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ABSTRACT

The demand for proactive and intelligent healthcare solutions has surged in recent years due to the increasing aging population. This rising number of chronic disease cases, and the need for real-time patient monitoring, especially in rural areas. This project describes the development of an Intelligent Healthcare Monitoring System that integrates fall detection, natural language communication, hybrid machine learning model-based health risk prediction, and real-time data capture. The main aim is to benchmark and continuously evaluate an individual's health status so that early intervention can occur in hybrid machine learning model which incorporates both the Random Forest and Decision Tree classifiers. While the RF adds robustness and increased predictive accuracy, the DT provides a simple and interpretable way to make a decision. The hybrid method meets the demands of interpretability and performance through a combination of these two methodologies with a weighted decision-making approach in the context of a complicated, noisy real-world health data scenario. The model utilizes 13 input features. These features were selected because they are indicative of a user's physiological state and they have clinical value in the interpretation. This data input is securely collected and transmitted in real-time through the NODE-RED interface using the MQTT protocol. The data is subject to several preprocessing steps before analysis to maintain quality and to ensure generalization. These steps may include noise reduction, missing value imputation, and data augmentation. The classification model uses a hybrid technology to produce a classification accuracy of 97.93% across three health risk classes low, medium, and high with 80% full data set for training and the remaining 20% for testing. To give the user feedback about the health prediction made by the hybrid technology with the LLM model is used to generate feedback in an engaging, conversational form that is human-readable, and will assist with usability and accessibility of the system. The Streamlit chatbot enhances health awareness and engages users by allowing the user to enter their parameters as features, to provide simple health guidance. One of the most useful features of the system is the GPS location-based tracking, which is enabled when a fall or catastrophic health event occurs. To allow for a swift response and increase the chance of a successful intervention, the system automatically sends the patient's location to the patient's designated emergency contacts or health professional contacts. The system has great utility potential for eldercare programs, personal health care channels, and rural health support mechanisms, where it can overcome the challenge of accessing medical care with reliance on technology.

Chapter-1

1. INTRODUCTION

The rise of intelligent technologies and the increasing demand for patient-centered care have led to a shift in the healthcare sector in recent years. The growing rates of chronic disease, aging populations, and the need for prompt medical action have brought about a focus on continuous health monitoring solutions [1]. As such, healthcare systems around the world are introducing smart systems into their healthcare communities, as a way to mitigate the relationship gap between patients and healthcare professionals and make healthcare more readily available particularly in areas lacking healthcare access.

The project aims to develop an intelligent healthcare system that facilitates the continuous observations and monitoring of significant health attributes. The objectives of this system are specifically created enhance healthcare delivery by promoting preventative care, facilitating the early detection and reporting of abnormal health attributes, and allowing for timely alerts [2]. Traditional healthcare models generally depend on human examinations and frequent visits to favor a continuous stream of care through intelligent interpretation, automatic data and digital collection, and user-friendly interfaces.

The proposed system therefore has an overall framework with the intention of addressing development holistically with a suite of features to support accuracy, efficiency, and access. It empowers users to help themselves by knowing about their health to promote awareness and proactive health management. In addition, it thus remains as useful to healthcare professionals and caregivers in making the best decision for those in both clinical and non-clinical environments by updating users with actionable information at the appropriate time. From a tech perspective, the project intends to be modular and scalable to respond to the evolving demands of healthcare. The architecture can add use cases or new demographics since it provides a flexible approach to secure data transmission, real-time processing, and interactive visualization [3]. The system also has alerts to notify users and stakeholders of critical potential health risks, and for users to react or pay attention.

This project contributes to a global effort to create smarter, more inclusive, and more efficient medical ecosystems through the IoT and application of intelligent systems in healthcare [4]. With an element of alerts, automatic assessment, and real time monitoring and informing of users, the proposed system not only contributes to the singular health outcomes of individuals, but contributes to the greater aim of more responsive, preventive, and data-driven healthcare delivery and engagement.

1.1 BACKGROUND

Technology is being used increasingly in today's healthcare space to elevate medical care standards and access. Conventional healthcare systems often rely on periodic assessments, which can introduce delays in diagnosis and intervention. This can be especially problematic for patients with chronic illnesses, the elderly, or residents in rural locations with limited access to healthcare resources. Recent years have seen the launch of intelligent healthcare systems as a mechanism to address these issues.

These systems allow for continuous monitoring of essential health metrics, offer real-time reminders, and assist with early detection of potential health risks [5]. They provide the opportunity for individuals to adopt a more active role in managing their health and can help alleviate strain on the healthcare system by decreasing the need for human participation in data collection and aggregation. Despite increased interest in intelligent technologies, many existing solutions are too complex, high cost, or lack the necessary integration for seamless real-time monitoring and alerts. This project seeks to confront these challenges by designing an intelligent, readily available, and efficient health monitoring solution that can provide timely assistance, enhance preventive care, and work towards the global goal of intelligent, smart, and data-driven healthcare.

1.2 PROBLEM STATEMENT

The availability of timely, continuous, and personalized medical management challenges our healthcare systems across the globe, particularly for those living with chronic illnesses, the aged, and in some cases the poor and rural. Most healthcare delivery models are traditionally prescriptive, and occasionally the poor outcomes of delaying diagnosis of serious illness only become apparent after the fact. While diagnostics continue to evolve, at the time of this publication, they are external and primarily reactive to in-person clinic visits and examinations. Undiagnosed illness can increase complications, healthcare costs, and in certain situations, mortality.

Furthermore, existing healthcare models lack timely response service and continuous monitoring capabilities. Patients often have a difficult time identifying early signs of decline, and when intervention becomes necessary, their caregiver or medical personnel may not be alerted promptly. Medical emergencies require timely decision-making, which is generally not possible without timely alerts and provided health insights.

Despite the advent of a multitude of health monitoring services in recent years, many monitoring solutions have limited scalability, affordability, integration, and usability. Some systems may not have many real-time data analytic capabilities, record a limited number of health indicators, or they may offer generic alerts that are not user-friendly or location-aware. Furthermore, many of these systems do not embed intelligent decision-support capabilities that would support early risk prediction, and do not account for the unique characteristics of individual users.

The limitations, a fully comprehensive, intelligent, and scalable healthcare monitoring system is warranted that shares health data in real-time, will automatically analyze time-series data, and generate alerts in a timely manner. The system should support user development at home, while they travel, and also be pragmatic outside a clinical setting, while providing new insights of trends to both patients and caregivers.

Through this project we want to provide a solution to the causes of these limitations and create an intelligent and personal monitoring system that will provide real-time alerts, user-focused health status assessments, integrated location support, continuous data collection, predicate health analytics, and distributed data analysis. Our goal is to contribute to better healthcare across all settings, improve preventative care for all users, and limit hospital-based monitoring where possible by providing continuous, intelligent home health support that is easy to access.

1.3 AIMS AND OBJECTIVES

1.3.1 AIMS:

The objective of this project is to design a holistic, intelligent healthcare monitoring system that allows for real-time observation, analysis, and alerts of critical health measures. The system will support enhanced preventive care, decrease reliance on hospital services for monitoring, and assist patients, caregivers, and health practitioners to identifying potential health dangers sooner rather than later. The system could potentially improve health outcomes and access to care, particularly for marginalized or isolated groups, by combining intelligent decision support, near-continuous data monitoring, and simplicity for all types of users and uses.

1.3.2 OBJECTIVES:

1. **To develop and apply a framework for ongoing health assessment:**

We want to establish a practical and efficient framework that continually collects, assesses, and monitors the health status of the user. This involves monitoring physiological measures that can indicate the user’s current health status. It is critical to continuously bring together health assessment as it helps prevent an acute depression in health status enables continuous monitoring and improves early detection.

2. **To develop an intelligent health system for risk assessment classification and health alerts:**

One of the significant goals of the project is to integrate smart decision-making capabilities that can use data patterns to classify a user’s health state into normal, moderate risk, or critical risk state. The system will generate health alerts when the data patterns signify anomalies or incidents so that appropriate action can be taken without delay.

3. **Utilizing analytics to identify trends in health and take early action:**

By examining user health data trends over time, the system will be able to identify subtle deviations in standard health conditions that are not necessarily serious but could denote a pattern of abnormalities that indicates an underlying problem. It allows users and medical professionals to act swiftly with preventive care before health deteriorates.

4. **Including patient location monitoring grounded on GPS for emergency response:**

The system will automatically forward the user's location to pre-configured emergency contracts or healthcare providers. The function is especially crucial for older users, single people, or patients in need of immediate assistance since it accelerates response times and increases the possibility that an intervention will be effective.

5. **To ensure location-based context awareness when spotting an illness or fall in a patient:**

The system will be designed to link health alerts with the spatial information of user constantly. Location information will help to improve situational awareness and the responsiveness of emergency support systems in case of aberrant vitals or identified falls.

6. **Guarantees of privacy, data security, and adherence to healthcare data standards:**

The system will contain encrypted channels and safe storage methods to protect user data. It will be built I line with data protection rules and healthcare compliance criteria to ensure confidentially, integrity, and trust. Users will be able to view and control their data, thus access to sensitive material will be restricted.

7. **To conduct simulation, testing, and performance evaluation in the real world:**

The proposed system will undergo a thorough testing procedure in real environments to evaluate its accuracy, dependability, performance, and usability. Simulated healthcare scenarios will be created to evaluate the responsiveness of the alerts, the accuracy of the health classification logic, the precision of the location tracking, and the user experience of the interface.

8. **To promote easily accessible, customized, and preventative healthcare:**

The project seeks to transform traditional healthcare from a reactive to a proactive and preventive approach. By providing individualized insights, encouraging self-awareness, and continuously monitoring health, the system aims to reduce emergency incidents, save healthcare expenses, and enhance long-term patient outcomes.

1.4 THESIS LAYOUT

Chapter 1: This section introduces the motivation, background, and objectives for developing an intelligent healthcare monitoring system.

Chapter 2: This section discusses existing smart healthcare technologies and identifies gaps address by the proposed system,

Chapter 3: This section proposes a new algorithm for the research topic and explains its working.

Chapter 4: This section evaluates and analyzes the new algorithm, model evaluation, and user interface outcomes.

Chapter 5: This section discusses system performance, effectiveness its risk detection and concludes with key findings.

Chapter 6: This section summarizes contribution, lists derived publications, and outlines potential future enhancements.

Chapter-2

LITERATURE REVIEW

Chike Nwibor et al. [6] provide an IoT-based remote health monitoring system that measures oxygen saturation levels (SpO2), heart rate, and blood pressure. The device monitors vital signs continuously using single photoplethysmography (PPG) signals and machine learning techniques. Future research will concentrate on user experience perspectives and potential therapeutic applications, including monitoring people on antihypertensive medications and predicting changes in vital signs.

S. Arun Kumar et al. [7] recommended lowering the mortality rate from lung diseases and premature heart attacks. An intelligent health monitoring system that combines cloud, IoT, and machine learning is proposed in this paper. Vital signs are collected by sensors, and machine learning predicts 86% of disease types. Wearable sensor technology and telemedicine integration may be utilized in the future to enhance remote health monitoring.

Agrawal et al. [8] demonstrate the use of wireless pressure sensor insoles to lower the risk of falls in the elderly. Of the six machine learning models that were assessed, logistic regression had the highest AUC (0.82) and random forest had the best accuracy (0.82) and specificity (0.88). To enhance fall risk prediction, the subsequent study investigates deep learning methods and novel gait parameters.

Ubaid Ullah et al. [9] examined current developments in healthcare using Quantum Machine Learning (QML). Out of 2,038 articles published between 2018 and 2023, 49 are found to be relevant. Most focus on QML algorithms that utilize photos and patient data from EHRs. The QRF, QKNN, and Qsvm models are known to be used to solve healthcare issues. The difficulty of performing a thorough search and the lack of precise quantum data are two of the disadvantages.

Salini et al. [10] stated in this paper that pregnancy issues require prompt attention. Cardiotocography (CTG) test analysis done by hand is laborious and imprecise. ML has great potential despite its drawbacks. Care for expectant mothers and fetuses can be enhanced by interdisciplinary teamwork and technological innovation.

Sengupta et al. [11] investigated how ML and wearable technology can be combined to treat strokes. This collection of research, which includes studies in six categories such as activity recognition and clinical score estimation, spans the years 2009 to 2023. By analyzing the advantages, disadvantages, and potential applications of wearable sensors and machine learning for post-stroke mobility analysis, the study seeks to guide researchers in this area.

Shanthakumara et al. [12] investigate how to incorporate IoT and ML into health monitoring, with a particular emphasis on wearable technology like smartwatches. IoT-collected data, including heart rate, blood pressure, and temperature, is used by ML algorithms to examine medical conditions. Algorithm accuracy, according to the exhibition examination, is 75% for KNN, 86% for SVM, 83% for Naive Byes, 74% for Decision Tree, and 81% for Logistic Regression. Future developments aim to increase the number of sensors and develop more complex machine learning algorithms, with a focus on deep learning approaches.

M. Muhammad Arslan et al. [13] examine developments in vital sign monitoring systems that incorporate wireless communication, sensor technology, and machine learning (ML) algorithms. Research indicates that machine learning models like KNN (92% accuracy), SVM (94% accuracy), and SGD (97% accuracy) are good at classifying the health status of patients. Real-time monitoring is improved by combining window-based applications with strong error-checking protocols; future work will concentrate on increasing training datasets and enhancing diagnostic accuracy.

Abdullah Baihan et al. [14] introduce a wearable health monitoring system for pilgrims performing the Hajj and Umrah that uses a deep reinforcement learning model called Deep Q Network (DQN) to make context-aware, adaptive alert decisions. To monitor vitals and guarantee safe distancing based on crowd density, the system uses wristbands embedded with sensors (temperature, SpO2, ToF, and heart rate). The system demonstrated improvements in data analysis rate (14.58%), density detection (16.12%), recommendation accuracy (15.79%), and reduced distortion error (11.57%) when evaluated at 5- to 60-minute intervals.

Jie Zhou et al. [15] explain a flexible-encapsulated, wearable, non-invasive blood pressure (BP) monitoring system that uses piezoelectric micro-machined ultrasound transducers (PMUT). This motion-resistant, small (less than 2g) device uses ultrasonic pulse-echo to measure arterial diameter and has a high signal-to-noise ratio (>29 dB). With a mean absolute error of less than 4 mmHg (systolic) and less than 3 mmHg (diastolic), and a heart rate error of less than 3 bpm, it computes pulse wave velocity to estimate blood pressure. Its dependability for continuous, real-time blood pressure monitoring is confirmed by a strong correlation (0.951–0.998) with conventional techniques.

Himi et al. [16] present smartwatch-based "MedAi" multi-disease prediction systems. Using machine learning techniques like K-Nearest Neighbour, Random Forest, and Support Vector Machine, it attains exceptional accuracy (99.4%). After that, research will focus on expanding the dataset, creating the smartwatch, adding more diseases, and launching the mobile app.

G. R. Pradyumna et al. [17] examine the development and importance of the Internet of Medical Things (IoMT) in revolutionizing healthcare via remote monitoring, telemedicine, and real-time data collection. It draws attention to how machine learning, security, privacy, interoperability, and ethical issues are all integrated. IoMT adoption is hampered by issues like scalability and data management, even with advances in technology. The study emphasizes the need for sustainable, power-efficient IoMT-enabled Smart Healthcare systems for reliable and safe healthcare device networks and recommends more efficient, lightweight intrusion detection systems.

Chapter-3

METHODOLOGY

3.1 PROPOSED MODEL:

To accurately assess a person's health based on several physiological and environmental factors, a hybrid machine learning model that combines the benefits of both Random Forest and Decision Tree classifiers has been developed for the proposed Intelligent Healthcare monitoring system. To ensure a balance between interpretability and predictive performance, the hybrid approach was chosen, especially when working with complex, real-world health data that frequently contains noise and variability.

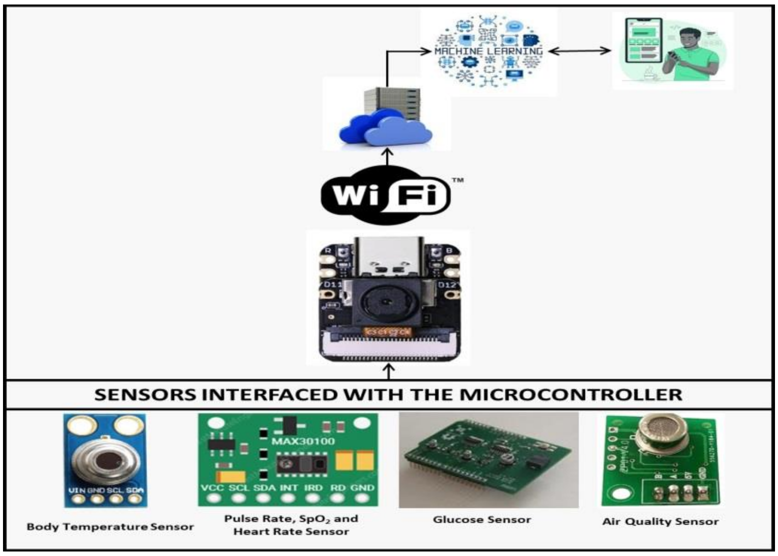

Figure 3.1: Proposed Smart Healthcare Monitoring System Architecture

The decision tree algorithm is well known for its transparency and ease of use because it provides a transparent, rule-based framework for decision-making. It may, however, overfit when used on noisy datasets or applied to large feature spaces. However combining multiple decision trees, random forest, an ensemble learning techniques, reduces variance and improves accuracy and robustness. Combining these two techniques, the hybrid model leverages the interpretability of a single decision tree and the generalization potential of a random forest to increase the system's overall efficiency.

Thirteen input features are used by the model: age, systolic and diastolic blood pressure, body temperature, accelerometer, gyroscope values along three axes each, UV exposure rate, heart rate (bpm), and SpO_2 (%) as shown in Figure 3.1 on p.9. These characteristics were chosen with care because of their clinical importance and capacity to represent the physiological state of the user. To enhance model generalization and performance, the data gathered from real-time sensor readings is preprocessed to eliminate noise, normalize outliers, and impute missing values.

Following preparation, the data is divided in an 80:20 ratio into training and testing sets. The same dataset is used to train the Random Forest and Decision Tree classifiers. To avoid overfitting, the Random Forest model is set up with 100 estimators, and hyperparameters like split criteria and depth are optimized. Both models are used to generate predictions for each test sample. When the outputs agree, the shared prediction is maintained. Because of its ensemble nature and better generalization to unknown data, the Random-Forest Model employs a weighted approach in conflict situations, increasing the confidence of its output. To facilitate a quicker emergency response in the event of a fall or other serious medical condition,, the system also includes GPS-based patient location tracking, which allows the user's geographic location tracking, which allows the user's geographic location to be recorded in real-time.

Three categories are created by the final model based on the user health risk. These classifications are based on predefined thresholds for each feature, which are provided by medical standards and expert guidelines. Metrics such as accuracy, precision, recall, F1-score, and confusion matrix were used to assess the model's performance. The hybrid model consistently outperformed standalone classifiers with an overall accuracy above 97%, proving its suitability for real-time health risk prediction. The trained hybrid model is serialized using Python's pickle module and then integrated into a Streamlit-built chatbot interface. It improves the system's overall responsiveness and dependability, making it a useful instrument for ongoing health monitoring, particularly in high-risk or remote settings.

3.2 METHODOLOGY

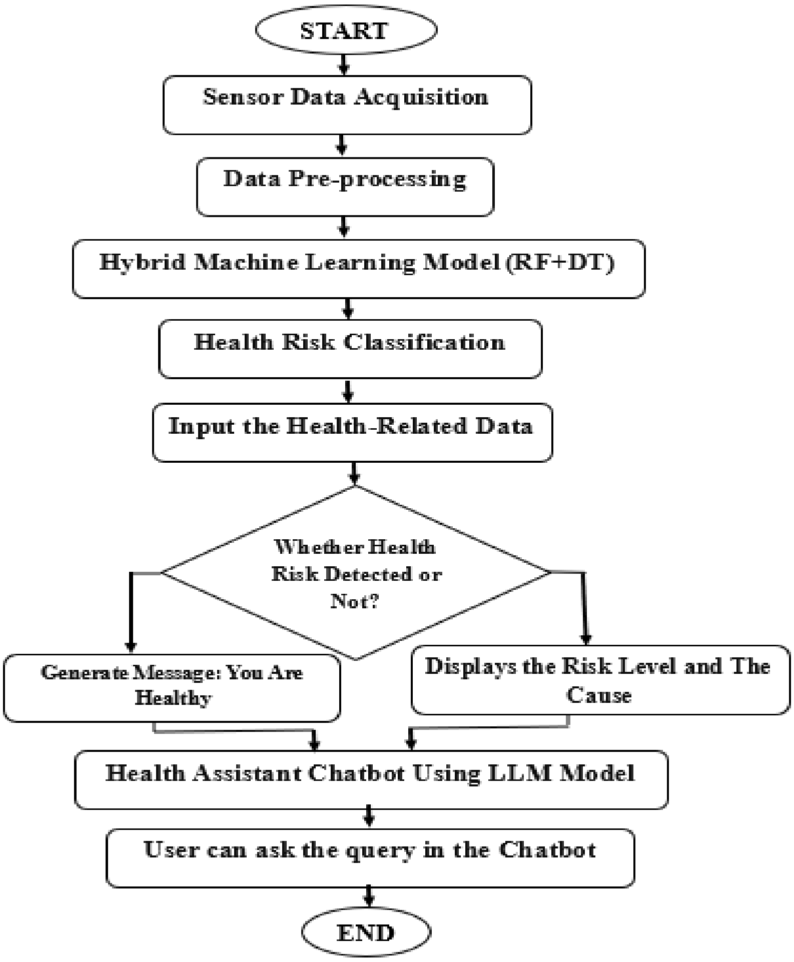

Figure 3.2: Working Flowchart of Smart Healthcare Monitoring System

The Intelligent Healthcare Monitoring System was developed using a multi-stage, systematic methodology that includes real-time data collection, IoT integration, data preprocessing and hybrid machine learning model development, intelligent alert generation, and deployment through an intuitive chatbot interface enhanced by a Large Language Model (LLM) as shown in Figure 3.2 on p.11. For proactive and preventive care, the system provides seamless health monitoring, risk classification, and emergency alerts.

3.2.1 Data Gathering in Real-Time from Health Band

A wearable health band device is used to gather physiological and environmental health data in real-time at the start of the project. Vital signs and parameters were gathered as follows:

- Time in seconds
- The age
- Blood oxygen saturation, or SpO_2 (%)

- The heart rate (bpm)
- Blood pressure measurements
- X, Y, Z Accelerometer Readings
- X, Y, and Z gyroscope readings
- UV Exposure Level
- Body Temperature in degrees Celsius

These parameters are crucial for assessing a user's physiological state. They are frequently employed to identify ailments like environmental stress, hypoxia, fever, cardiovascular instability, and excessive motion, which can indicate falls.

3.2.2 IoT Communication Using MQTT and Node-RED

The MQTT (Message Queuing Telemetry Transport) protocol was implemented using Node-RED to enable effective and lightweight communication between the wearable device and the server [18]. This setup included:

- MQTT topics are used to send sensor readings to a central broker.
- After parsing the incoming data and logging it in structured CSV format, Node-RED subscribed to the topics.
- Real-time data was visualized through Node-RED dashboards during testing and development.

Low latency, dependable data transfer, and expandability for future sensor integration were all guaranteed by this IoT framework.

3.2.3 Feature Engineering and Data Preprocessing

To get it ready for machine learning, the gathered dataset was carefully preprocessed:

- Noise Handling: To lessen variability brought on by changes in the environment, raw values were normalized and smoothed.
- Missing Data: Incomplete data rows were either discarded or imputed.
- Synthetic Data Generation: To simulate real-world sensor inconsistencies, additional samples were generated by adding Gaussian noise.

- Feature Enhancement: Using controlled value generation, columns like "Age," "Body Temp (°C)," "UV Rate," and "Gyroscope readings" were added or expanded.

- Random Age Assignment: Random age values ranging from 18 to 90 were added to replicate a range of age demographics.

The finished dataset, Health_Monitoring_Dataset.csv, was prepared for training and risk labeling.

3.2.4 Classification and Labeling of Health Risks

Based on predetermined medical thresholds, a Health_Risk class was assigned to each data instance:

- Low Risk (0): Every parameter falls within the typical range.

- Mild deviations (e.g., HR slightly above 90 bpm, SpO_2 95–96%) are considered a medium risk (1).

- Critical abnormalities (e.g., SpO_2 < 92%, Temp > 38.5°C, BP > 140/90 mmHg, or excessive gyro/acceleration values) are considered high risk (2).

Each row's health risk level was determined by a rule-based function. While a critical_alert flag detected situations in which several parameters simultaneously exceeded safe thresholds, a secondary binary flag (alert_flag) indicated any abnormal condition.

3.2.5 Proposed Hybrid Machine Learning Model (Decision Tree + Random Forest)

To classify health conditions accurately, two tree-based classifiers were combined to create a hybrid ensemble learning model:

- Decision Trees (DTs) are used because of their interpretability, simplicity, and capacity to use if-else rules to model intricate nonlinear relationships.

- To lower variance, improve accuracy, and avoid overfitting, Random Forest (RF) is an ensemble of several decision trees trained on various data and feature subsets.

Example Workflow:

1. By deleting columns like Time (s), IR Value, Red Value, and Health_Risk, features (X) were extracted.

2. The target label (y) was set to Health_Risk.

3. The train-test ratio was 80:20.

4. Individual training was done on both models.

5. A weighted approach or majority voting was used to combine their predictions, with Random Forest being given more weight because of its superior generalization.

6. We calculated and compared performance metrics (accuracy, precision, recall, and F1-score) with other stand-alone models (e.g., KNN, SVM, Gradient Boosting).

7. With a classification accuracy of over 99%, the hybrid model performed better than the others.

8. Pickle was used to save the finished model so it could be integrated into the live chatbot.

3.2.6 Intelligent Warning System

Dual logic was used in the implementation of an intelligent alert mechanism to guarantee the prompt detection of abnormal readings:

- Rules-based on thresholds: Send out notifications when any parameter deviates from established clinical bounds. For instance, heart rate < 60 or > 100 beats per minute.

- Critical Multi-Condition Alerting: The system raises a critical alert if more than two important health parameters concurrently cross thresholds.

This system makes sure users are alerted to potentially harmful trends that point to worsening health conditions in addition to isolated anomalies.

3.2.7 An Algorithm for Detecting Falls

A distinct logic was incorporated to identify falls, which pose a significant risk to senior citizens. The reasoning was predicated on:

- Acceleration values on any axis greater than 20 m/s^2

- Gyroscope readings that are more than 300°/s

A fall is strongly indicated by such a sudden and powerful movement combination. An emergency notification is sent out when the event is flagged by the system.

3.2.8 Online Health Tracking Interface for Chatbots

A chatbot interface based on Streamlit was created to make the system interactive and easy to use. The following tasks are carried out by the chatbot:

- All vital signs can be entered by the user.

- Predicts health risks by loading the trained hybrid model.

- Shows a positive health assessment message (such as "Healthy," "Mild Risk," or "Critical Risk").
- Enumerates the precise parameters that set off the alarm.
- Alerts users of fall detection.
- Displays recommendations or warnings according to conditions found.

Users are empowered by this chatbot to evaluate their health and take appropriate action.

3.2.9 Conversational Support Driven by LLM

A Large Language Model (LLM) was incorporated into the system to improve its intelligence and usability to:

- Use natural language to interpret health information and alerts.
- Give conversational advice, such as what to do if you have a fever or low SpO_2.
- Respond to user inquiries regarding system usage or health metrics.
- Lower the technical hurdle for users who are not experts.

The LLM serves as a virtual health assistant, adding conversational awareness to the analytical backend.

3.2.10 Ngrok Deployment for Remote Access

Without requiring cloud infrastructure, external users can access the local Streamlit app via a public URL thanks to the application's ngrok deployment. This made it possible for:

- User interaction in real time from any device with an internet connection.
- Easy sharing of the monitoring tool with healthcare personnel.
- Demonstration of a prototype without complete cloud hosting.

3.3 ALGORITHM 1: Algorithm of Hybrid Model

Let,

- $D = \{(p_1, q_1), (p_2, q_{2)}, \ldots, (p_n, q_n)\}$: Dataset of n samples
- $p_i \in R^{13}$: Feature vector of 13 health parameters

- $q_i \in \{0,1,2\}$: Health risk labels (0=LOW, 1= Medium, 2=High)
- f_{DT} : Decision Tree Model
- f_{RF}: Random Forest Model
- f_{Hybrid} : Final Ensemble Decision
- $LLM()$: Large Language Model Response Generator
- $A \subset$ p: A Subset of features exceeding safety thresholds
- P: Prompt to the LLM
- R: Response from the LLM

Step 1: Collected input data $p_i \in R^{13}$ in real time, where:

$$p_i = [Age, SpO_{2,} HR, BP, Accel_{x,} Accel_y , Accel_{z,} UV, Gyro_{x,}\ Gyro_{y,} Gyro_{z,}\ Temp]$$

Step 2: Apply preprocessing to D:

- Handle missing data
- Normalize or scale p_i

Step 3:

Define function c(p_i) → q_i based on medical thresholds:

$$2, if\ any\ critical\ condition\ is\ detected$$

$$p_i = 1,\ if\ any\ moderate\ condition\ is\ detected$$

$$0, otherwise$$

Step 4: $D_{train}, D_{test} = TrainTestSplit(D, 80\ \%\ train, 20\%\ test)$

Step 5: Train both classifiers on D_{train}:

$$f_{DT} \rightarrow Train\ Decision\ Tree\ on\ D_{train}$$

$$f_{RF} \rightarrow Train\ Random\ Forest\ on\ D_{train}$$

Step 6:

For each test instance $\subset D_{test}$:

$q_{DT} = f_{DT}(p), q_{RF} = f_{RF}(p)$

Hybrid Prediction Rule:

$$f_{Hybrid}(p) = \begin{cases} q_{DT,} if\ q_{DT} = q_{RF} \\ q_{RF}, Otherwise\ (RF\ takes\ priority) \end{cases}$$

Final predicted label:

$$\hat{q} = f_{Hybrid}(x)$$

Step 7:

Define alert set $A \subset$ p:

$A = \{p_j \in p | p_j\ exceeds\ medical\ thresholds\}$

Raise:

- alert_flag=1 if |A| ≥ 1
- critical_alert=1 if |A| > 2

3.4 ALGORITHM 2: Algorithm of Conversational LLM Response

- $p_i \in R^{13}$: Input Feature vector
- $\hat{q} \in \{0,1,2\}$: Final health risk prediction from the hybrid model
- $LLM()$: A pre-trained language model mapping prompts natural language output
- $A \subset$ p: Set of alert features where each $p_j \in A$ exceeds the safe threshold
- P: A Constructed prompt string is given to the LLM
- R: Final natural language response

Step 1:

Each feature $p_i \in p$ is evaluated against a medical threshold function G_j. The alert set A is defined as:

A= $\{p_j \in p | p_j > G_j^{max}$ or $p_j > G_j^{min}$

Where G_j^{max}, G_j^{min} are the medically safe bounds for the feature p_j.

Step 2:

Define a formatting function $\emptyset: A \cup \{\hat{q}\} \rightarrow$ string that converts alerts and risk levels into natural language text. Then:

$P =$ The user has the following issues: $+ \sum_{p_j \in A} \emptyset(p_j)$+"Risk Level"+ $\emptyset(\hat{q})$

Where:

$$\emptyset(p_j) = p_j = value, which\ is\ outside\ the\ safe\ range.$$

$$\emptyset(\hat{q}) = \begin{cases} Low, \hat{q} = 0 \\ Medium, \hat{q} = 1 \\ High, \hat{q} = 2 \end{cases}$$

Step 3:

Given the constructed prompt P, the LLM is a function:

$LLM: P \rightarrow R$

Where $R \in NL$, the space of natural language explanations.

$$R = LLM(P)$$

Chapter-4

RESULTS AND ANALYSIS

4.1 DATASET SUMMARY

A real-time wearable health monitoring system provided the majority of the dataset used in this investigation. It comprises environmental and physiological factors that are crucial for assessing a user's health. Continuous monitoring with sensor-equipped hardware was used to record these parameters, which were then sent to a central data processing system via the MQTT protocol. Time (s), Age, SpO_2 (%), Heart Rate (bpm), Systolic and Diastolic Blood Pressure, Accelerometer readings (X, Y, Z in m/s^2), Gyroscope readings (X, Y, Z in °/s), UV Rate, and Body Temperature (°C) are the dataset's primary features as shown in Figure 4.1 on p.19. These characteristics were picked because of their clinical value in identifying environmental exposure, fall hazards, respiratory distress, and cardiovascular abnormalities.

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
Time (s)	Age	SpO2 (%)	Heart Rate	Systolic BP	Diastolic B	IR Value	Red Value	Accel X (m	Accel Y (m	Accel Z (m	UV Rate	Gyro X (Â°	Gyro Y (Â°	Gyro Z (Â°	Body Tem	Health_Risk
0	30	98.1988	75.7483	141	116	53812.5	51748.4	-0.3174	0.74534	8.74287	5.02516	-0.508	-4.3489	78.9241	37.6152	1
1	87	96.6846	94.7806	104	101	58730.7	58919	-0.5123	0.55062	9.94163	11.3211	60.4185	75.2918	-37.361	36.1583	2
2	28	99.4414	88.8382	161	68	54522.5	50766.9	0.78226	0.67555	10.0566	8.80959	31.2122	-79.925	-18.982	37.0815	1
3	86	95.3898	63.092	150	72	58543.2	50466.2	-0.8707	-0.1553	9.22535	7.01168	-39.949	9.3552	68.7469	37.693	2
4	68	95.1593	83.8967	110	102	52572	54985.5	-0.4388	0.7113	9.93416	2.05415	88.8169	-48.356	83.6431	36.1622	1
5	55	99.4612	92.215	172	93	56932.4	54077.6	0.32707	-0.4303	9.83944	2.6413	-76.859	20.0699	48.5053	36.5405	1
6	36	98.6421	67.4935	176	75	59484.7	57324.5	-0.8102	0.34297	9.90517	0.48027	14.9584	-94.036	38.5902	37.6362	1
7	64	95.299	71.4206	164	64	50697.4	59467.2	0.5751	-0.5718	9.32143	9.82639	-41.137	15.5067	-14.175	36.1815	1
8	59	97.2829	68.1755	164	60	52411.7	50022.6	0.05373	-0.792	9.27433	7.51849	-73.981	96.1731	-57.988	35.9624	0
9	46	97.1103	68.4421	177	99	54797.6	50683	-0.1253	0.20622	9.19149	8.67421	-56.64	-27.198	-23.921	35.6327	1
10	72	97.9435	61.645	113	81	56782.7	56512.2	-0.7133	0.00234	10.1425	0.82176	-2.5441	-75.607	16.5819	36.3681	1
11	42	96.4813	91.0729	92	107	57666.8	55813.1	-0.5319	0.25984	9.62095	11.9596	17.9994	33.0361	-9.8407	36.4472	2
12	32	97.5893	70.7839	111	105	59564.4	59450.5	0.18918	-0.2086	9.3855	10.3394	53.1915	-15.124	-104.19	35.7688	1
13	73	97.9374	95.2006	142	117	59046.6	58098.8	-0.2904	-0.8641	9.68926	2.28712	73.8882	46.6361	2.66269	37.5987	1
14	43	99.6403	72.2496	91	85	59443.7	58535.2	-0.1646	1.04516	11.1879	1.47458	14.0776	54.7467	54.3731	36.2866	0
15	41	95.4521	66.6105	177	93	50657.2	54078.6	-0.0687	0.52479	9.85319	2.10122	-21.572	51.6909	121.961	36.8728	1
16	74	95.9361	89.8823	119	109	52982.2	54249.2	0.27231	-0.2627	9.69159	3.35263	51.9956	-0.2235	-44.9	36.6341	1
17	58	98.4443	73.5368	127	117	59307.8	55633.5	1.48968	0.04446	9.49514	6.26503	-30.63	91.6728	16.4713	36.9133	0

Figure 4.1: Dataset of Smart Healthcare Monitoring System

Moreover, each record was classified as low, medium, or high health risk based on domain-specific thresholds. The finished dataset had enough samples to adequately train and assess machine learning models, was balanced, and was clean.

4.2 HYBRID MODEL

The suggested system makes use of a hybrid machine learning model that combines the advantages of Random Forest (RF) and Decision Tree (DT) classifiers. The hybrid approach ensures a balance between interpretability and robustness. While the decision tree provides a clear and traceable decision path, the random forest enhances predictive performance through ensemble averaging. A weighted combination of the two models that is managed by a tunable parameter β, the final prediction is both precise and adaptable. This method significantly improves classification reliability and attains a high degree of accuracy in identifying health risk levels, particularly when dealing with complex or noisy health data.

$$\hat{w} = \beta . RF_{Prediction} + (1-\beta). DT_{Prediction} \quad (4.1)$$

The random forest model is controlled by a weight parameter called β, which affects the outcome prediction

It's a number between 0 and 1, where:

• The decision Tree model has complete control when β = 0.

• The Random Forest model has full influence when β = 1.

4.3 LARGE LANGUAGE MODEL (LLM)

To support the hybrid classifier and enable natural language communication with users, the system incorporates a Large Language Model (LLM). The structured input from the hybrid model is converted into conversational, approachable feedback by the LLM. By including a second adjustable parameter, α, the system ensures that the final messages are accurate and personalized by combining the LLM's responses with pre-existing medical templates. This enhances the system's usability and accessibility, especially for users who might not be familiar with medical jargon. The result of the hybrid predictive engine and LLM-based communication is an intelligent, interactive healthcare system that successfully communicates risk and recommendations to the end user while also continuously monitoring important parameters.

$$R_{Final} = \alpha . L + (1-\alpha). T \quad (4.2)$$

- T: Rule-based template response
- L: Response generated by LLM
- $\alpha \in [0,1]$: Weight parameter controlling the influence of the LLM
- R_{Final} : Final output response is shown to the user

4.4 PERFORMANCE PARAMETER OF SMART HEALTHCARE MONITORING SYSTEM

The hybrid health risk classification model, which combines RF and DT classifiers, performs exceptionally well in predicting health risk levels. As demonstrated in Table 4-1 on p.20, the model achieves an impressive 97.93% accuracy rate with outstanding precision, recall, and F1-scores in each class. Specifically, class (health risk level 0) shows perfect recall and a strong F1-score of 0.9229, while class 1 (health risk level 1) performs exceptionally well with a precision of 0.9962 and an F1-scores of 0.9839. Class 2 (health risk level 2) does remarkably well, with an F1-score of 0.9948 and perfect precision. The combination of RF ensemble averaging and DT transparency guarantees a reliable and intelligible model that can manage complicated and noisy health data. Because it offers reliable decision paths and high predictive accuracy, this hybrid approach works incredibly well for health risk classification tasks in real-world applications.

Table 4-1: Performance Parameter of Smart Healthcare Monitoring System

Class level	Precision	Recall	F1- Score	Support
Level 0	0.8568	1.0000	0.9229	1095
Level 1	0.9962	0.9719	0.9839	6483
Level 2	1.0000	0.9897	0.9948	2422
Accuracy			0.9793	10000
Macro Average	0.9510	0.9872	0.9672	10000
Weighted Average	0.9819	0.9793	0.9799	10000

A comparison of training and testing accuracy is essential for assessing the hybrid model's performance and capacity for generalization, which combines Random Forest and Decision Tree classifiers. Overfitting, a situation in which the model performs well on training data but is unable to generalize to unseen data, may be indicated if the training accuracy is noticeably higher than the testing accuracy as shown in Figure 4.2 on p.22. The testing accuracy of 97.93% in this instance, however, indicates that the model generalizes well and that there is little variation between the training and testing accuracies. The robustness of the model in actual health risk prediction scenarios is confirmed by this high degree of accuracy on the test set.

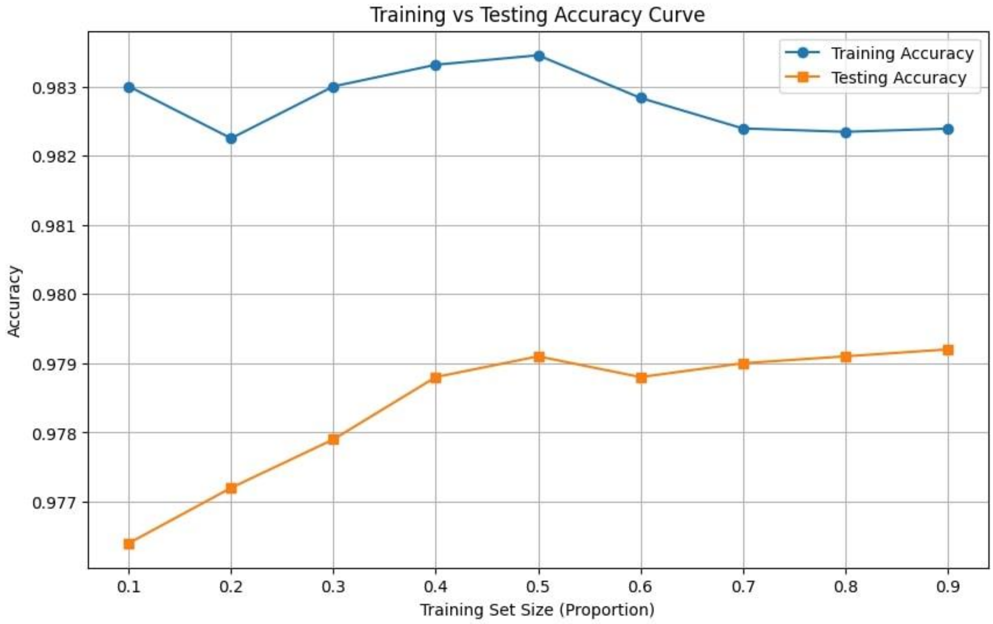

Figure 4.2: Training vs. Testing Accuracy of Hybrid Model

The confusion matrix, which provides a comprehensive examination of the model’s performance across all classes, supports this conclusion. As seen in Figure 4.3 on p.22, it displays the percentage of cases of each health risk level(0,1,2) that are correctly and incorrectly classified. The model produces accurate predictions for all classes when the confusion matrix has strong diagonal dominance, or high values along the diagonal. Fewer misclassifications are reflected by minimal off-diagonal values, demonstrating the hybrid model's ability to reliably and minimally distinguish between various health risk levels.

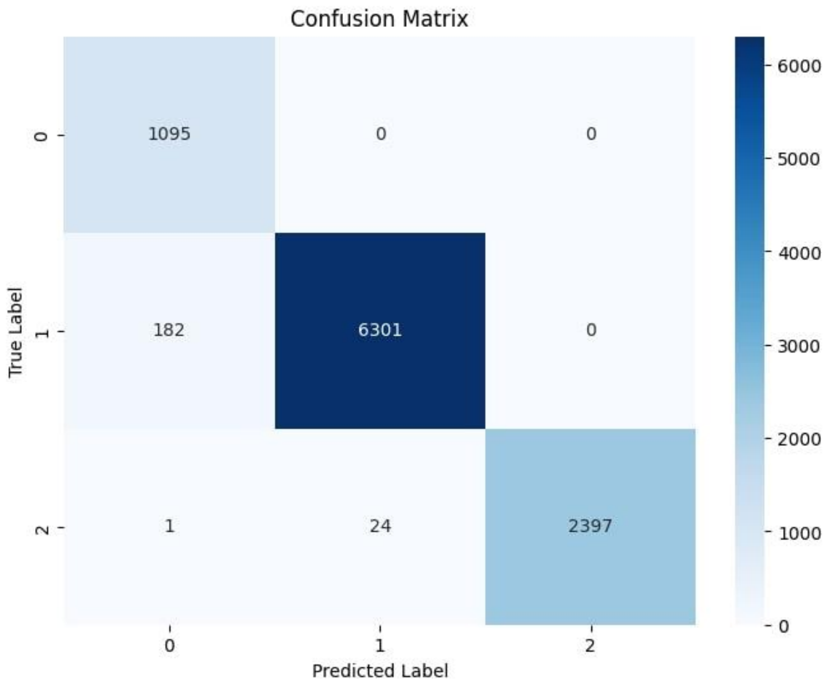

Figure 4.3: Confusion Matrix of Machine Learning Model

4.5 USER INTERFACE

The health monitoring system's output interface is made to help users easily comprehend and act upon complex health data. The three health risk levels low, medium, and high and color codes for easy identification are displayed. The system identifies which of the parameters such as SpO_2, heart rate, blood pressure, and body temperature, etc. is responsible for the elevated risk for each risk level. For instance, the system will make it obvious if it determines that a high-risk level is caused by high blood pressure as shown in Figure 4.4 on p.23. The system ensures that the user receives straightforward explanations by providing natural language feedback produced by a Large Language Model (LLM) in addition to the risk level. Based on the risk factors that have been identified, the interface also offers practical suggestions, like altering one's lifestyle or consulting a doctor.

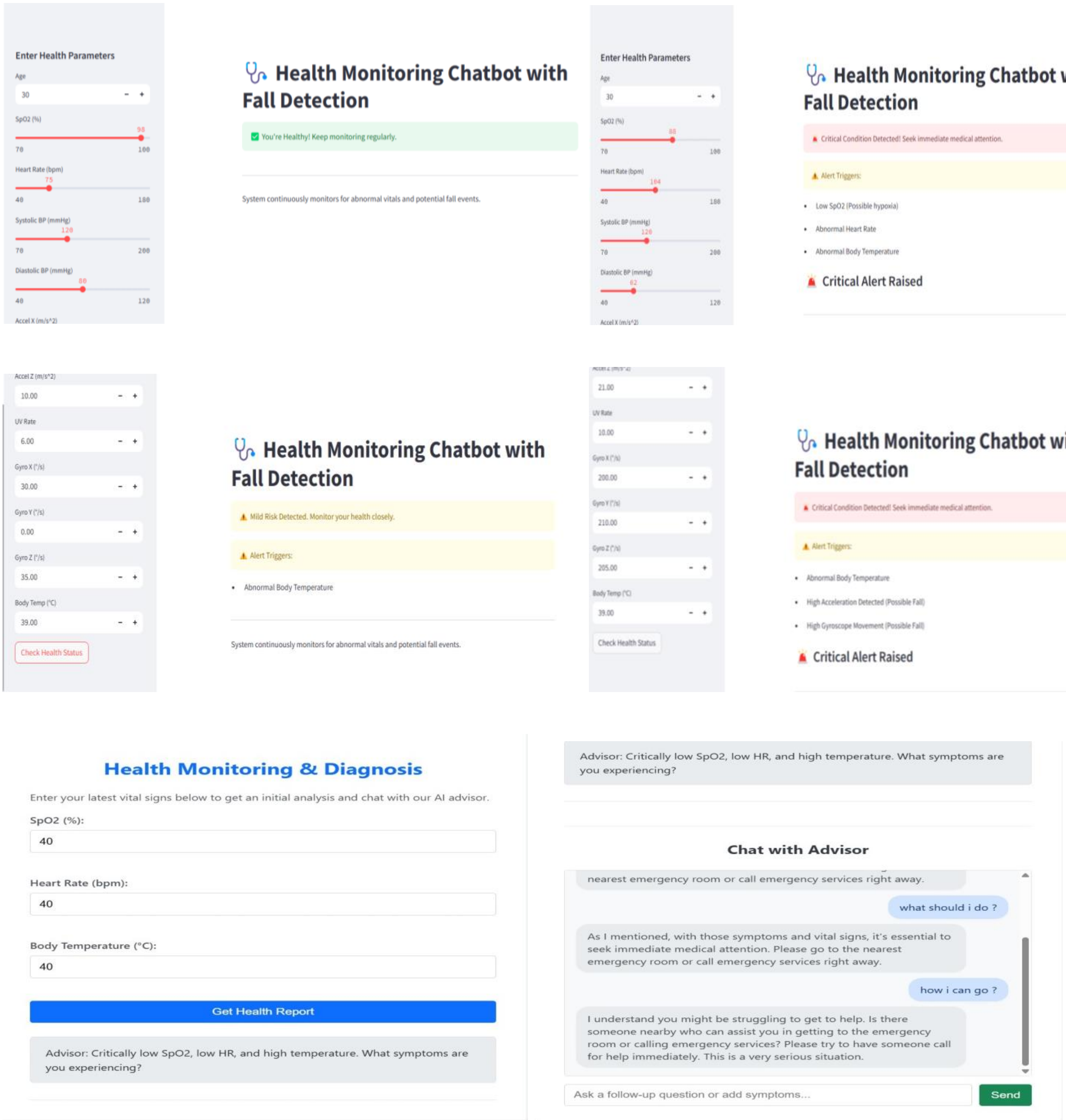

Figure 4.4: User Interface of Smart Healthcare Monitoring System

Chapter-5

DISCUSSION AND CONCLUTION

5.1 DISCUSSION

5.1.1 Experimental Setup and Criteria

The performance, dependability, and user interface of the proposed intelligent healthcare monitoring system were evaluated through several controlled tests, the experiments used real-time data collected from wearable health devices, including vital physiological and environmental factors such as blood oxygen saturation (SPO2), heart rate blood pressure, body temperature, etc. These values were transmitted in real-time, ensuring seamless data transfer and storage using MQTT protocol and an IoT setup based on NODE-RED [19]. To ensure robustness, the original data was preprocessed to handle noise, missing values, and outliers.

After cleaning and labeling it in accordance with the clinical threshold, the dataset was divided into training and testing sets in an 80:20 ratio. The system was evaluated using two basic ML classifiers, RF and DT. A hybrid strategy was employed to capitalize on the distinct advantages of each classifier DT's interpretability and RF's ensemble stability. Several combinations of influence were examined during testing to determine the optimal fusion and ensure accurate health risk prediction across a wide range of inputs.

5.1.2 Performance Evaluation of the Hybrid Model

The hybrid model produced very positive results across all performance metrics. It was able to categorize medical conditions into low, medium, and high-risk groups with remarkable accuracy and consistency. The model showed remarkable accuracy in distinguishing abnormal physiological patterns in cases with borderline symptoms, which are often misclassified in traditional systems.

Comparative analysis showed that the hybrid model consistency outperformed both individual classifiers and conventional ML models in terms of balanced accuracy and overall stability. The system's ability to correctly identify high-risk cases with few false positives demonstrated its value in critical health monitoring applications.

5.1.3 Evaluation of Conversational Chatbot with LLM

Prediction and user communication are equally crucial in healthcare systems. To solve this an LLM was added to the platform, which converts structured data outputs into natural language responses. The LLM was given thorough prompts based on estimated risk levels and recognized health abnormalities.

The chatbot responses were evaluated based on the following criteria: clarity, relevance, tone, and the ability to offer actionable insights. Feedback from simulated user interactions demonstrated that the LLM-generated responses were easy to understand, medically coherent, and context-sensitive. The combination of rule-based messages and dynamic responses maintained a dependable and instructive user experience without compromising personalization.

5.2 CONCLUSION

A comprehensive solution for user safety and real-time health assessment is provided by the proposed system [18]. It integrates continuous physiological data collection, hybrid ML-based health-risk prediction, and a natural language response system to deliver accurate and comprehensible health insights. With an impressive 97.93% accuracy rate, the hybrid model effectively divides users into low, medium, or high health risk groups by combining RF and DT classifiers.

One notable feature of the system is its ability to detect significant events such as falls or sudden declines in health status [19]. In these scenarios, the system not only generates real-time alerts but also actively finds and reports the patient's location, enabling timely intervention or support [20]. This location-awareness feature significantly increases the system's usefulness in emergencies, especially for elder patients or patients under remote supervision.

The addition of a conversational interface powered by LLM, which allows users to receive personalized and intelligible health advice, further improves the system's accessibility. The system has a lot of potential to promote proactive health monitoring, early risk assessment, and responsive care in both clinical and private settings.

Chapter-6

SUMMARY, PUBLICATIONS AND FUTURE WORK

6.1 SUMMARY

The development of an intelligent healthcare monitoring system that can identify falls, assess health in real-time, and interact with users in an intuitive manner is demonstrated by this project. The system gathers important physiological and environmental data, including heart rate, SpO2, blood pressure, etc. A hybrid ML model that blends RF and DT classifiers was developed to recognize a person's health risk precisely. The model's impressive 97.93% classification accuracy demonstrated that it was effective in identifying low, medium, and high-risk medical conditions.

To increase accessibility, an LLM was added to the system, providing conversational explanations based on the predicted health status. In emergencies where prompt medical attention is necessary, this feature is essential. The system is ideal for personal healthcare, senior monitoring, and remote medical support since it successfully integrates health monitoring, intelligent decision-making, and user-centric communication into a single platform. The LLM improves user understanding the engagement by efficiently translating structured outputs into perceptive, readable feedback.

Additionally, the location-awareness features of the system allow it to determine and report the user's exact location in the event of a fall or unanticipated illness. In emergency where prompt medical attention is necessary, this feature is essential. The system is ideal for personal healthcare, serial monitoring, and remote medical support since it successfully integrates health monitoring, intelligent decision-making, and user-centric communication into a single platform.

6.2 PUBLICATION

[1] T. Bhowmik, D. Mitra and P. Chatterjee, "Machine Learning Based Crop Recommendation Model in Precision Agriculture," *2024 International Conference on Emerging Smart Computing and Informatics (ESCI)*, Pune, India, 2024, pp. 1-6, doi: 10.1109/ESCI59607.2024.10497421.

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[3] P. Chatterjee, D. Mitra, T. Bhowmik, R. Nath, K. Dutta and A. Deyasi, "Predicting Tea Quality Based on Antioxidant and Polyphenol Content Using Ensemble Machine Learning Model," *2024 IEEE International Conference of Electron Devices Society Kolkata Chapter (EDKCON)*, Kolkata, India, 2024, pp. 482-487, doi: 10.1109/EDKCON62339.2024.10870624.

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6.3 FUTURE SCOPE

Although the system created for this project has demonstrated a great deal of promise, several improvements and research extensions are planned to further expand its reach, flexibility, and practical impact:

***6.3.1 Integration with Advanced GPS and GIS Services**:*

By integrating sophisticated location-tracking tools like geofencing, route history, and proximity alerts, emergency response times can be shortened and caregivers can monitor patients' whereabouts in real-time.

6.3.2 Real-time Integration with Emergency Services:

To minimize response times during critical incidents, future iterations of the system could be integrated with emergency services, like hospitals or ambulances, to automatically send alerts with patient location and vitals.

***6.3.3 Continuous Learning Framework*:**

The model can stay current with changing patient profiles and health trends by putting in place an adaptive learning system that allows the model to retrain itself on fresh data.

6.3.4 Enhanced Fall Detection with Audio & Visual Feedback:

Combine accelerometer/gyroscope data with camera-based pose estimation or audio detection (such as abrupt loud noises) to increase fall detection accuracy and lower false positives.

6.3.5 Security and Privacy Enhancement:

Improving security and privacy would involve implementing stringent access control procedures, anonymization, and end-to-end encryption to safeguard private health information and guarantee adherence to laws like GDPR and HIPAA.

6.3.6 Comprehensive Clinical Validation:

Collaborating with hospitals and other healthcare facilities to carry out practical trials will confirm the system's efficacy on a broader scale and offer valuable information for optimizing the model for a range of demographics and ailments.

6.3.7 Integration with Electronic Health Records (EHR):

This system can be synchronized with hospital-based EHRs to help keep a continuous and thorough patient profile that physicians and caregivers can access.

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