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An IoT-Based Health Monitoring System with Real-Time Location Identification for Emergency Response

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Abstract

Limitation of the classical health monitoring and location tracking technology tends to impair human safety and operational efficiency during emergency health situations. Traditional systems are usually not sufficient in capturing real-time physiological data, are lowly connected in far places and must be triggered manually during emergency situations. This study introduces the design and deployment of an Internet of Things (IoT)-based solution that would overcome these drawbacks and allow permanent physiological monitoring and geolocation in real time. The system is supplemented with wearable sensors that can measure the most vital health parameters, including the heart rate, the blood oxygen saturation (SpO_2), and the geography position, measured with the assistance of the MAX3010 sensor module. The sensor data are delivered to an HTTP-enabled IoT server and shown in a web-based dashboard, which provides an opportunity to remotely monitor the patient in real-time and respond immediately in case of emergency. In addition, it introduces another line of approach, namely enhancing situational awareness, operational responsiveness, and survival of individuals in potentially dangerous circumstances.

Keywords
Internet of Things (IoT), Health Monitoring System, Real-Time Location Tracking, Blood Oxygen Saturation, Pulse Oximeter Sensor.

1. Introduction
Modern life constitutes a rapid technological change in the 21st century, and one of the most significant changes has become the Internet of Things (IoT). The internet is used to connect physical devices, sensors, and computing systems with the Internet, which allows the exchange of real-time data and autonomous decision-making through IoT. It has brought revolution in smart manufacture in industry by optimizing entire production in real time (Tasnim et al., 2024). Its dynamic development has significantly impacted the healthcare and emergency response systems due to the ability to operate in continuous monitoring, data-driven analytics, and intelligent communication networks. The combination of IoT, wearable sensors, cloud computing, and edge processing has increased the possibilities of more situational awareness and making decisions in extreme settings. However, individuals at far away or unsafe places still experience issues of low situational awareness, lapsed medical attention, and ineffective communication. The victims may suffer injuries, dehydration, fatigue, or thermal stress in case of natural or remote incidents and this may deteriorate unless attended to immediately and assisted. The commonly known and widely used traditional monitoring instruments either based on manual reporting or individual GPS trackers are not fitted with real-time physiological functions such as heart rate and oxygen saturation. This disintegration does not allow responding to the emergencies better and reduces the level of success of the rescue operations. To overcome such shortcomings, the growing opportunities of the IoT have been the driving force to the development of unified systems that consider real-time health monitoring and precise location services. Coordination of positional and physiological data is also essential in a situation of severe matter to prevent deaths and improve the control of the emergency situation. The article presents a complete IoT model, which is based on sensor fusion, wireless communication, and analytics to enhance situational awareness and create the ability to be responsive in life-threatening scenarios.

1.1 Objectives

The main goal of the research is to develop and deploy a smart IoT-based system that could observe the health state continuously and track the position in real time in order to provide a quick reaction when the health condition is critical. Such a system is hoped to be able to monitor the main physiological indicators of the condition of primary users, such as heart rate and oxygen saturation (SpO_2) of primary users to facilitate preventing and responding to possible health emergencies. In addition, it aims at integrating real-time location tracking using an HTTP-based internet of things server and visualizing the obtained health and location data using a web-based user interface (WEB UI) to access and manage the emergency effectively.

2. Literature Review

Real-time monitoring and emergency response in extreme and remote settings have been transformed through the addition of the IoT technology to healthcare and tracking systems. Remote soldier monitoring system, which was developed early by Xinfeng and Wang (2012), showed the possibility in acquiring vital signs wirelessly and locating the soldier in a manner aided by satellite-based communication, though accuracy and processing speed were limited. In 2016 to 2019, more noninvasive systems incorporating wearable sensors have been developed, capable of measuring physiological levels and environmental factors to improve the levels of safety and comfort in people in harsh environments (Aqueveque et al., 2016; Patil et al., 2017; Murdock and Hagen, 2018; Kulkarni et al., 2019). These works focused on low-cost hardware integration, cloud computing, and wireless data transmission as the basis of the IoT-based health monitoring within military and industrial contexts. Nevertheless, issues like the short battery life, incomprehensive physiological tests, and unreliable data connections remained, and they encouraged innovative efforts to make the system efficient in data management and strong in the design of the system.

Recent developments are aimed at improving the accuracy of the data, its energy efficiency, and intelligent decision-making by artificial intelligence (AI), cloud analytics, and Low Power Wide Area Networks (LPWAN). Examples of such systems include the smart bike monitoring system by Muhamad et al. (2020), which monitors the cyclists through the IoT network to enable real-time monitoring of health and performance; the multilayer inference model by Kang et al. (2020); the accident alert system through the use of GPS and GSM to better emergency response by Mounika et al. (2021); and the wireless sensor network by Garg et al. (2021), which is used to monitor the mountaineering. To allow football players to have an overall evaluation of their health and respond quickly in case of an emergency, emerging technologies have merged smart vests and clothing, wearable sensors and gadgets, LoRa communication, and AI-based predictive algorithms (Jiang et al. (2021), Sahu et al., 2022; Ardina et al. (2022), Aggarwal et al., 2023; Pund et al. (2023), Donavalli et al., 2024, Surender et al The integration of physiological tracking, positioning, and secure communication (Wearable gadgets (Prasanna et al., 2022) and wearable sensors (Evangeline C. et al., 2024) and other products (Smart Soldier Jacket and IoT-based mountaineering systems (Chandra et al., 2024; Evangeline et al., 2024) are product examples) represent the merging of physiological monitoring, location tracking, and safe communication and provide better situational awareness and operational safety.

Sabarimuthu et al. (2022) proposed and developed an IoT module to help soldiers communicate with the base station in case of injuries, but Schweizer et al. (2022) emphasized that more objective data on the level of fatigue among soldiers was needed to prevent the occurrence of accidents and injuries due to lack of attention or decreased vigilance. In addition, Vinoth Kumar et al. (2023) suggested a system that combined health monitoring, location tracking, and communication to enhance the safety of climbers, whereas R. Govarthan et al. (2023) provided a comprehensive approach to enhancing the safety and operational performance of soldiers in the battlefield with the help of a medical monitoring system. Conversely, Abdulmalek et al. (2024) made a strong IoWT-HHMS that was designed to monitor the health of people in real time that demonstrated an amazing accuracy in the measurement of vital signs. Mathematician Zadeh was the first person who described Fuzzy logic that is paraller to human thinking and has multiple values (Farhan et al. 2018). This logic expresses smaller, medium, and higher. Generally, binary logic has crisp values, while the fuzzy sets deal with fuzzy values (Farhan et al.., 2021). Several scientists used this logic in health monitoring systems. A research team lead by Al-Dmour had discussed an equivalent warning system that utilizes fuzzy logic techniques to categorize patients' status analyzing health parameters like pulse and blood pressure (Al-Dmour et al., 2019).

Network coverage, data security, sensor reliability, and long-term power management are some of the major concerns in spite of these developments. The current research expands these findings to define and resolve the inherent technological gaps in the IoT-based emergency health and tracking system to enhance reliability and responsiveness in emergent situations of critical applications.

3. Methodology
To design a smart IoT-enabled device for health monitoring and location tracking in emergencies, a system has been developed with the help of STM32 microcontrollers, sensors. An HTTP IoT server, and then represent the data via a WEB UI interface.

3.1 Block Diagram
Fig. 1 shows the block diagram of the IoT-based Health Monitoring & Location Tracking System for Emergency Situations. This system is developed for real-time monitoring of emergency health parameters, such as heart rate and oxygen saturation. Alongside that, this system ensures constantly real-time location tracking by integration of GPS Antenna and GSM Antenna for efficient location tracking system. In this system, DC power supply has been used. The system has used STM32 as microcontroller. Heart Rate and Pulse Oximeter Sensor Module - MAX30102 has been used to read and collect the heart rate and blood oxygen saturation (SpO_2) data of the user in real-time. The result is a substantial advancement in comparison to pertinent works from recent years.

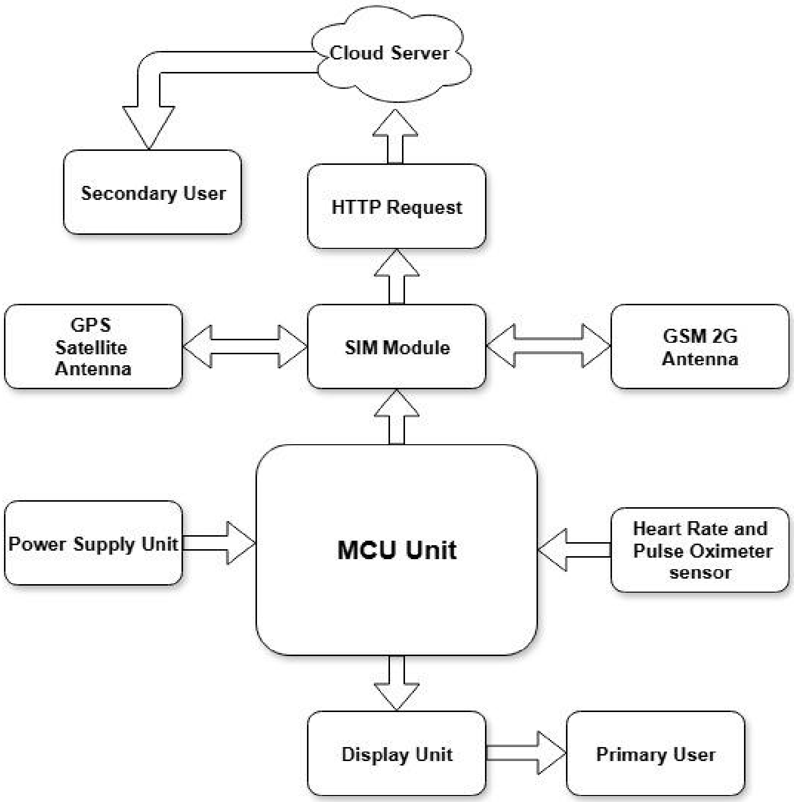


Figure 1. Block Diagram of IoT-enabled Health Monitoring & Location Tracking System

3.2 Health Monitoring & Location Tracking device data on LCD Display of Primary Users
This developed system consists of various sensors and other modules. We discuss the sensor outputs displayed on the LCD, accompanied by relevant figures and explanations. Figure 1 shows that when the system and STM32 microcontroller are started and the initialization process is completed with all sensors, the system displays its name on the 16x2 LCD blue backlight display.

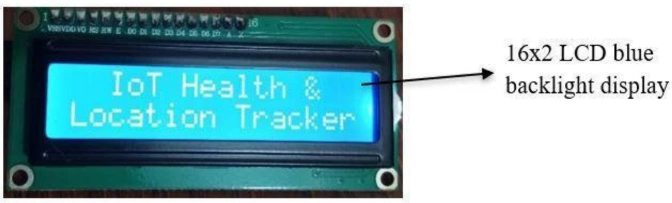


Figure 2. Initialization of the process of the system

Figures 2, 3, 4, 5, and 6 display a conditional yes-no notification system alongside other emergency-related alerts, all presented on a 16x2 LCD featuring a blue backlight for primary users.

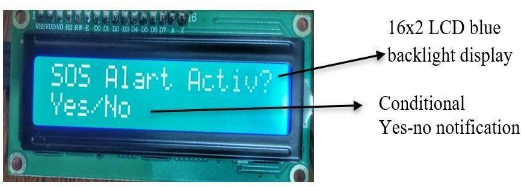


Figure 3. Showing conditional yes-no notification on 16X2 LCD blue backlight display

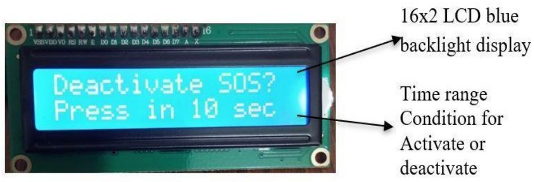


Figure 4. Showing time range condition for deactivate notification on 16X2 LCD blue backlight display

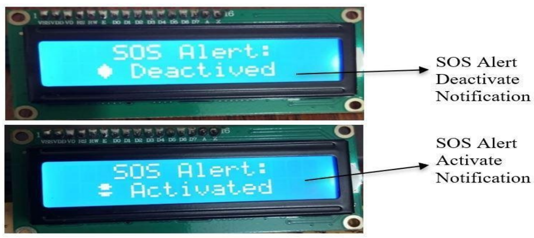


Figure 5. Showing the image after activating & deactivating the alert on the 16X2 LCD blue backlight display

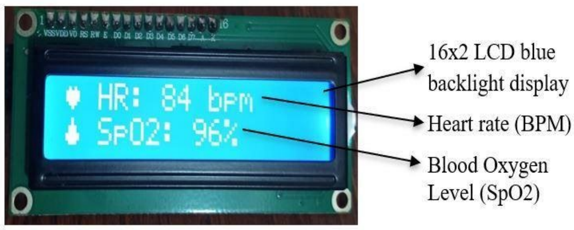


Figure 6. Showing Heart rate (BPM) and Blood Oxygen Level (SpO2) on 16X2 LCD blue backlight display

3.3 Flow Chart

Figure 7 represents the flow chart of an IoT-enabled system for health monitoring and a location tracking system device for emergencies. The objective here is to develop a real-time vital health monitoring and location tracking system for individuals.

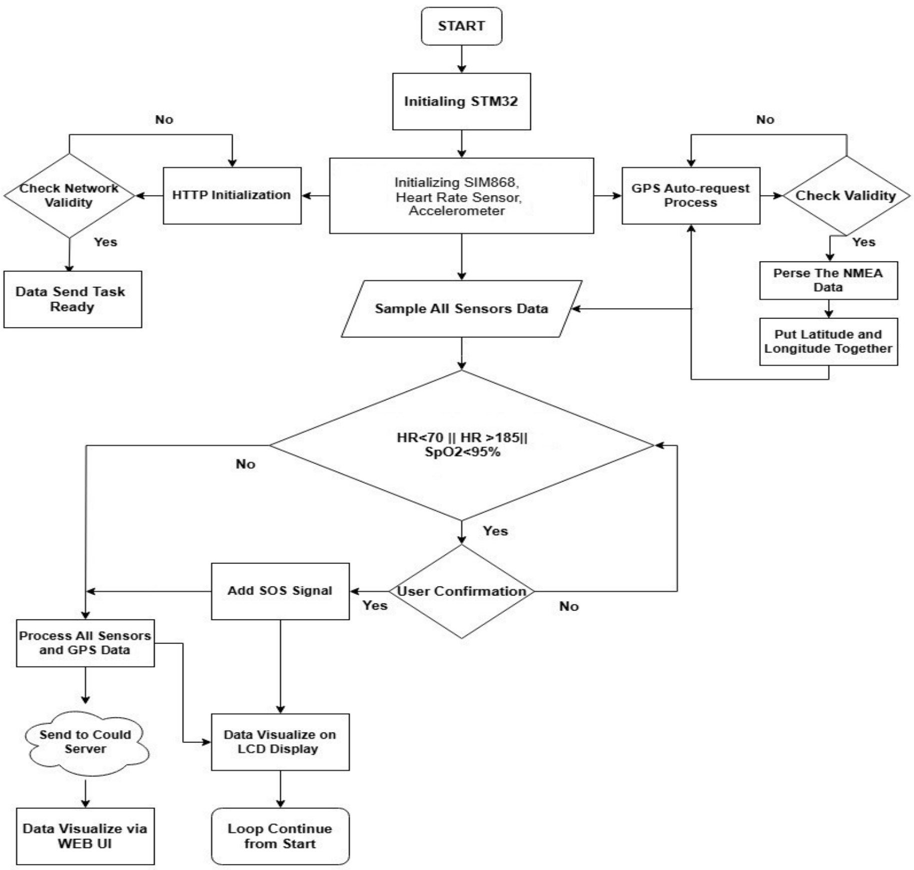


Figure 7. Flow Chart of IoT-based Health Monitoring & Location Tracking System

After that, the system processes all of the data from the sensors and GPS, then it uploads it to a server in the cloud and visualizes it through an LCD and a web-based user interface for remote monitoring. At long last, the process is finished off with the visualization of the data.

4. Result

4.1 Accuracy Detection and Confusion Matrix Table with Calculation for Sensors and the Overall System

Table 1 displays 25 distinct heart rate data from our Heart Rate and Pulse Oximeter Sensor Module MAX30102 as Sensor Reading [Predicted Value], along with 25 actual heart rate data from the Medical Pulse Oximeter as Actual Heart Rate [True Value] for comparison and better understanding of accuracy. We have classified these data into two categories: Normal and Emergency.

Table 1. Heart rate reading from: Heart Rate and Pulse Oximeter Sensor Module - MAX30102 & Standard Pulse Oximeter

Test #	Primary User Activity Status	Sensor Reading (bpm) [Predicted Value]	Actual Heart Rate (BPM) [True Value] Pulse Oximeter	Classification (Predicted) Sensor	Classification (True) Pulse Oximeter
1	Resting	67	72	Emergency	Normal
2	Resting	85	84	Normal	Normal
3	Resting	92	93	Normal	Normal
4	Light Physical Activity	113	111	Normal	Normal
5	Light Physical Activity	108	107	Normal	Normal
6	Light Physical Activity	123	124	Normal	Normal
7	Moderate Exercise	139	142	Normal	Normal
8	Moderate Exercise	148	149	Normal	Normal
9	Moderate Exercise	156	157	Normal	Normal
10	Intense Exercise	186	183	Emergency	Normal
11	Intense Exercise	189	188	Emergency	Emergency
12	Intense Exercise	196	197	Emergency	Emergency
13	Moderate Exercise	146	145	Normal	Normal
14	Moderate Exercise	138	138	Normal	Normal
15	Resting	97	95	Normal	Normal
16	Resting	84	85	Normal	Normal
17	Sleeping	56	57	Emergency	Emergency
18	Sleeping	51	50	Emergency	Emergency
19	Sleeping	55	54	Emergency	Emergency
20	Resting	81	82	Normal	Normal
21	Moderate Exercise	136	134	Normal	Normal
22	Light Physical Activity	117	116	Normal	Normal
23	Intense Exercise	183	194	Normal	Emergency
24	Moderate Exercise	146	145	Normal	Normal
25	Moderate Exercise	152	151	Normal	Normal

Figure 8 shows a graph with 25 heart rate measurements taken from the Heart Rate and Pulse Oximeter Sensor Modules during different situations, such as resting, light activity, moderate exercise, intense exercise, and sleeping.

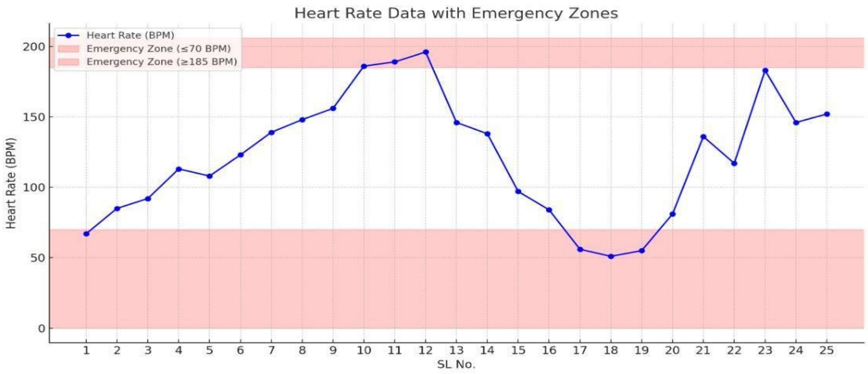


Figure 8. Heart Rate Sensor Module Output Data Graph for Heart Rate

Table 2 represents the confusion matrix with TP, TN, FP, FN for the heart rate sensor.

Table 2. Confusion Matrix Table with data of Heart Rate (BPM)

Predicted / Actual	**Predicted Normal**	**Predicted Emergency**
Actual Normal	17 (TN)	2 (FP)
Actual Emergency	1 (FN)	5 (TP)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = \frac{5 + 17}{5 + 17 + 2 + 1} = \frac{22}{25} = 88\%$$

$$Precision = \frac{TP}{TP + FP} = \frac{5}{5 + 2} = \frac{5}{7} \approx 0.7143 = 71.43\%$$

$$Recall = \frac{TP}{TP + FN} = \frac{5}{5 + 1} = \frac{5}{6} \approx 0.8333 = 83.33\%$$

$$F1\ Score = 2 \times \frac{Precision\ \times Recall}{Precision + Recall} = 2 \times \frac{0.7143 \times 0.83335}{0.7143 + 0.83335} \approx 2 \times \frac{0.5952}{1.5476} \approx 0.768 = 76.8\%$$

Table 3 represents 25 distinct blood oxygen saturation level data from our Heart Rate and Pulse Oximeter Sensor Module MAX30102 as Sensor Reading [Predicted Value], along with 25 actual blood oxygen level data from the Medical Pulse Oximeter as Actual Blood Oxygen Level [True Value] for comparison better understanding of accuracy. We have classified these data into two categories: Normal and Emergency.

Table 3. Blood Oxygen level (SpO_2) reading from: Heart Rate & Pulse Oximeter Sensor Module - MAX30102 & Standard Pulse Oximeter

Test #	Primary User Activity Status	Predicted SpO_2 (%) [Predicted Value] Sensor	Actual SpO_2 (%) [True Value] Pulse Oximeter	Predicted Class Sensor	True Class Pulse Oximeter
1	Resting	98	98	Normal	Normal
2	Resting	96	97	Normal	Normal
3	Resting	97	98	Normal	Normal
4	Light Physical Activity	96	96	Normal	Normal
5	Light Physical Activity	96	96	Normal	Normal
6	Light Physical Activity	95	96	Emergency	Normal
7	Moderate Exercise	94	93	Emergency	Emergency
8	Moderate Exercise	92	92	Emergency	Emergency
9	Moderate Exercise	94	94	Emergency	Emergency
10	Intense Exercise	93	93	Emergency	Emergency

11	Intense Exercise	93	93	Emergency	Emergency
12	Intense Exercise	92	92	Emergency	Emergency
13	Moderate Exercise	94	94	Emergency	Emergency
14	Moderate Exercise	96	96	Normal	Normal
15	Resting	97	97	Normal	Normal
16	Resting	99	98	Normal	Normal
17	Sleeping	91	91	Emergency	Emergency
18	Sleeping	92	92	Emergency	Emergency
19	Sleeping	92	92	Emergency	Emergency
20	Resting	97	97	Normal	Normal
21	Moderate Exercise	96	94	Normal	Emergency
22	Light Physical Activity	97	97	Normal	Normal
23	Intense Exercise	93	94	Emergency	Emergency
24	Moderate Exercise	96	93	Normal	Emergency
25	Moderate Exercise	94	94	Emergency	Emergency

Here, Figure 9 presents a graph depicting 25 measurements of blood oxygen saturations as percentages, obtained from the Heart Rate and Pulse Oximeter Sensor Modules under various conditions, including resting, light activity, moderate exercise, intense exercise, and sleeping. The red-shaded area below 95% signifies the emergency zone for blood oxygen saturation.

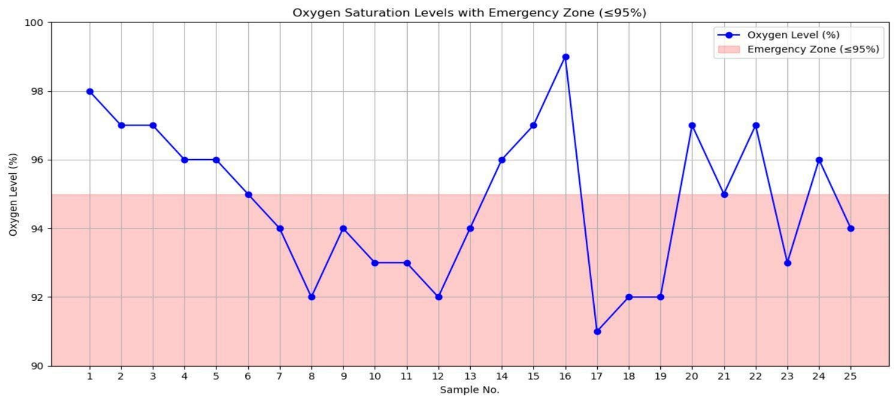


Figure 9. Pulse Oximeter Sensor Module Data Graph for Blood Oxygen Saturation

Table 4 shows the Confusion Matrix with TP, TN, FP, FN: for Blood Oxygen Sensor.

Table 4. Confusion Matrix Table with data of Blood Oxygen Level (SpO_2)

Confusion Matrix with TP, TN, FP, FN: for Blood Oxygen Sensor		
Predicted / Actual	**Predicted: Emergency (1)**	**Predicted: Normal (0)**
Actual: Emergency (1)	15 (TP)	1 (FN)
Actual: Normal (0)	1 (FP)	8 (TN)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = \frac{15 + 8}{15 + 8 + 1 + 1} = \frac{23}{25} \approx 0.92 = 92\%$$

$$Precision = \frac{TP}{TP + FP} = \frac{15}{15 + 1} = \frac{15}{16} \approx 0.9375 = 93.75\%$$

$$Recall = \frac{TP}{TP + FN} = \frac{15}{15 + 1} = \frac{15}{16} \approx 0.9375 = 93.75\%$$

$$F1 - Score = 2 \times \frac{Precision\ \times Recall}{Precision + Recall} = 2 \times \frac{0.9375 \times 0.9375}{0.9375 + 0.9375} \approx 2 \times \frac{0.8789}{1.875} \approx 0.9375 = 93.75\%$$

Table 5 presents 25 distinct sets of latitude and longitude data obtained from our GPS antenna operating at 1575.42 MHz, integrated with Google Maps as GPS Sensor Output [Predicted Value]. It also includes 25 actual location data points, randomly selected from GPS-enabled smartphones using Google Maps, which serve as actual output [True Value] for comparison and a clearer understanding of accuracy. Our classification rule for GPS accuracy was, if Deviation ≤ 10 meters, then Accurate, and if Deviation > 10 meters, then Inaccurate.

Table 5. GPS Module Sensor readings from GPS Module for Accuracy Reading & Standard GPS reading comparison

Test #	True Latitude	True Longitude	GPS Latitude	GPS Longitude	Deviation (m)	True Class	Predicted Class
1	24.041574	90.239955	24.041531	90.239949	4.79	Accurate	Accurate
2	24.038608	90.240518	24.038618	90.240528	1.51	Accurate	Accurate
3	24.035521	90.24111	24.035521	90.241091	1.93	Accurate	Accurate
4	24.028477	90.24246	24.028481	90.242426	3.48	Accurate	Accurate
5	24.028113	90.238094	24.028113	90.238084	1	Accurate	Accurate
6	23.852004	90.371037	23.852046	90.371069	5.64	Accurate	Accurate
7	23.853042	90.370774	23.853022	90.370806	3.98	Accurate	Accurate
8	23.874004	90.379607	23.873968	90.379620	4.24	Accurate	Accurate
9	23.87455	90.400318	23.874531	90.400354	4.17	Accurate	Accurate
10	23.849485	90.371211	23.849456	90.371250	5.06	Accurate	Accurate
11	23.76802	90.421658	23.768024	90.421688	3.11	Accurate	Accurate
12	23.760336	90.41044	23.760378	90.410482	6.33	Accurate	Accurate
13	23.753976	90.404072	23.754020	90.404040	5.82	Accurate	Accurate
14	23.761456	90.408102	23.761435	90.408118	2.85	Accurate	Accurate
15	23.768754	90.412147	23.768709	90.412160	5.17	Accurate	Accurate
16	24.047335	90.238765	24.047362	90.238808	5.32	Accurate	Accurate
17	24.036947	90.241007	24.036956	90.241008	1	Accurate	Accurate
18	24.031362	90.241936	24.031336	90.241892	5.28	Accurate	Accurate
19	24.028468	90.242441	24.028478	90.242444	1.12	Accurate	Accurate
20	24.027329	90.234696	24.027327	90.234702	0.7	Accurate	Accurate
21	23.772654	90.415867	23.772679	90.415854	3.12	Accurate	Accurate
22	23.772917	90.417689	23.772919	90.417726	3.82	Accurate	Accurate
23	23.771305	90.422237	23.771103	90.422019	31.5	Accurate	Inaccurate
24	23.768559	90.422653	23.768155	90.422222	62.76	Accurate	Inaccurate
25	23.768296	90.413275	23.767896	90.412996	52.65	Accurate	Inaccurate

Table 6 represents the confusion matrix with TP, TN, FP, FN for GPS Module.

Table 6. Confusion Matrix Table with the data of GPS Module

Confusion Matrix with TP, TN, FP, FN: for GPS Module		
Accurate \ Inaccurate	**Predicted Accurate**	**Predicted Inaccurate**
True Accurate	22 (TP)	3 (FN)
True Inaccurate	0 (FP)	0 (TN)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = \frac{22 + 0}{22 + 0 + 0 + 3} = \frac{22}{25} \approx 0.88 = 88\%$$

$$Precision = \frac{TP}{TP + FP} = \frac{22}{22 + 0} = \frac{22}{22} \approx 1 = 100\%$$

$$Recall = \frac{TP}{TP + FN} = \frac{22}{22 + 3} = \frac{22}{25} \approx 0.88 = 88\%$$

$$F1 = 2 \times \frac{Precision \ \times Recall}{Precision + Recall} = 2 \times \frac{1 \times 0.88}{1 + 0.88} = \ 2 \times \frac{1.76}{1.88} \approx 0.936 = 93.6\%$$

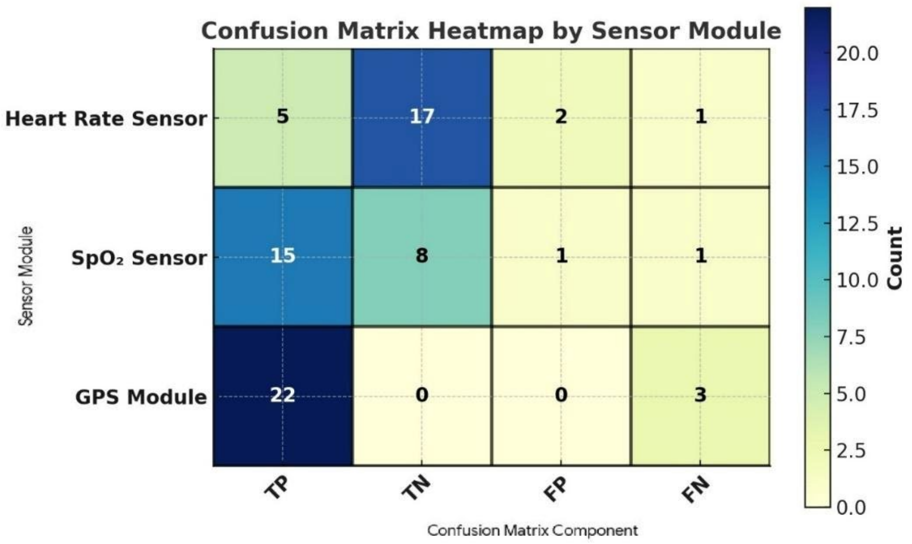
4.2 Confusion Matrix Analyses for Accuracy

Table 7 displays the overall output data count with the confusion matrix-related categories for each relevant sensor in our system. We did our experiments at least 25 times for each sensor, and we categorized each output into four groups for analysis using the confusion matrix module. We can also the see accuracy and error percentage of each sensor here. Finally, this table displays the system's overall average accuracy. And this general average accuracy offers meaningful information about the work of our sensors and indicates the areas where it can be improved. We can also compare these results with earlier researches and hence further test the efficiency of our approach as well as improve our methodologies to be used in future experiments.

Table 7. Data Collection Table for Accuracy Calculation by Confusion Matrix

Sl. No.	Sensor Module	TP [True Positive]	TP [True Negative]	FP [False Positive]	FN [False Negative]	Error (%)	Accuracy (%)
1	Heart Rate Sensor (MAX30102)	5	17	2	1	12	88
2	SpO_2 Sensor (MAX30102)	15	8	1	1	8	92
3	GPS Module	22	0	0	3	12	88
Overall System Error /Accuracy				**Average Error: 10.67%**			
					Average Accuracy: 89.33%		

Figure 10 shows the confusion matrix of our system in terms of the final accuracy of the system with each sensor module. In the accuracy detection, the accuracy (TP, TN, FP, or FN) of the prediction is determined using the assistance of the IoU threshold. It indicates the number of predictions that are right and wrong given a class. It assists in realizing the classes that are being conflated by models as other classes.



Predicted Labels

Figure 10. Confusion Matrix of Overall Sensor Module Accuracy with Predicted Labels

The highlighted portion is the detection result of the network. The visual representation will enable a better evaluation of the performance in various categories to implement specific, targeted improvements. The study of the discrepancies will help us to fine-tune our algorithms and increase the accuracy of the system in the real world.

5. Conclusion and Recommendations

Our proposed system tried to transcend the conventional boundaries through the incorporation of multiple crucial health tracking applications, say, heart rate, oxygen saturation, and fatigue detection with more accurate geolocation tracking services. This solution is inexpensive and adaptable in its barebones version, not only is it sealing the fatal loopholes that the existing systems have been unable to close but it is also opening the door to smarter, faster and more dependable emergency responses in the high-danger and poorly-connected world. We offer a wholeness that develops situational awareness, increases the safety in the operation, and facilitates the life-saving interventions in case of seconds, which is achieved by combining the intersecting needs of people into one, unified platform. The system may be a viable option when implemented on a large scale in third-world countries, as hardware integration is cheaper and can produce up to 89.33 percent accuracy. Nevertheless, we also realized that there are certain limitations in the present, including connectivity problems occasionally, sensor accuracy, and dependence on power. The next generation of this system might include satellite communication, such as Starlink, low-power edge AI processing, and stronger sensor arrays, further increasing this system's reliability and autonomy. Thus, we have not only offered a physical, functional prototype but also put into the limelight the innovative possibilities of the IoT in securing individuals who pass by the most hostile locations on our planet. Health and safety monitoring in tough environments looks promising with the future that we still face in integrating the digital and the physical environment, and could save lives.

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Ahmed Farhan serves as a senior lecturer in the Department of Mechatronics Engineering at World University of Bangladesh (WUB). He earned his Bachelor of Science (B.Sc.) in Electrical and Electronic Engineering from Islamic University of Technology (IUT) with the prestigious OIC scholarship. Following his undergraduate studies, he pursued a Master of Engineering (M. Eng.) at Harbin Engineering University (HEU) with the support of the esteemed CSC scholarship provided by the China Scholarship Council. The move was an indication of his desire to enhance his knowledge in the field of engineering and technology. Mr. Farhan was an intellectual, industrious and highly determined student who showed a high level of curiosity, academic and work ethic throughout his academic life that made him stand out to his peers. His main studies include biomedical engineering, image processing and renewable energy but with the main aim of coming up with new innovative solutions which are based on the principles of engineering and the application to the real world.

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