RESEARCH PAPER

A Smart AI-IoT Integrated System for Continuous Health Monitoring and Adaptive Drug Delivery in Personalized Healthcare

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Abstract
Health is important to live life to the fullest. When a person leads a healthy lifestyle, the body remains healthy and the mind is active and fresh. Living a healthy life would extend longevity and also regenerate the body and mind. Having good health is of core importance to human happiness. With the help of Smart Health System, we aim to provide a healthier and a better life to its user with remote monitoring of various physiological parameters such as body temperature, heart rate, blood oxygen saturation, pulse rate etc. Advancement of technology brought up various devices to measure physiological parameters such as heart rate, SPO2, body temperature. The scope of these devices can be expanded more with help of IoT and Cloud technology. It can enable patients as well as doctors to keep track of those from time to time. Patients suffering from hypertension, stress need to check their blood pressure or heart rate more frequently and every time they have to visit a hospital to get this done. But with the help of remote Smart Health System patient can update his records from home and doctor can assess those readings remotely and give feedback on them.
During recent pandemic situation traditional healthcare sector has gone through various changes. Currently there are various wearable smart bands which tracks exercise routine of people through measurement of pulse rate Smart Health System would be specifically designed for hospital, doctors and their patients where patient
can remotely record own physiological parameters as and when necessary as recommended by doctors. The doctors can remotely observe this data and can accordingly change treatment of the patient.
This Smart Health System interaction will help everyone to save their time and money as whole information would be available about patient on few clicks anytime over internet because of cloud technology. Defiantly interaction of this system with patient and doctor is used for User wellbeing and peace.

Keywords Interaction, Random Forest Algorithm, Stress Management, IOT, Cloud Technology, User Wellbeing
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Introduction

Advancement of technology brought up various devices to measure physiological parameters such as heart rate, SPO2, body temperature. The scope of these devices can be expanded more with help of IoT and Cloud technology. It can enable patients as well as doctors to keep track of those from time to time. Patients suffering from hypertension, stress need to check their blood pressure or heart rate more frequently and every time they have to visit a hospital to get this done. But with the help of remote Smart Health System patient can update his records from home and doctor can assess those readings remotely and give feedback on them This system can provide probable stress level of an individual based on Galvanic Skin Response values.
Human-computer interaction (HCI) can greatly enhance stress management for user well-being by creating intuitive and user-friendly interfaces that facilitate interaction between individuals and machine learning-based stress management systems. Here's how HCI can be integrated into stress management using machine learning:

1. **User-Centered Design**:
Employ user-centered design principles to create interfaces that prioritize the needs, preferences, and capabilities of users. Conduct user research, interviews, and usability testing to understand user behaviors and preferences regarding stress management.

2. **Intuitive Interfaces**:
Design interfaces that are intuitive and easy to use, especially for individuals who may be experiencing stress. Utilize familiar metaphors, clear visual cues, and

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minimalistic designs to reduce cognitive load and enhance usability.

3. **Real-Time Feedback**:
Provide real-time feedback on users' stress levels and progress through interactive visualizations, notifications, or alerts. Design feedback mechanisms that are easily interpretable and actionable, guiding users towards effective stress management techniques.

4. **Adaptive Interfaces**:
Develop interfaces that adapt to users' preferences, behaviors, and stress levels over time. Utilize machine learning algorithms to personalize interface elements, content, and recommendations based on individual users' needs.

5. **Multi-Modal Interaction**:
Support multi-modal interaction techniques such as voice commands, gestures, and touch-based inputs to accommodate users with diverse abilities and preferences. Enable seamless transitions between different interaction modalities to enhance usability and accessibility.

6. **Context-Aware Systems**:
Build systems that are aware of users' context, such as their location, activity, or social environment, to provide contextually relevant support for stress management. Incorporate contextual information into interface design and decision-making processes to enhance the effectiveness of interventions.

7. **Engagement and Motivation**:
Design interfaces that promote user engagement and motivation by incorporating elements of gamification, social interaction, and positive reinforcement. Use persuasive design techniques to encourage users to actively participate in stress management activities and adhere to recommended interventions.

8. **Transparent Communication**:
Foster transparent communication between users and machine learning-based stress management systems by providing explanations, justifications, and transparency regarding system behavior and recommendations. Design interfaces that enable users to understand how their data is being used and empower them to make informed decisions about their stress management practices.

9. **Continuous Evaluation and Iteration**:
Continuously evaluate the usability, effectiveness, and user satisfaction of HCI designs for stress management through iterative design cycles and user feedback. Use data-driven insights to iteratively improve interface design, interaction patterns, and intervention strategies based on user needs and preferences.

By integrating HCI principles into machine learning-based stress management systems, it's possible to create user- friendly, engaging, and effective interfaces that empower individuals to better manage stress and improve their overall well-being.

Literature Survey

The intersection of Human-Computer Interaction (HCI), stress management, and mental health technologies has become a rapidly evolving research area. Several studies have explored diverse approaches to designing systems that can detect, monitor, and support individuals in managing stress. These works collectively demonstrate how activity-centered design, wearable and mobile sensing, machine learning, and empathetic interaction design contribute to user-centered stress management solutions.

Cox et al. (2017) introduced an activity-centered approach to requirements elicitation for stress management applications. Unlike traditional user-centered design that primarily focuses on user characteristics, this approach emphasizes users' daily activities as a basis for system design. By anchoring design decisions in the context of how stress emerges in everyday life, their work highlighted the importance of understanding the lived experiences of users to ensure meaningful support. This user–activity alignment is a recurring theme across later studies, which sought to integrate technological sophistication with practical usability.

The role of sensing technologies is another significant strand of research. Milella et al. (2020) conducted a systematic review of wearable sensors for monitoring stress in workplace environments. Their findings illustrated the potential of physiological measures such as heart rate variability, skin conductance, and movement patterns to provide real-time insights into stress levels. While this promises objective and continuous monitoring, the review also noted challenges related to sensor accuracy, comfort, and the ethical implications of workplace surveillance. Wang et al. (2018) extended this line of inquiry into real-world urban settings, using passive sensing data such as mobility and phone usage to predict daily stress levels. Their exploratory study revealed that ambient and unobtrusive sensing could provide scalable stress detection; however, the complexity of urban life raised issues of contextual interpretation, highlighting the need for more nuanced models.

Machine learning and mobile platforms form a third dimension of innovation. Azari et al. (2021) reviewed smartphone-based stress detection using machine learning, emphasizing the advances in algorithms capable of analyzing multimodal data such as text, speech, and behavioral patterns. While these techniques demonstrate high potential, the review underscored the crucial role of HCI in ensuring interpretability, transparency, and user trust in such systems. Schueller and Zalta (2014) addressed these concerns through MyMoodCoach, a personal informatics system designed to support mental health management. Their work demonstrated the feasibility of combining data-driven analysis with HCI principles such as feedback, personalization, and user engagement, showing how mobile applications can act as supportive companions rather than intrusive monitors.At a broader conceptual level, Szymczak and Hornbæk (2015) positioned HCI as central to supporting and understanding stressful experiences. Their work argued that interactive systems should not merely measure stress but must also respond sensitively to emotional states, enabling reflection and self-awareness. Similarly, Kjeldskov et al. (2019) emphasized the interplay between user needs and HCI in designing mobile technologies for mental health. They showed that successful applications must strike a balance between technological capability and emotional resonance, ensuring that interventions align with individual preferences, contexts, and coping mechanisms.

From 2025 onwards, research has deepened in several new directions. van den Berg et al. (2025) conducted a narrative review of wearable stress management technologies, identifying facilitators such as interactivity and barriers such as discomfort, privacy concerns, and mismatches between physiological signals and users' subjective experiences. Similarly, Motti and Faiz (2025) and Paniagua-Gómez et al. (2025) reviewed wearable biosensing and IoT-enabled stress detection, underscoring challenges of accuracy, scalability, and data ethics in real-world deployment. Neigel et al. (2025) advanced this by testing unobtrusive stress detection in everyday settings, revealing usability challenges when moving beyond laboratory contexts. Technical innovation also appears in the work of Schreiber et al. (2025), who introduced a multimodal dataset capturing varied stress types with strong benchmarks, and Xiao et al. (2025), who proposed HHISS, a model designed to improve generalizability across heterogeneous populations and contexts. Most recently, Neupane et al. (2025) explored the integration of wearables with large language model (LLM)-driven chatbots, showing how real-time adaptive interventions can complement stress detection, though also highlighting that not all detected stress events warrant immediate intervention.

Together, these newer contributions highlight a shift in stress management technologies from laboratory-based feasibility studies to real-world usability, personalization, and long-term engagement. They extend earlier findings by addressing user experience, heterogeneity, multimodal data integration, and the role of AI in delivering interventions. However, they also surface persistent gaps such as the need for longitudinal validation, better alignment between physiological signals and subjective stress, and ethical frameworks for privacy and trust. This trajectory shows that the future of HCI in stress management will rely not only on improving detection accuracy, but also on designing empathetic, adaptive, and ethically responsible systems that integrate seamlessly into daily life.

Here is the summarized version of literature survey.

Author & Year	Methodology	Findings	Limitations
Cox et al., 2017	Activity-centered HCI design	Improved stress management apps	Limited to lab-scale testing
Milella et al., 2020	Systematic review of wearables	Stress monitoring feasibility in workplace	Did not address predictive modeling
Azari et al., 2021	ML-based smartphone detection	High accuracy in detecting stress via mobile sensors	Battery and privacy concerns
Schueller & Zalta, 2014	Personal informatics app	Improved self-reporting of mood	Dependent on user input
Wang et al., 2018	Passive sensing in urban residents	Daily stress prediction achieved	Limited generalization to rural populations

Methodology

There are 5 major components in the Smart Health Monitoring System.

IoT Sensors –

i. Collect data and upload it on cloud.

ii. Here 2 sensors are being used which will send data to cloud database system

iii. MAX30102 Pulse Oximeter Sensor- MAX30100 sensor can measure blood oxygen saturation (SpO2) and heart rate.

iv. GSR Sensor – The GSR sensor detects changes in the electrical conductance of the skin, which is changed by the sweat glands. As sweat is good conductor. When a person experiences stress or emotional arousal, nervous system is triggered, leading to increased sweat gland activity. This results in an increase in the skin's electrical conductivity, which can be measured by the GSR sensor.

b. Cloud Database –

i. The cloud layer is makes sure that information is highly available and can be accessed from anywhere with authorized access to the system.

ii. Data collected from sensors is stored on cloud database and further it issued with ML model for stress level prediction

iii. It provides a way to transfer patient information from the patient level to the clinical level so that doctors can access and diagnose the vital organs of patients anytime, anywhere.

iv. Firebase Realtime Database - It is cloud hosted No-SQL database updates sensor values in real time without any daily which can be further accessed by web application, machine learning model and alert system

v. Blynk IoT - Blynk connects health indicators to the cloud and builds a code-free iOS, Android and web app to review real-time and historical data from devices, manage it from anywhere in the world, and get key reports. It also provides a dataflow API that tracks real-time data from sensors that can be used to provide useful inputs to machine learning algorithms.

c. Machine Learning Model –

i. This model will predict stress level of patient based on GSR, Heart Rate and SPO2 values and store the result into cloud database.
ii. Model predicts stress in 10 levels

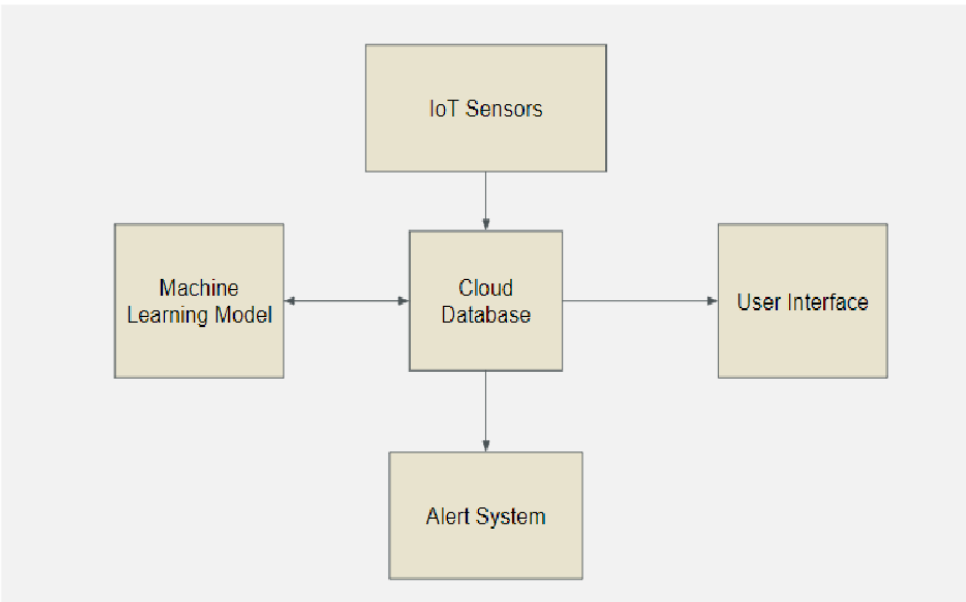
TABLE III. STRESS LEVELS

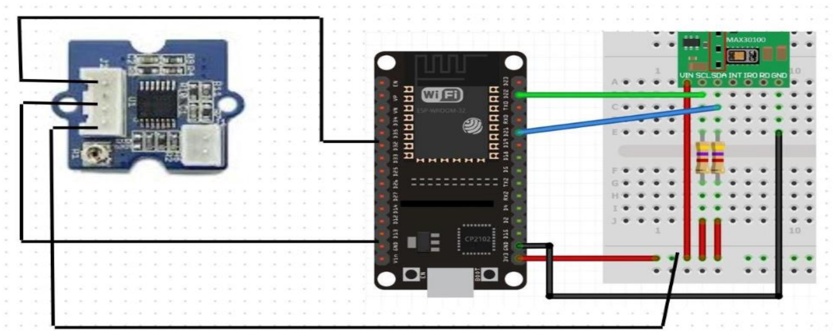
0	Normal	5	Moderatly High
1	Very Low	6	High
2	Low	7	Very High
3	Moderately Low	8	Extreme
4	Moderate	9	Danger

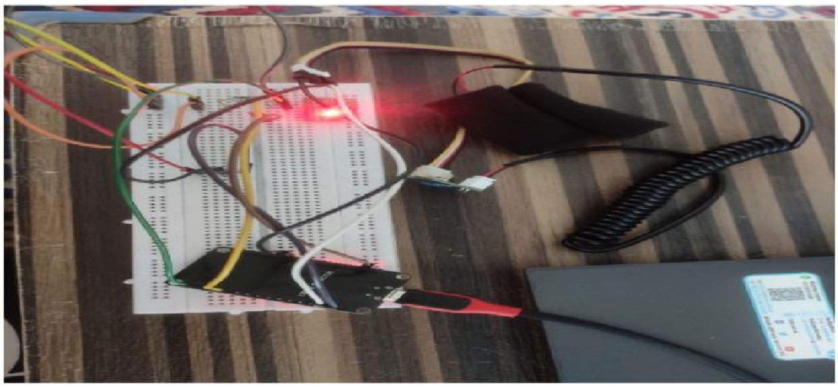
iii. Dataset contains patients' data recorded under various conditions with total 4890 entries.

d. User Interface
i. IoT sensor values and predicted stress levels are displayed on the web application
ii. It will also display threshold values based on machine learning model
iii. Data collected from IoT sensors would be visualized in form of graph sand charts for better understanding.

e. Alert System –
i. System will send alerts based on threshold values for health parameters through email or SMS
ii. These threshold values will be generated from Machine Learning model trained from available datasets
iii. User can decide who can receive alerts at the time of account creation and can also customize frequency of alerts as the priority of health parameters.







Stress Detection Algorithm Dataset Description Wearable Stress Classification dataset by MIT –

a. It contains 4890 observations

b. Data collected for a project at MIT that included anthropometric measurements of young drivers in a variety of stressful environments. Stress, such as rush hour, highway, traffic lights, and rest periods creates stress. Easy reading.

c. The dataset is freely available

d. Dataset predict stress level in the scale of 0-1

ii. Algorithm from research paper titled as – “An IoT based Real-Time Stress Detection System for Fire-Fighters “

TABLE II. STRESS CLASSIFICATION ALGORITHM TABLE

HEART RATE IN BPM

GSR READINGS	< 60	60-100	100-130	130-150	150-180	180-200	> 200
0-100	9	4	5	6	7	8	9
101-200	9	3	4	5	6	7	9
201-300	9	2	3	4	5	6	9
301-400	9	1	2	3	4	5	9
401-512	9	0	1	2	3	4	9

TABLE III. STRESS LEVELS

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4	Moderate	9	Danger

Stress Detection Regression Algorithm Comparative Analysis:

```
  return self._update_inplace(result)
---STRESS DETECTION REGRESSION ALGORITHM MODEL ACCURACY RESULTS ---
Model: Linear Regression
MSE: 0.23
R2 Score: 0.06
-----------------------------------
Model: Decision Tree
MSE: 0.22
R2 Score: 0.10
-----------------------------------
Model: Random Forest
MSE: 0.15
R2 Score: 0.41
-----------------------------------
Model: AdaBoost
MSE: 0.19
R2 Score: 0.23
-----------------------------------
Model: Gradient Boosting
MSE: 0.16
R2 Score: 0.35
-----------------------------------
Model: K-Nearest Neighbors
MSE: 0.17
R2 Score: 0.30
-----------------------------------
Model: Support Vector Regression
MSE: 0.27
R2 Score: -0.09
-----------------------------------
```

Dataset is tested with 7 different regression algorithms and scores are as below:

ii. Mean Squared Error –
MSE measures the average squared difference between the predicted values and the actual values in a regression problem. It provides an indication of how well the predicted and actual values align. MSE is calculated by taking the average of the squared differences between the predicted values (y_pred) and the actual values (y_true)

iv. R-squared (R2) score:
R2 score measures the proportion of the variance in target variable that is predictable from the features in a regression model.
It provides an assessment of how well the model captures the variation in the data. R2 score ranges from 0 to 1, with 1 resulting a perfect fit and 0 resulting that the model does not explain any of the variability in the target variable.
v. Based on R2 Score and MSE values Random Forest Algorithm gives better results with MSE – 0.15 and R2 Score – 0.41

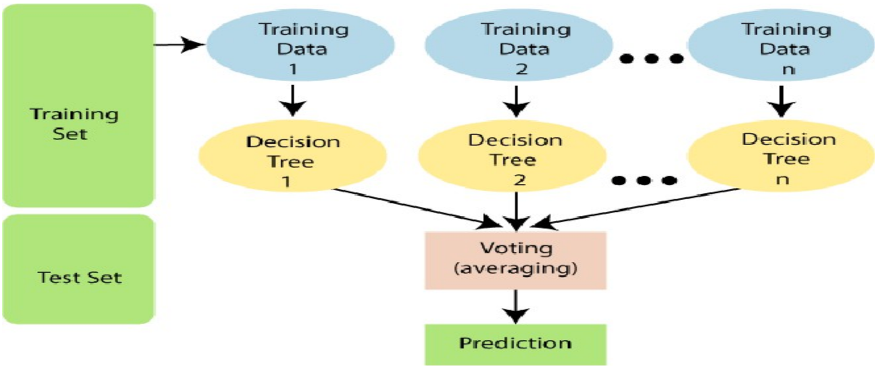
Random Forest Algorithm:
Random Forest is an learning algorithm which adds up number of decision trees to create a more robust and accurate model. It is commonly used for both classification and regression tasks. The algorithm gets its name from the fact that it creates an ensemble of "random" decision trees.

Working of Random Forest Algorithm:

i. Random sampling:
Random Forest uses a technique called bootstrap aggregating, or bagging, for creating number of subsets of the original dataset. Where every subset is created by randomly sampling the data with replacement. These subsets are known as "bootstrap samples."

ii. Decision tree construction:
For each bootstrap sample, a decision tree is constructed. However, unlike trational decision trees, Random Forest introduces randomness during the tree construction process. At each node of the tree, instead of considering all features, only a random subset of features is considered for finding the best split. This helps in reducing the correlation between the trees and promotes diversity within the forest.

iii. Voting and prediction:
Once all the decision trees are constructed, predictions are made by taking a majity vote (in case of classification) or averaging (in case of regression) the predictions of all the individual trees.



Hardware Components:

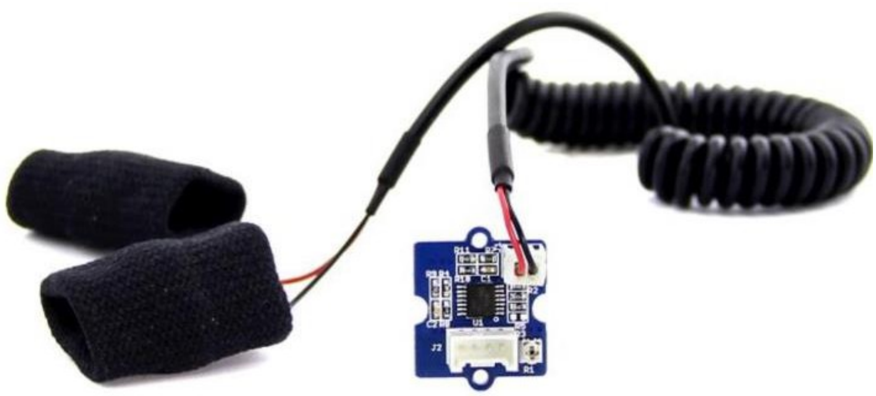
Max30100 Sensor –MAX30100 sensor can measure blood oxygen saturation (SpO2) and heart

rate. It uses a technique called photo plethysmography (PPG), which involves illuminating the skin and measuring the light absorption caused by blood flow. The sensor includes red and infrared (IR) LEDs that emit light into the tissue. The photodetector then measures the amount of light that is reflected or absorbed by the blood vessels. It is designed to operate at low power, making it suitable for portable and battery-powered devices. Accuracy of Max30100 Sensor - A study by IJEECS showed that the MAX30102 measures accuracy for heart rate and oxygen saturation (SpO2) of 97.11% and 98.84%, respectively.

ii. GSR Sensor –

GSR sensors provide an objective means of assessing stress levels. Traditional self-reporting methods rely on individuals' subjective perception of their stress levels, which can be influenced by various factors and may not always be accurate. GSR sensors, on the other hand, provide a physiological measure that is independent of self- reporting biases, making them valuable tools for stress assessment. Real-Time Monitoring: GSR sensors can provide

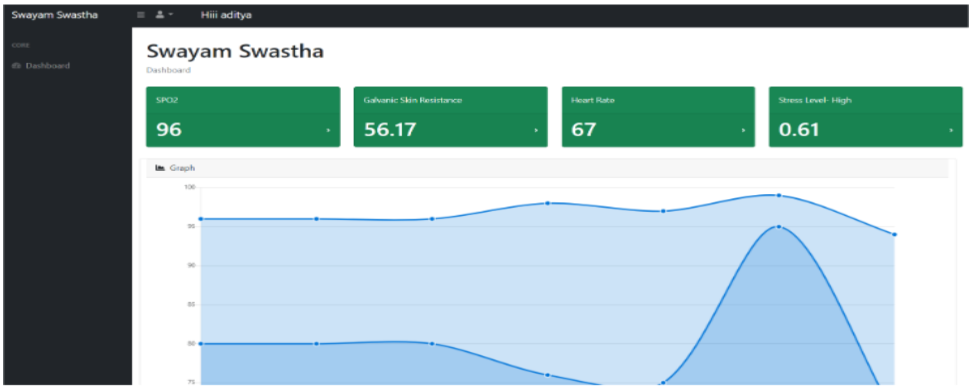
real-time monitoring of stress levels. As the sensor measures changes in skin conductance almost instantly, it can provide immediate feedback on stress responses.

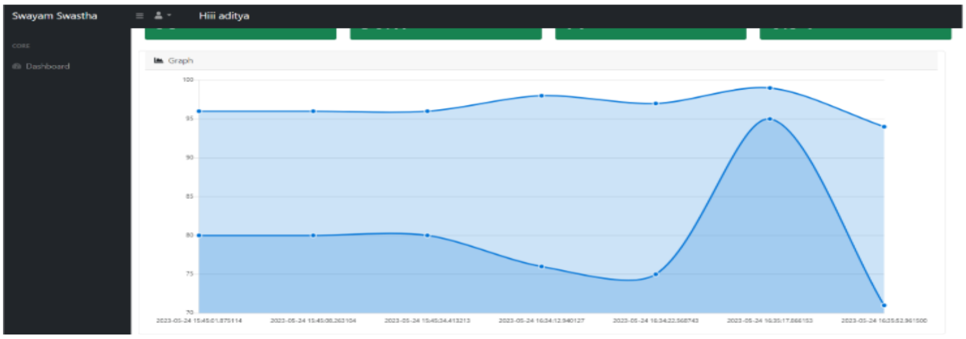


iii. ESP 32 –

The ESP32 is microcontroller with support of Wi-Fi and Bluetooth. Sensors are connected with ESP32 and the same readings are uploaded on cloud through it.

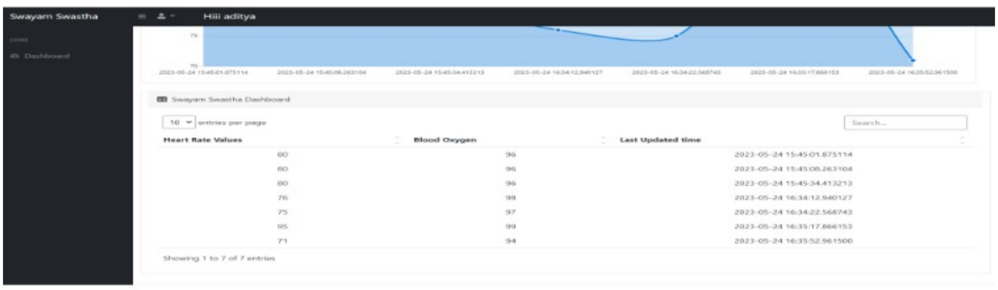
Results:

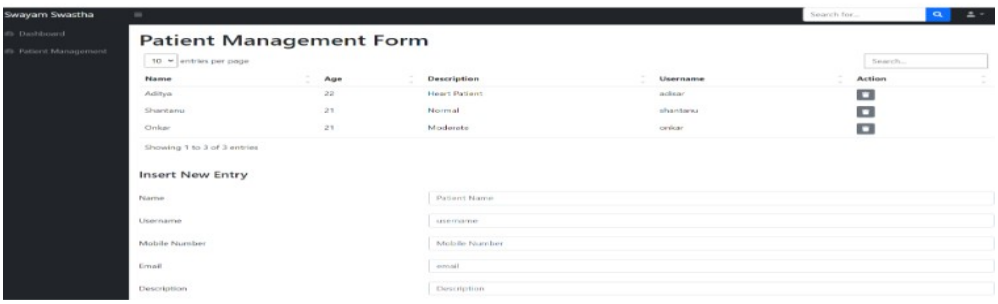




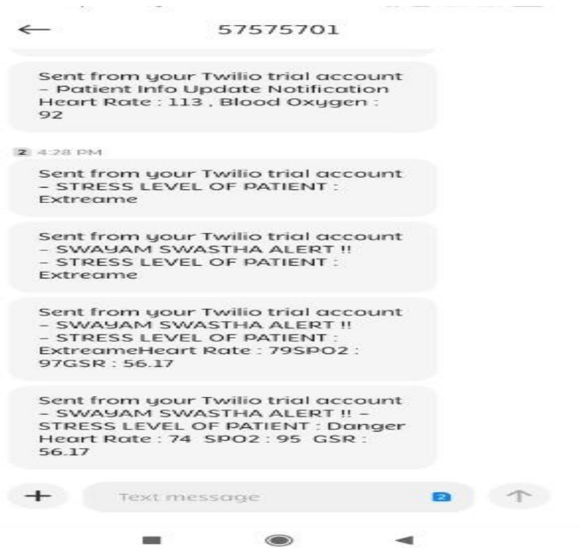
i.

ii. Web Application –

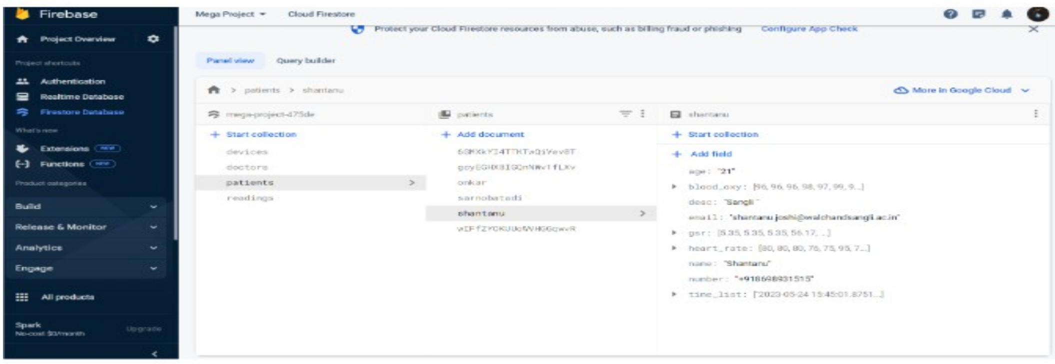




i. Alert System



iii. Cloud Database



The system achieved robust stress prediction using Random Forest. Comparative results are shown in Table 2.

Algorithm	MSE	R^2
Linear Regression	0.35	0.12
Decision Tree	0.28	0.21
SVM	0.25	0.29
Random Forest	0.15	0.41

Applications:

I. This system improves flexibility of healthcare system by providing remote access healthcare parameters.

iii. Integrated with Stress Detection Machine Learning Model can predict stress level of patient and it can alert patient relatives about it.

iv. Heart Rate of patient can be tracked through this system and same is visualized with help of graphs such that any irregularity in heart rate readings can be detected easily.
v. System will be useful for patients who cannot visit hospital on daily basis but needs monitoring of heart rate constantly cause of any special conditions.
vi. Blood oxygen rate is important health parameter for patients suffering with Asthma, Covid-19, Heart diseases this system can monitor blood oxygen levels remotely and alert if patient has readings beyond threshold.

Conclusion

In this paper, the integration of human-computer interaction (HCI) with machine learning holds significant promise for enhancing stress management and user well-being. Through intuitive interfaces, real-time feedback, adaptive systems, and context-aware designs, HCI principles can be leveraged to create user-friendly applications that effectively detect, monitor, and mitigate stress. The literature survey highlights the importance of user-centered design, personalized interventions, and continuous evaluation in developing effective stress management solutions. By synthesizing insights from HCI research with advances in machine learning, we can create innovative tools that empower individuals to better understand and manage their stress levels, ultimately improving overall quality of life.

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