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HealthGuard: Real-Time Health Monitoring and Emergency Alert System

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Abstract: In today's fast-paced world, the need for continuous health monitoring and rapid response to emergent medical situations is paramount. "HealthGuard" is a cutting-edge real-time health monitoring and emergency alert system designed to address this critical need. Leveraging the power of IoT sensors and advanced data analytics, HealthGuard offers a comprehensive solution for tracking and responding to individual's health conditions, ensuring timely intervention when necessary.

This system employs a network of sensors to continuously collect data on key physiological parameters. HealthGuard utilizes state-of-the-art algorithms to analyze this data in real-time, enabling the early detection of anomalies and stress-indicating patterns. It sends instant alerts to medical professionals, nearby healthcare facilities, or emergency services when critical thresholds are breached. This ensures that individuals receive prompt medical attention when their health is at risk, potentially saving lives in emergency situations.

Keywords: Real-time data, Alert System, IoT, Sensors, Healthcare.

I. INTRODUCTION

In recent years, the integration of advanced technologies into healthcare systems has revolutionized the delivery and monitoring of healthcare. Realtime monitoring systems have emerged as a key component to ensure prompt intervention and improve the outcomes of patients. Among these, the "HealthGuard" system provides comprehensive real time monitoring and emergency alert capabilities in addition to major advances in healthcare technology.

In order to meet the critical need for continuous monitoring of patient's health parameters and timely detection of emergency situations, the HealthGuard system is designed. HealthGuard provides healthcare providers with unique insights into patient's well-being through the use of a combination of sensors, data analytics, and communication technologies. This enables pre-emptive intervention when needed. Critical signs such as heart rate, oxygen saturation, temperature and fall detection is one of the major features of HealthGuard.

These parameters, which ensure that there is no interruption of the patient's daily activity, shall be monitored constantly via non-invasive sensors. The collected data shall be transmitted in a secure manner to a central monitoring station, where it shall be analysed in real time by algorithms.

In addition to real-time monitoring, HealthGuard has an automated alert system that will automatically sound an alarm in the event of crises or unexpected readings. Instant alerts are sent to family members and healthcare professionals through GPS and GSM modules so they may respond swiftly and receive medical aid immediately.

II. LITERATURE REVIEW

In the paper [1], the authors of the paper built a health monitoring system which monitors the temperature, humidity and pulse rate of the patients. A heart beat sensor is used to calculate pulse rate and DHT11 sensor is used to calculate the temperature and humidity of a patient. This author used Node MCU as microcontroller, a Wi-Fi module and LCD screen to display data in digital format.

From [2], a system is proposed that provides the doctors, a tele-monitoring platform that monitors the patients continuously. The sensor data which is collected is transferred to a server using a device. The doctors can monitor this data through the server more easily. A patient's medical history, which includes the medical reports and medications and its timings are stored in the cloud for the future purpose. Also proposed a system that enables monitoring of their parents if they are living abroad.

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The paper [3] explains the development of a medicine reminder and dispensing machine, which helped the doctors, nurses and caregivers to help patients without being in contact with them during the covid pandemic situation. The track of medicine consumption timestamps is stored in a SD card for future reference by doctors. It is useful for elders who forget to take their medicines as per prescription by the doctors for their medical conditions.

When the world is hit by Covid-19, there is a need for a monitoring system described in [4], the doctors cannot go in contact with patient. This system monitors a patient who is in stage 1. It uses temperature, blood oxygen level and heart rate sensors to gather data and store in a server. In case of any emergencies like a drop in blood oxygen levels, an alert is immediately sent so that a life can be saved beforehand. The system generates alerts to the nearest hospitals in case of emergency.

The paper [5] concentrates on elderly people, because falls in that age can lead to severe situations too. So, monitoring that is really important and they need immediate help and medication as soon as possible which might sometimes save their lives too. This system uses a classifier to detect falling using the image descriptors or the features.

III. DESIGN AND METHODOLOGY

A. System Architecture

HealthGuard, uses a couple of sensors to collect the data from a human body. Temperature, heart rate, SPO2 and fall detection readings are obtained by using two sensors. MAX30102 sensor is used to collect the temperature, heart rate and SPO2 readings from a human body. ADXL345 sensor is used to determine the fall detection. The data that is generated by sensors is stored to a database. The data that is stored is used for training the machine learning model and the predictions are made accordingly. The results are displayed on the web application and the alerts are generated whenever the readings exceed the threshold. The SMS alerts are raised when the fluctuations in the readings are witnessed. GPS alerts are raised whenever the fall is detected.

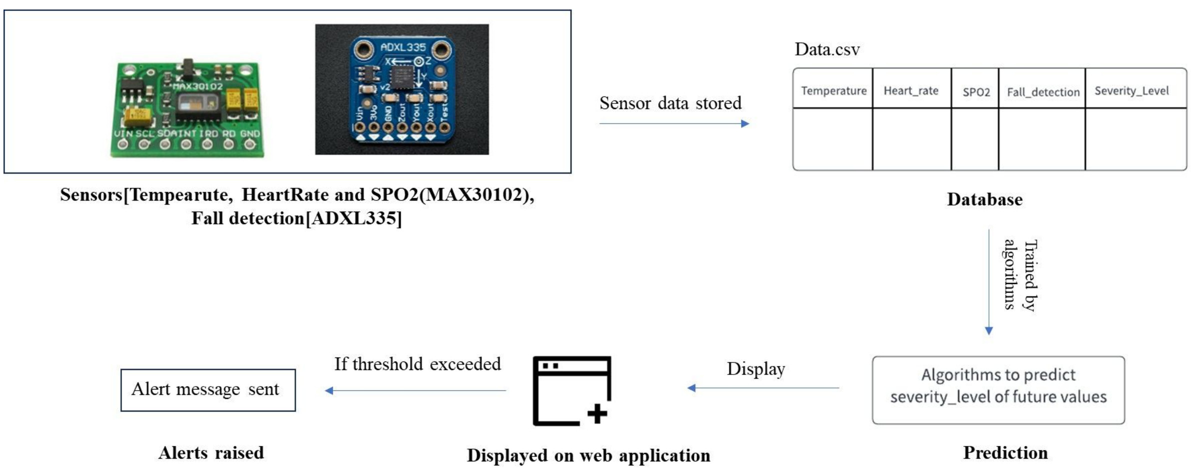

Fig.1 System architecture

B. Real-Time Monitoring

HealthGuard gathers real-time data on vital signs and other health metrics using a variety of sensors and wearable technology. These sensors could be accelerometers, temperature sensors, pulse oximeters and heart rate monitors. HealthGuard uses machine learning techniques to instantly assess the streamed data after it has been received. By taking severity level into account, these algorithms find patterns, trends, and anomalies in the health data, enabling early identification of possible health hazards or emergency situations.

Several sensors are integrated by the HealthGuard system to provide thorough real-time health monitoring and emergency detection. An overview of the sensors used is provided below:

1) *MAX30102:* The MAX30102 sensor is a multipurpose sensor that measures temperature, heart rate and oxygen saturation (SPO2). It makes use of photoplethysmography (PPG) technology to identify variations in blood volume inside the tissue's microvascular bed. HealthGuard can identify anomalies such as irregular heart rhythms or low oxygen saturation, and provide early warning indicators of possible cardiac events or respiratory problems by continually monitoring heart rate and SPO2 levels.

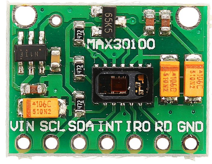

Fig.2 MAX30102 sensor

2) *ADXL335:* An accelerometer, the ADXL335 sensor measures variations in movement and acceleration. It is specifically used for fall detection, which is an essential function for guaranteeing people's safety and wellbeing especially the elderly and those with mobility problems. The fall detection sensor on HealthGuard is always on the lookout for abrupt changes in orientation or acceleration that could signal a fall. The device detects a fall and sends out a warning, allowing for quick medical attention and help in order to stop additional injuries.

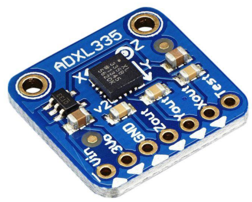

Fig.3 ADXL335 sensor

3) *IR Sensor:* A sophisticated infrared (IR) sensor is an essential element in the "HealthGuard" system that allows for medication tracking. The way this sensor works is that it looks for infrared radiation from objects that are in its range of view. The IR sensor, which is completely integrated into the monitoring system, guarantees real-time tracking of drug use. Its great sensitivity and precision ensure that the data gathered is reliable. The IR sensor is essential for ensuring patient safety and enabling early medical intervention because of its smooth integration into the broader health monitoring ecosystem.

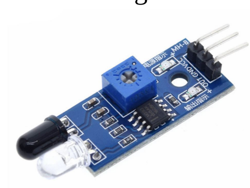

Fig.4 IR sensor

4) *NodeMCU:* The NodeMCU is an essential component of equipment in the "HealthGuard" system, enabling smooth transmission of data and connectivity within the emergency alert and real-time health monitoring system. The NodeMCU facilitates continuous communication between different sensors and the central system by utilizing its embedded Wi-Fi capabilities. It is ideal for deployment in a variety of healthcare contexts because to its small size and low power consumption, which guarantees continuous monitoring of physiological parameters and medication compliance. Furthermore, the NodeMCU's adaptability is increased by its compatibility with a variety of sensors and peripherals, enabling customized monitoring solutions customized to the requirements of specific patients. The NodeMCU's scalability and strong performance enable medical professionals to provide timely and preventive treatment, which improves patient outcomes inside of the HealthGuard system.

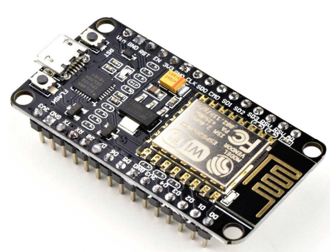

Fig.5 NodeMCU microcontroller

In conclusion, the HealthGuard system's combination of sensors for temperature, heart rate, SPO2, and fall detection allows for thorough monitoring of vital signs and activity patterns. And NodeMCU microcontroller is used for the purpose of transmission of data to other systems. An IR sensor is used for medicine tracking. HealthGuard can improve the safety and wellbeing of people in its care by using data from these sensors to deliver timely alerts and interventions.

C. Dataset

This dataset consists of 5000 records of data that depicts various conditions of a person and the corresponding severity levels. Temperature is recorded in Fahrenheit, Heart rate is recorded in beats per minute (BPM), SPO2 is expressed in percentage and binary indicator (0 or 1) for fall detection, where 1 indicates a fall detected. Severity level classification, indicating the severity of the detected event (0 – Normal condition, 1 - Low severity, 2 - High severity).

Table I
RANGES OF TEMPERATURE, HEART RATE AND SPO2 WITH EACH SEVERITY TYPE

	Normal	Less Severe	Highly Severe
Temperature	97-95	99.5-101.3	101.4-107.5
Heart_rate	60-100	100-120	120-220
SPO2	95-100	90-94	80-90

To avoid disparity, different combinations of the values are taken and analyzed as shown in Table II, to determine the severity level. If the readings are normal, the severity level is assigned as 0. If fall is detected, but the readings are normal then it is considered as less severe so severity level of 1 is assigned. If any one value varies, if it goes out of normal range, then the severity level 1 is assigned. If two or more values differ from their normal ranges then the severity level is assigned as 2.

Table II
assignment of severity level based on the Type of Variation

Temperature	Heart_rate	SPO2	Fall_detection	Severity_Level
Normal	Normal	Normal	0	0
Normal	Normal	Normal	1	1
Vary	Normal	Normal	0 or 1	1
Normal	Vary	Normal	0 or 1	1
Normal	Normal	Vary	0 or 1	1
Vary	Vary	Normal	0 or 1	2
Normal	Vary	Vary	0 or 1	2
Vary	Normal	Vary	0 or 1	2
Vary	Vary	Vary	0 or 1	2

The below table is a sample of the dataset Data.csv. In this way based on the ranges of Temperature, Heart rate, SP02 and fall detection, the severity level is depicted in the dataset by using Tabel II as the reference.

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Table III
Sample Of Dataset [Data.csv]

Temperature	Heart_rate	SPO2	Fall_detection	Severity_Level
97.622209	100	95	0	0
100.88738222	98	98	0	1
97.9866996	115	98	0	1
98.6331018	78	93	0	1
105.95477184	159	97	1	2
98.48267525	143	83	1	2
102.8590625	98	89	0	2
105.67912475	198	86	1	2

D. Emergency Alert System

The HealthGuard emergency alert system is improved by the integration of GPS (Global Positioning System) and GSM (Global System for Mobile Communications) technologies, which allow for exact position monitoring and communication during emergencies.

1) *GPS-enabled Location Tracking:* HealthGuard uses GPS technology to pinpoint people's exact locations in real time. Position updates are continuously provided by GPS receivers built into mobile or wearable devices. Even in unfamiliar or isolated regions, emergency responders and caregivers may locate people in danger quickly thanks to location tracking. It guarantees prompt support and shortens response times, increasing the efficacy of emergency operations.

Fig.6 NEO-6M GPS Module

2) *Emergency Alerts with GSM Communication:* HealthGuard uses GSM technology for communication in addition to GPS. Wearable gadgets with incorporated GSM modules or cellular connectivity allow emergency warnings and notifications to be sent to specified recipients. HealthGuard notifies family members, caregivers, and healthcare providers via GSM networks when an emergency occurrence is recognized. Important details like the person's current location, vital indicators, and the emergency's type are included in these notifications.

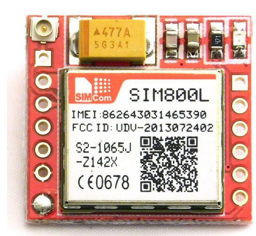

Fig.7 SIM800L GSM Module

IV. IMPLEMENTATION AND RESULTS

A. Implementation Overview

The final setup is as below. The components used are NodeMCU microcontroller, ADXL335 sensor, MAX30102 sensor, IR sensor, GPS NEO-6M module, GSM SIM800L module, Buzzer, Jumper wires and USB cable. The connections are made by connecting the ground pins to the ground pins of the NodeMCU, connecting the power pins [VCC] to 5V of the NodeMCU and each of the sensor and the components are connected to specific GPIO pins.

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SCL pins of both MAX30102 and ADXL335 are connected to pin D1 of NodeMCU and SDA Pins of both MAX30102 and ADXL335 are connected to pin D2. Buzzer Pins are connected to pin D3. Pin OUT of IR sensor is connected to pin D5. GPS module TX pin is connected to pin D6. GSM module Pin is connected to D7 pin. So, in this way the connections are done.

A USB cable is used to connect the NodeMCU to the system for power supply to the whole hardware.

The required code for NodeMCU is dumped into it. And it runs using that logic whenever the power is supplied. The ML algorithms are executed by using the port number generated when the USB is connected. The predictions are made based on the random forest algorithm. The alerts are generated whenever the values go beyond normal ranges. This logic is configured in code for NodeMCU. The alert SMS message format is also configured in the code of NodeMCU. It also consists of the location of the person also. The IR sensor detects and tracks the medicine consumption. A double beep indicates the consumption of the medicine, that is identified by the movement. This is the final hardware setup and its connections.

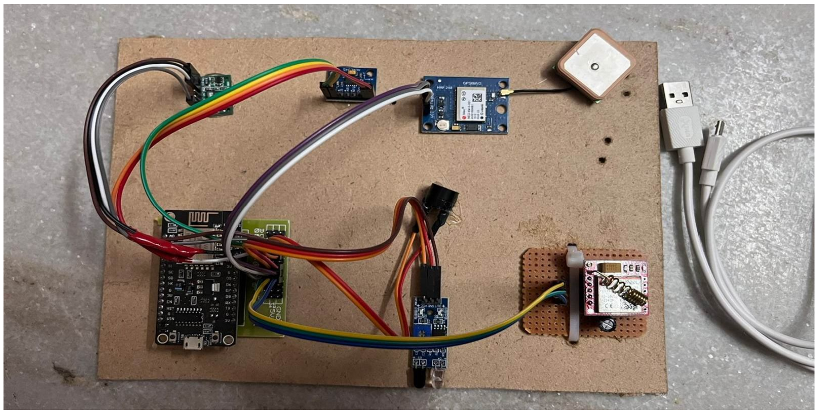

Fig.8 Final Setup

B. Comparative Machine Learning Algorithms

For the prediction part, four different machine learning algorithms are compared and analyzed and the one that gives good accuracy with the data is selected to evaluate the severity level of the new sensor data. The algorithms that are used:

1) *Logistic Regression:* A probabilistic framework for severity level prediction is provided by logistic regression, which models the relationship between input features and the probability of various severity levels. The probabilistic output from logistic regression is projected probabilities for every severity level. Decision-makers can use the anticipated probability to make well-informed decisions and gain a sophisticated grasp of the uncertainty around severity level projections. Interpretability is provided using logistic regression, which enables analysis of the coefficients corresponding to each input feature and their influence on severity level prediction.
2) *SVM:* SVMs can be trained on historical data with severity labels and features pertaining to emergencies or medical issues. Based on its attributes, the SVM model learns to classify an instance's severity level. SVMs can forecast severity levels across several categories or levels since they can perform multi-class classification jobs. Severity levels in healthcare can be classified as normal, moderate, or severe. Based on input features, SVMs can be trained to categorize occurrences into one of three severity levels. SVMs can enhance severity level prediction by using feature engineering approaches to extract pertinent information from raw data. Through constant updating of the model with feedback and incoming data, the system may adjust to changing circumstances and gradually increase prediction accuracy.
3) *KNN:* Based on comparable examples in the dataset, KNN can be used to categorize health disorders or emergency scenarios according to their severity. A new instance's severity level is determined by the procedure using the majority class of its k-nearest neighbours. Based on the severity levels of comparable cases in the dataset, KNN can forecast a patient's condition's level in a health monitoring system. Healthcare professionals can use this information to determine the seriousness of the condition and to distribute resources appropriately. When datasets have unequal severity levels, meaning that certain classes occur more frequently than others, KNN could show biases in favour of the dominant class. Class imbalance problems can be addressed and the model's capacity to forecast severity levels across all classes improved by employing strategies like oversampling, under sampling, or the use of class weights. The selection of the KNN's k-value, or number of nearest neighbours, can have a substantial impact on prediction accuracy, improve the model's generalization capabilities, and reduce overfitting or underfitting problems.

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4) *Random Forest:* Random Forests can be trained to categorize emergency situations or medical illnesses according to the severity using a variety of variables, including symptoms, vital signs, demographic data, and environmental aspects. Random Forests enable accurate classification by capturing intricate correlations between severity levels and input variables through the construction of an ensemble of decision trees. Multi-class classification jobs can be handled using Random Forests, which makes it possible to anticipate severity levels across several categories or levels. The ability to classify severity levels into various categories or classes—from minor occurrences to severe emergencies—is made possible by this flexibility. By offering insights into the significance of features, Random Forests facilitate the identification of critical elements that influence the prediction of severity levels.

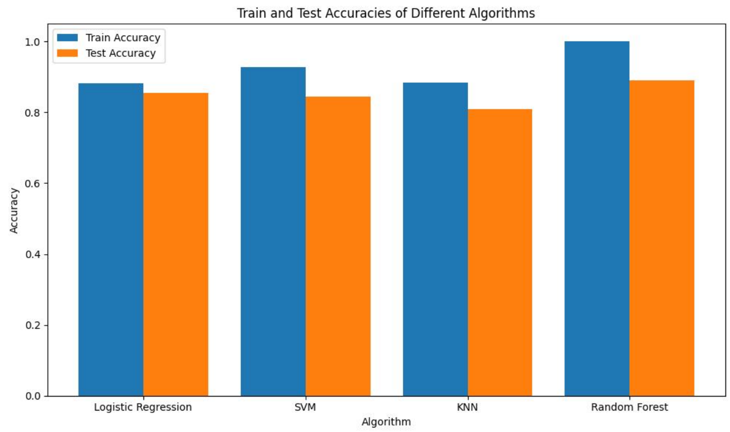

Fig.9 Training and Testing Accuracy comparison

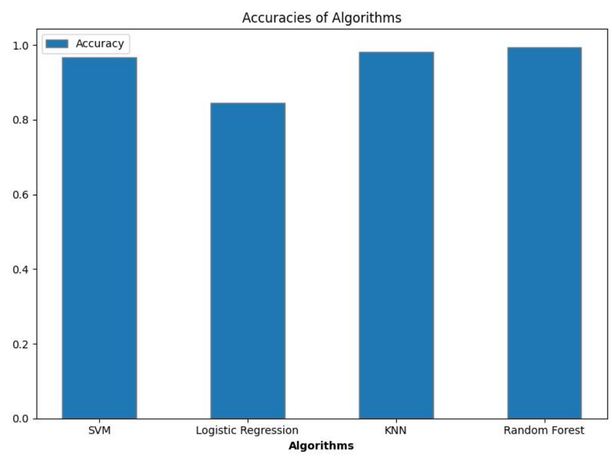

Fig.10 Accuracy plot

C. Performance Evaluation Metrics

1) *Precision:* Precision is a metric that expresses how well the model predicts favourable outcomes. Within the framework of a health monitoring system, precision would represent the percentage of anticipated health emergencies or alerts that actually occur. High precision indicates a high likelihood of accuracy when the system sounds an alert.
2) *Recall:* Recall, sometimes referred to as sensitivity, gauges how well a model can accurately identify every pertinent incident. Recall in the context of health monitoring would mean the percentage of real health emergencies or alarms that the system accurately identifies. A high recall rate indicates that the majority of real emergencies and alarms are successfully captured by the system.
3) *F1-Score:* The harmonic mean of recall and precision is the F1-score. It offers a harmony between recall and precision. The F1-score is frequently employed because it takes into account both false positives (precision) and false negatives (recall) in scenarios where both accuracy and recall are crucial. Good overall performance in terms of recall and precision is indicated by a high F1-score.

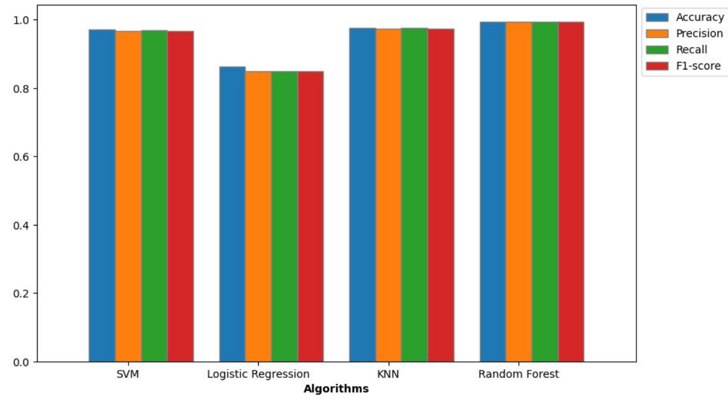

Fig.11 Performance evaluation comparison

D. Result Analysis

By comparison, random forest algorithm is predicting the severity level more accurately. So random forest algorithm is used for the purpose of prediction. And when the values vary from their normal ranges and represent the severity, then the alerts as shown below are sent along with the location. The number to receive alerts can be configured as per the user requirement. One can let the alerts to be sent to family member or family doctor. An IR sensor is used to detect if the medicine is being taken in corresponding time prescribed, if any.

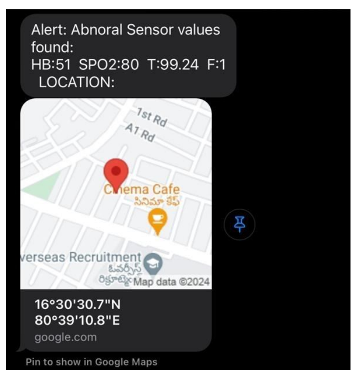

Fig.12 Alert messages that are sent when the severity level is abnormal

V. CONCLUSIONS

Utilizing state-of-the-art hardware and machine learning algorithms, the "HealthGuard" real-time health monitoring and emergency alert system represents a substantial advancement in healthcare technology by offering thorough monitoring and prompt intervention for people with health concerns. The NodeMCU microcontroller is used in conjunction with sensors MAX30102 and ADXL335 to continuously monitor physiological parameters and movement. This allows the system to provide real-time insights into the health status of the user. We conducted extensive testing and research to evaluate the effectiveness of several machine learning algorithms, such as Random Forest, SVM, KNN, and Logistic Regression.

The Random Forest algorithm was surprisingly the best performer, exhibiting the highest level of accuracy in severity level prediction. This demonstrates how well ensemble learning approaches handle complicated health data collected from sensors. Furthermore, by informing caregivers or emergency services of the user's precise location, the integration of GPS location-based SMS alerts utilizing GPS NEO-6M and GSM SIM800L modules guarantees quick reaction during emergencies. This function improves the system's performance under dire circumstances and may even save lives. Furthermore, the system gains an additional layer of capability with the addition of an IR sensor to detect medication usage. HealthGuard's ability to monitor medication adherence allows it to send out alerts when a prescription is not taken as directed, allowing for proactive intervention and better patient care overall. This is how HealthGuard works.

VI. ACKNOWLEDGMENT

The timely completion of this journal paper on emergency alert and real-time health monitoring systems is largely due to the tremendous assistance of various academics and researchers in the field of healthcare technology. Their diversity of knowledge and proficiency has greatly improved the quality of our investigation. We would like to express our heartfelt gratitude to the authors of the sources that were analysed for their hard work, which has resulted in insightful information, data, and methodology that have made it easier to develop and validate our real-time health monitoring and emergency alerting system.

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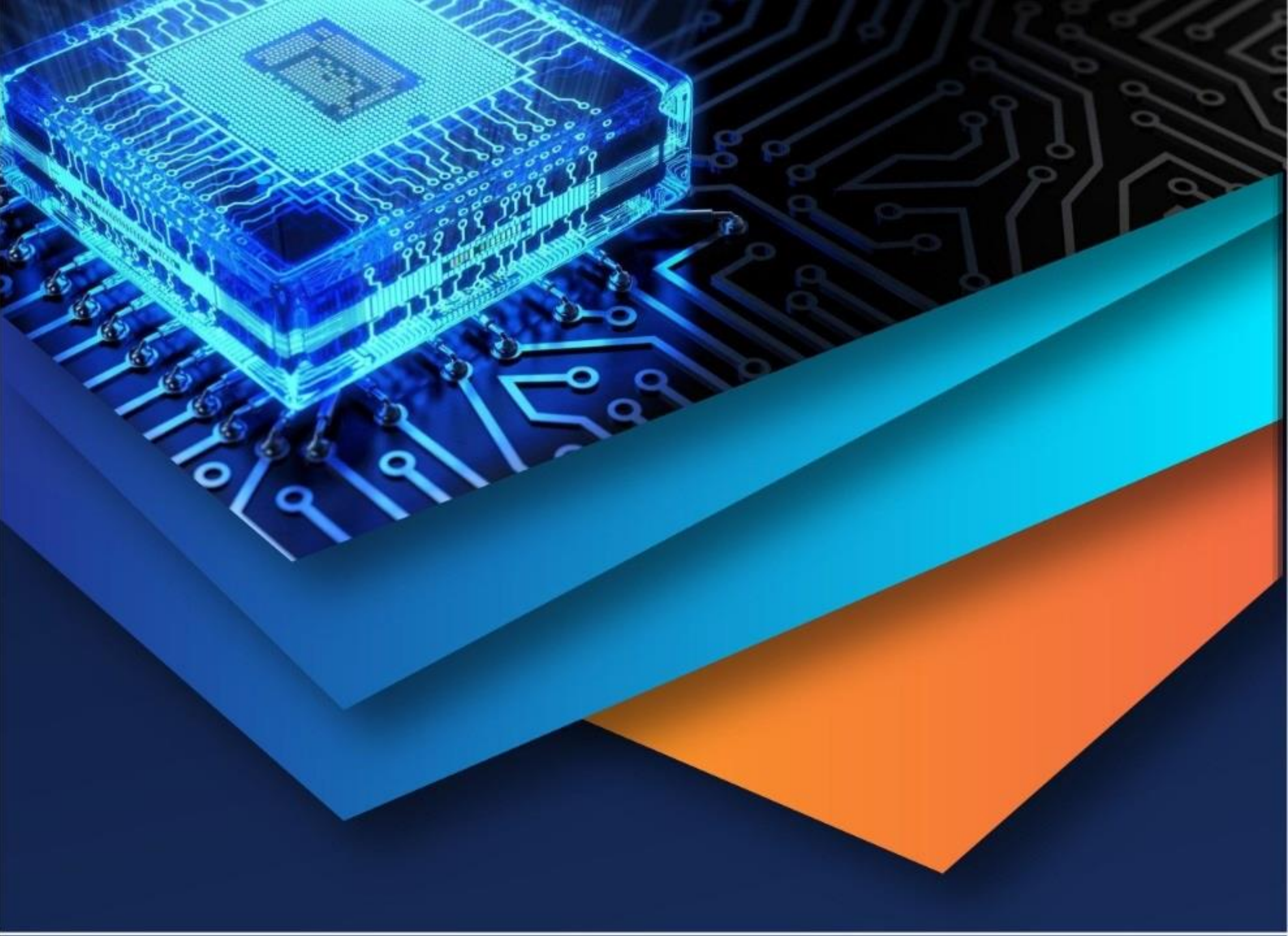

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