includes both additive and subtractive effects of the External Signal Interference (ESI) on the sensor readings, as shown in Table vi. The dataset used for training and testing the abnormality detector model was divided into four activities, each of which contained 90,000 records, which were split in a 70-30 ratio. The records were equally distributed among normal data, data affected by additive ESI, and data affected by subtractive ESI. Figures 3 and 4 display the distribution of the dataset for each activity and their vital sign. The x-axis of each subplot shows the range of vital signs, and the y-axis represents the density of the data at any given point. Normal data is represented by zero (0), data affected by additive ESI is represented by one (1), and data affected by subtractive ESI is represented by two (2).

TABLE vi: Effect of External Signal Interference (ESI) on vitals

Type of External Signal Interference (ESI)	Effect on vitals
Additive	Increase by 20 to 30%
Subtractive	Decrease by 35 to 45%

Finally, our framework utilizes a dataset consisting of hourly time series data spanning three months, which contains 2180 records. Of these records, 7% are associated with an EWS value ranging from 0 to 12. The distribution of the testing dataset for each vital sign is illustrated in Figure 5, with the x-axis showing the normal data and EWS value data, and the y-axis representing the range of each vital sign. The width of the graph denotes the number of records at any given point, while the height represents the spread of the data across the range. Additionally, 12% of the records were abnormal records affected by external interference. The distribution of the dataset for each vital sign is shown in Figure 6, with the x-axis showing the range of vital signs and the y-axis representing the density of the data at any given point. Normal data is represented by zero (0), and data affected by the ESI is represented by one (1). First, we trained the initial model of our framework, which utilized the LSTM architecture, using one month of the dataset. Subsequently, we evaluated the model's performance on the remaining two months of data and simultaneously updated it based on the evaluation results.

B. Predictive Models

We propose a sophisticated and intelligent framework displayed in the figure 2 that monitors the health status of users in real time. As shown in algorithm 1, our system employs an initial model that is trained on the user's data. This initial model shall serve as a baseline to later monitoring and analysis of the user's vital signs. We have used Kalman Filter (as a linear predictor model) and Long Short-Term Memory (LSTM) (as a deep learning model) as our initial models.

Kalman Filter was chosen because of its capability to estimate the state of a system even when measurements are noisy. It predicts future state of a system based on previous and current states [41]. It is particularly suitable for modeling dynamic systems with uncertain observations, making it a

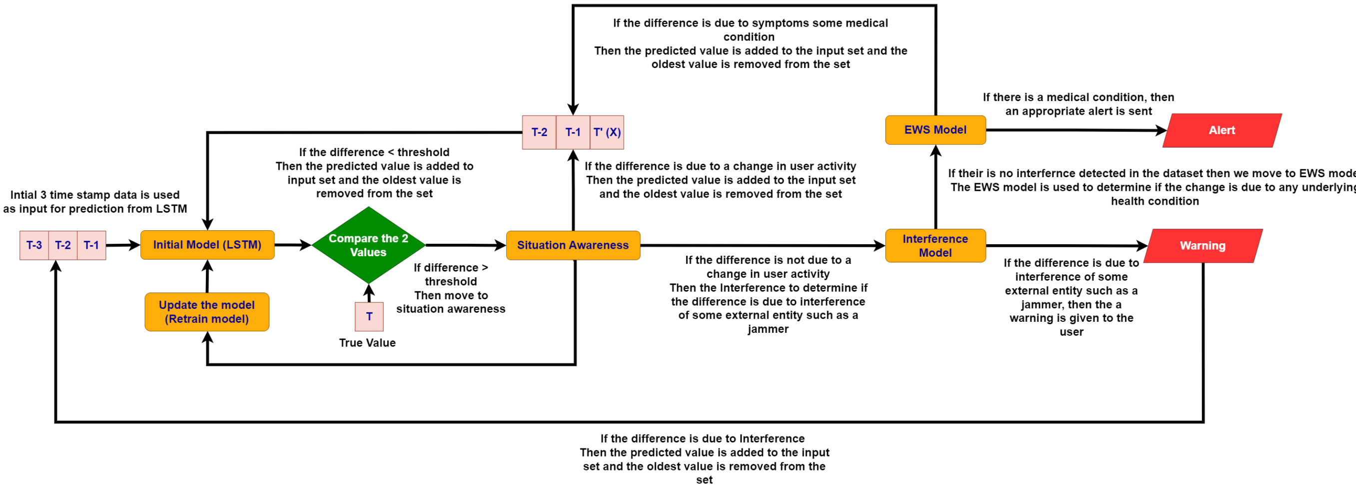


Fig. 2: Proposed Flow Diagram

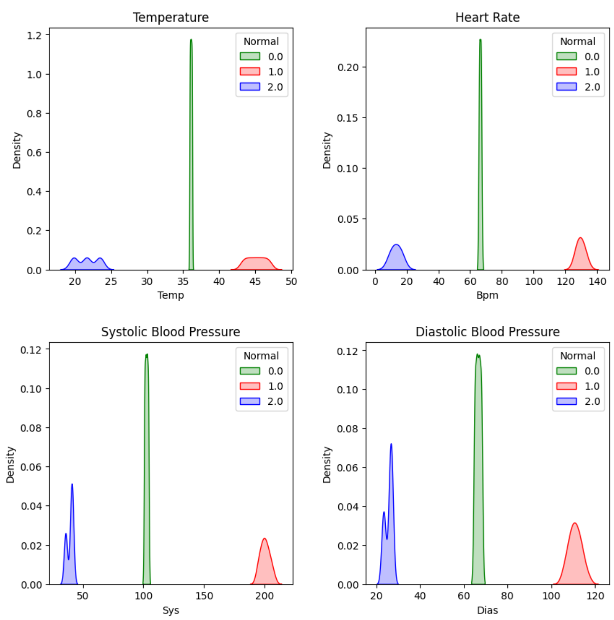


Fig. 3: Distribution of abnormality detection training/testing dataset for vitals while the user is sleeping

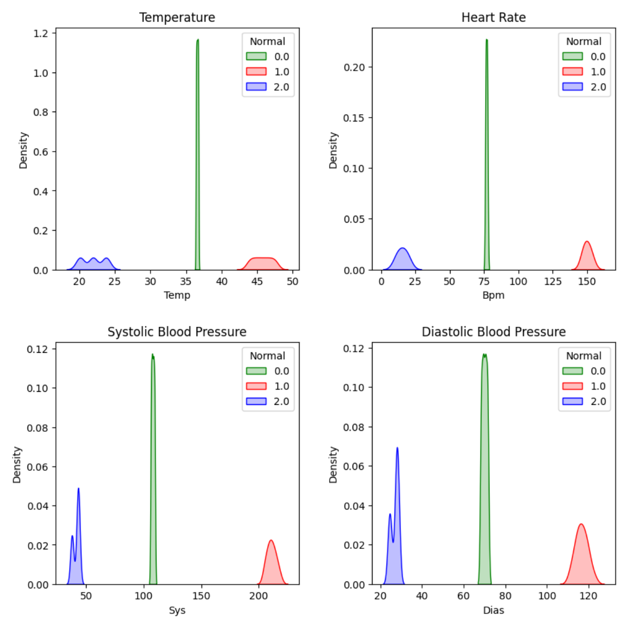


Fig. 4: Distribution of abnormality detection training/testing dataset for vitals while the user is sitting

valuable tool for processing real-time sensor data. By incorporating the Kalman Filter as an initial model, our framework can enhance the accuracy and reliability of the captured vital sign data, providing a strong foundation for subsequent analysis.

Furthermore, we selected Long Short-Term Memory (LSTM) as another initial model. LSTM is a type of recurrent neural network (RNN) specifically designed to handle sequential data [42]. Its unique architecture enables it to capture long-term dependencies and patterns within time series data. Through the utilization of LSTM, our framework can effectively capture and understand the temporal dynamics of the user's vital signs, leading to improved prediction and comprehension of changes in health status.

If sensor reading reveals deviation from the predicted reading of an initial model by a certain threshold, Situation Awareness model is activated to detect if the deviation is due to change in user's activity and weather conditions. If this is the case, our system will update the initial model and move to next prediction.

However, if the Situation Awareness model determines that the difference in readings is not due to a change in the user's activity or external factors such as weather, our system will activate the Interference model. The Interference model shall be used to detect any external interference, such as a jamming

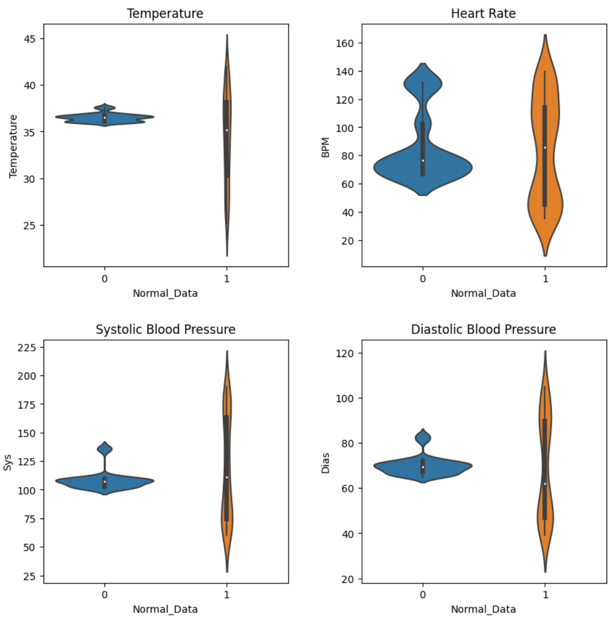


Fig. 5: Distribution of testing dataset for framework

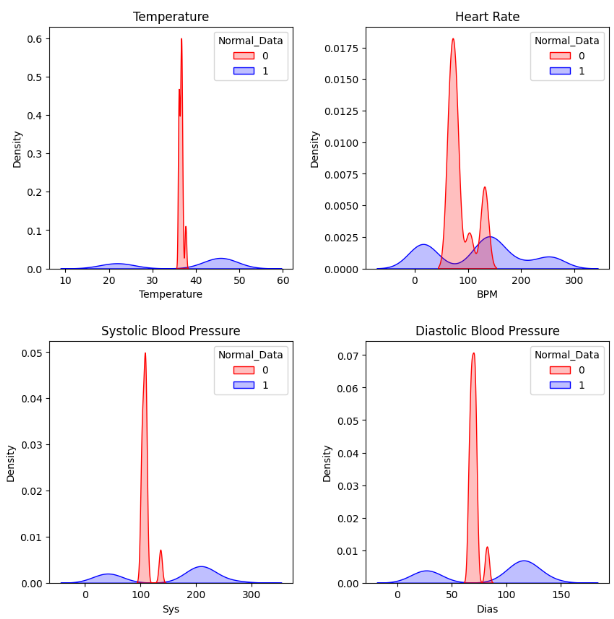


Fig. 6: Distribution of testing dataset for framework

device, which may affect the sensor readings.

If no external interference is detected, EWS model will be activated which will be used to determine whether a change in vital signs is indicative of any medical condition. If the EWS model detects a potential emergency condition, our system will update the initial model to account for the new information. This allows our system to continually adapt and improve its accuracy over time, ensuring that it is always providing the most accurate and reliable health monitoring for users.

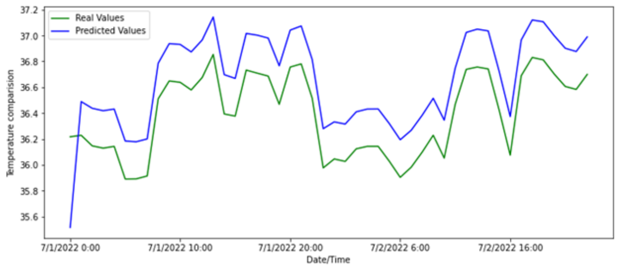
Algorithm 1 Psuedocode for proposed Self-Aware System

```
function MAIN
    INITIALIZE_MODEL
    SET_THRESHOLD(threshold_value)

    observations ← GET_OBSERVATIONS
    predictions ← GET_PREDICTIONS

    for i in range(length(observations)) do
        observation ← observations[i]
        prediction ← predictions[i]

        error ← CALCULATE_ERROR(observation, prediction)

        if error ≤ threshold then
            continue // Move to the next observation
        end if

        situation_awareness ←
CHECK_SITUATION_AWARENESS(observation)

        if situation_awareness then
            UPDATE_BASE_MODEL(observation)
            continue // Move to the next observation
        end if

        is_abnormal ←
CHECK_ABNORMALITY(observation)

        if is_abnormal then
            INDICATE_ABNORMALITY
        else
            ews ← CALCULATE_EWS(observation)
            GENERATE_EWS_WARNING(ews)
        end if

        observations ← GET_OBSERVATIONS
        predictions ← GET_PREDICTIONS
    end for

end function
```

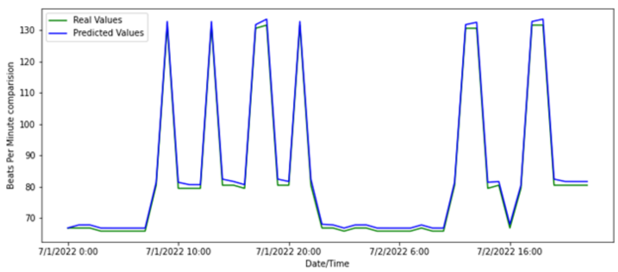
V. Simulation and Results

In this study, our objective was to enhance the accuracy of medical device readings by analyzing the data generated from these devices. To achieve this goal, we utilized a combination of deep learning and machine learning models in three main sections of our experiment.

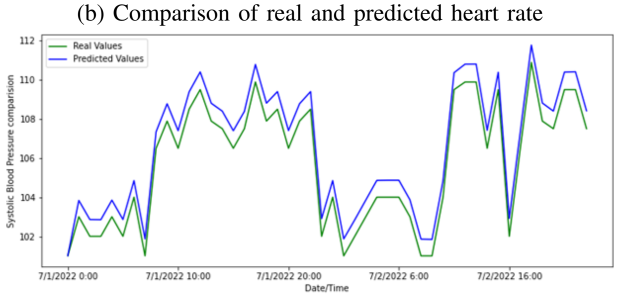
In the first section, we evaluated Kalman Filter and LSTM models for initial modeling. The performance of both models was assessed for all vitals for up to 48 hours and up to 24 hours, and the results are depicted in Figures 7 and 8 respectively. Although Kalman Filter showed higher accuracy, it only considered the last reading of the vitals when making



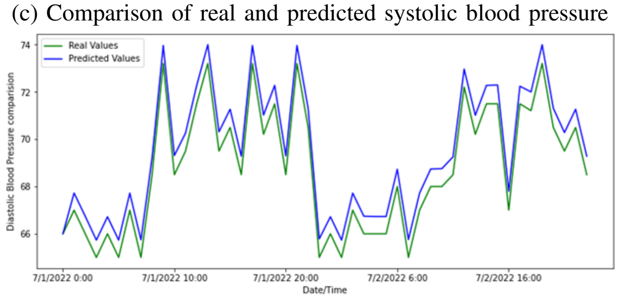
(a) Comparison of real and predicted temperature



(b) Comparison of real and predicted heart rate



(c) Comparison of real and predicted systolic blood pressure

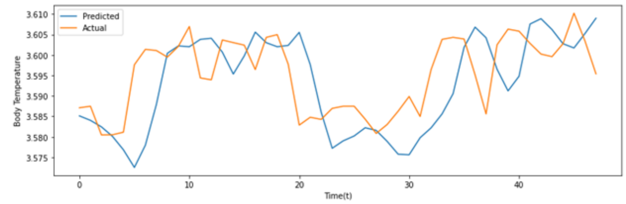


(d) Comparison of real and predicted diastolic blood pressure

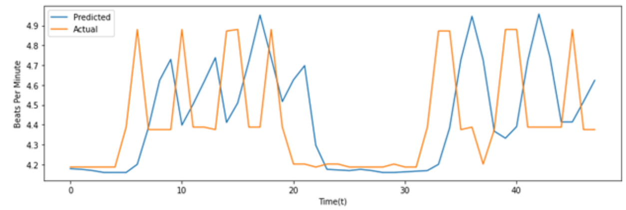
Fig. 7: Predictions by Kalman Filter

predictions, which was not suitable for our problem. Therefore, we selected LSTM as our initial model since it is a high-dimensional model and considered the last three readings when making predictions regarding the current vitals.

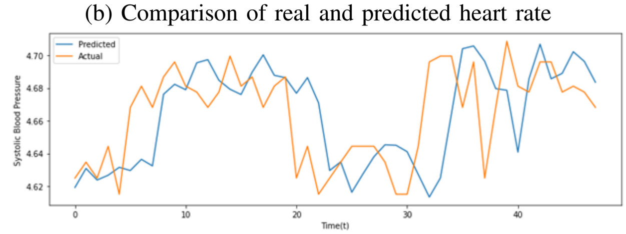
In the second section, we utilized random forest and decision tree classifiers to classify the Early Warning Score (EWS). The training and testing dataset for this model contained 19,500 records, divided into 13,650 records for the training dataset and 5,850 records for the testing dataset. Our analysis from Figures 9 and 10 revealed that both models were successful in classifying EWS values with high accuracy. However, after weighing the performance of both models, we selected the random forest classifier as our model of choice. This



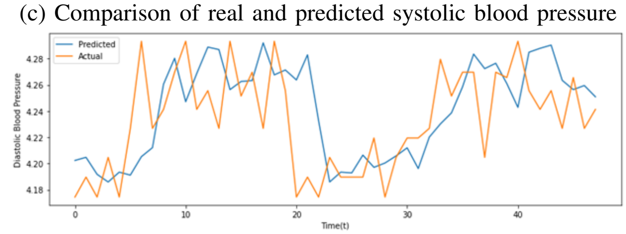
(a) Comparison of real and predicted temperature



(b) Comparison of real and predicted heart rate



(c) Comparison of real and predicted systolic blood pressure



(d) Comparison of real and predicted diastolic blood pressure

Fig. 8: Predictions by LSTM

decision was made based on the fact that the random forest classifier marginally outperformed the decision tree classifier in our framework.

In the third section, we employed a Support Vector Classifier (SVC) for our abnormality detection system. To train and test the model, we divided the dataset into four activities, each consisting of 67,500 records. The training dataset contained 47,250 records while the testing dataset contained 20,250 records. Our results, as shown in Figure 11, indicate that the SVC successfully detected and classify abnormal sensor readings caused by external interference with a high degree of accuracy.

In summary, the deep learning and machine learning models employed in this study were effective in predicting vitals, EWS values, and detecting abnormal sensor readings. Our findings highlight the potential of our system to enhance the accuracy and reliability of medical devices, which is critical for patient safety and quality of care.

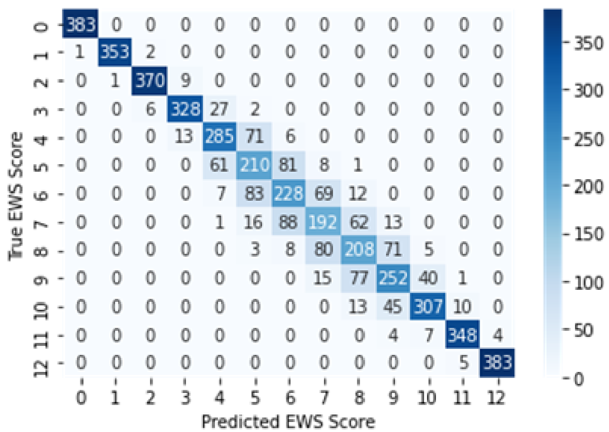


Fig. 9: Confusion matrix for EWS scores predicted using decision tree classifier

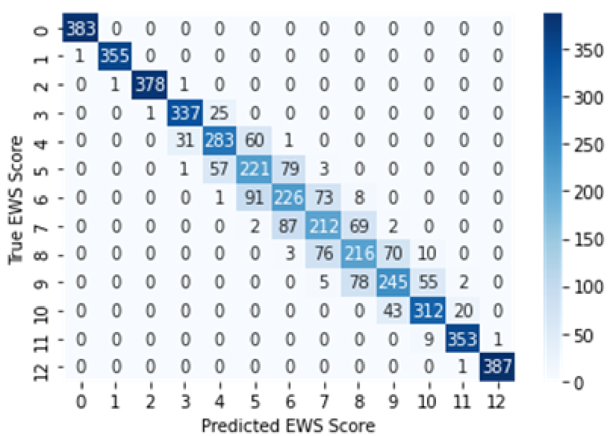


Fig. 10: Confusion matrix for EWS scores predicted using random forest classifier

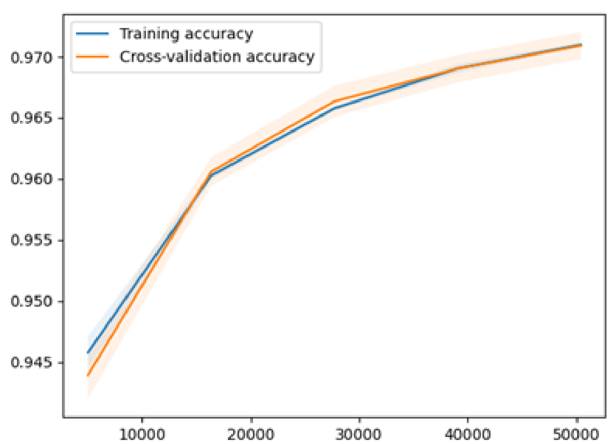


Fig. 11: Abnormality Detection Accuracy using Support Vector Classifier (SVC) - Comparison between Training and Cross-validation Accuracy

VI. Conclusion and Future Work

This paper presents a comprehensive framework integrating self-awareness, abnormality detection, and an early warning score to enhance the accuracy of data measured by medical devices and accurately predict users' current health status. The framework achieves high accuracy in detecting abnormal readings, inferring medical conditions, predicting activity-related vital changes, and overall health status predictions. Notably, the framework successfully detects 95% of abnormal readings, infers medical conditions in 68% of cases, and predicts activity-related vital changes with 98% accuracy. With an overall prediction accuracy of 94%, the framework meets its objectives effectively.

In the future, we plan to enhance the framework's accuracy for inferring underlying medical conditions by exploring new techniques and methods. We also intend to utilize transformers instead of LSTM for time series sequential data analysis and prediction. Additionally, we aim to expand our work to include different vital signs, user activities, and diseases, making our framework more comprehensive. Finally, our goal is to integrate our framework into smart health bands to provide affordable and accessible healthcare to a wider population. Our framework holds promising potential to revolutionize the healthcare industry by offering reliable and efficient early health diagnosis and management.

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