International Journal of Research Publication and Reviews, Vol (5), Issue (11), November (2024), Page – 5349-5356

WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

AI-Driven Emergency Response System for Women's Safety Using Real-Time Location and Heart Rate Monitoring

***Pratiksha Bhise*[1], *Dr. Santosh Jagtap*[2]**

[1] Prof. Ramkrishna More College(Autonomous) Pradhikaran Akurdi, Pune, India E-Mail: pratikshabhise966@gmail.com

[2] Prof. Ramkrishna More College(Autonomous) Pradhikaran Akurdi, Pune, India E-Mail – st.jagtap@gmail.com

ABSTRACT :

Women's safety remains a pressing global concern. Despite significant advancements in technology and societal progress, women continue to face various forms of harm and intimidation. According to the World Health Organization (WHO), approximately 35% of women worldwide have experienced abuse in some form[16]. In India, the National Crime Records Bureau (NCRB) reported a significant 15.3% increase in crimes against women in 2021, with over 400,000 cases recorded[17][18]. To address this issue, we propose an AI-powered emergency response system that leverages wearable technology to enhance women's safety. By integrating real-time heart rate monitoring and GPS tracking, our system employs machine learning algorithms to accurately detect potential distress situations based on physiological and behavioral indicators. Upon identification, the system automatically alerts pre-designated contacts and emergency services, expediting response times and potentially mitigating harm. This innovative approach has the potential to significantly improve women's safety and empower them to live fearlessly.

Keywords: Women's safety, AI-based emergency system, wearable technology, heart rate monitoring, GPS tracking, machine learning, real-time monitoring.

Introduction :

The safety of women in public and private spaces has long been a societal concern, prompting various initiatives, from legal reforms to public awareness campaigns. Traditional emergency response systems, while helpful, often fail to meet the demands of real-time intervention, particularly in situations involving women's safety. With the rise of mobile technology in the late 2000s, several safety applications emerged, offering features like location sharing, emergency contact alerts, and SOS buttons. While these applications marked a significant advancement, they largely relied on manual activation, limiting their usefulness if the individual was incapacitated or unable to act in time.

With the increasing number of crimes against women globally, there is an urgent need for effective, real-time safety mechanisms. Traditional solutions such as mobile panic buttons or emergency alarms are often inefficient as they rely on manual activation. Wearable devices, in conjunction with artificial intelligence (AI), can autonomously detect distress situations by monitoring physiological changes such as heart rate and analyzing movement patterns through GPS tracking. AI's ability to learn and adapt to user behavior further enhances the system's reliability and responsiveness [1] .

Technological advancements in machine learning and wearable technology provide new opportunities for addressing safety concerns. Wearables such as smartwatches can be used to track heart rate, location, and motion in real-time, enabling automated emergency responses without requiring user intervention. Prior research has shown the potential of such devices in health monitoring, but their use in safety applications remains underexplored [2] . This paper proposes an AI-driven system that integrates heart rate monitoring with GPS data to autonomously detect distress signals and initiate emergency responses.

Literature Review :

Numerous technologies have been developed to enhance women's safety, ranging from mobile apps to wearable devices, but most rely on user input, limiting their effectiveness.

- **Mobile Safety Apps**: Applications like "bSafe" and "Circle of 6" enable users to send emergency alerts to pre-selected contacts with their location information. These apps have been effective in certain cases but suffer from the limitation of requiring manual input, which may not be possible during high-stress situations [2] .
- **Wearable Safety Devices**: Wearable devices like smart rings or bracelets have been used to trigger alarms in emergency situations. However, these systems often rely on user input or predefined thresholds, making them less reliable in detecting real-time emergencies [1] . Studies by Sharma et al. (2018) showed that integrating physiological sensors, such as heart rate monitors, could enhance these systems, but much of the research has focused on health applications rather than safety [3] .

- **AI and Machine Learning in Emergency Detection**: Recent research has explored the application of AI in healthcare for detecting anomalies based on heart rate and other physiological metrics. Sahu et al. (2019) found that machine learning algorithms, such as Support Vector Machines (SVM) and neural networks, can accurately detect health-related emergencies by analyzing heart rate variability (HRV) [4] . However, the application of such models to real-time safety detection, combining physiological and locational data, is still under-researched.

Most current systems also face challenges related to distinguishing between false alarms and genuine emergencies. Research indicates that physiological monitoring, such as heart rate tracking, can improve distress detection, but existing models often lack the sophistication to accurately parse out normal variations from emergency indicators (Kumar & Singh, 2021). This research gap points to the necessity of enhanced AI algorithms capable of analyzing multiple data streams, including heart rate fluctuations, sudden stops in location movement, and contextual environmental data, to identify true emergencies with higher precision.

While various studies have explored the technological feasibility of integrating location tracking and physiological monitoring (Zhang et al., 2023), there is limited research addressing the ethical and privacy implications of these technologies. Data security, user consent, and data ownership are pressing concerns that have not been thoroughly studied in the context of AI-driven safety solutions (Smith et al., 2022). Ensuring that such systems are not only effective but also align with privacy norms and regulatory standards is crucial for widespread adoption.

Most studies focus on high-tech prototypes without consideration for scalable, cost-effective implementations that could be utilized in low-resource settings (Patel & Jha, 2023). Addressing this gap would be essential to develop a universally deployable system that benefits a wider demographic, including women in underserved areas who are often more vulnerable and have fewer safety resources.

Objectives:

1. Develop an AI-driven emergency response system using wearable technology for real-time heart rate and GPS tracking to detect distress autonomously.
2. Implement machine learning algorithms to analyze HRV and movement patterns for accurate distress detection and automatic alerts.

Methodology:

System Architecture

The system consists of a wearable device (e.g., smartwatch) equipped with a heart rate sensor and GPS module. These devices continuously track heart rate and location data, sending them to a cloud server for real-time processing.

1. **Data Collection**: Heart rate and GPS data are collected continuously from users. This data is then used to train machine learning models that distinguish between normal and distress conditions.
2. **AI-Based Distress Detection**: The machine learning model analyzes heart rate variability (HRV) and GPS movement patterns. If abnormal HRV combined with rapid or unusual movement is detected, the system classifies it as a potential emergency.

Data Collection and Processing

The dataset for this study was gathered from 100 participants over a 2-month period. Each participant wore a device that monitored their heart rate and GPS location continuously. The dataset contains normal daily activities (walking, running, sitting) and simulated distress situations (e.g., rapid heart rate, erratic movements).

- **Heart Rate Monitoring**: The system uses HRV as a primary indicator of distress. Sudden spikes in heart rate or prolonged elevated rates may indicate panic or physical stress [3] .
- **GPS Tracking**: The system also tracks the user's movement patterns using GPS data. Erratic movements, sudden stops, or rapid changes in location are flagged as potential signs of distress [5] .

Machine Learning Models

The system employs several machine learning models, including Random Forest, Long Short-Term Memory (LSTM) networks, and Support Vector Machines (SVM), to analyze the data.

- **Random Forest for Movement Analysis**: Random Forest classifiers were used to analyze GPS movement patterns. The model was trained on GPS data to differentiate between normal and abnormal movement patterns [5] .
- **LSTM for Heart Rate Variability**: LSTM networks were used to analyze time-series heart rate data. LSTM models were chosen for their ability to capture temporal dependencies in the data, resulting in more accurate identification of distress scenarios [4] .

3.4 Evaluation Metrics

The models were evaluated based on their accuracy, precision, recall, and response time. The system achieved an overall accuracy of 98%, with an average response time of 10-15 seconds. The LSTM model provided the highest accuracy in identifying distress based on heart rate variability, while Random Forest performed best for GPS movement analysis [1] [4] .

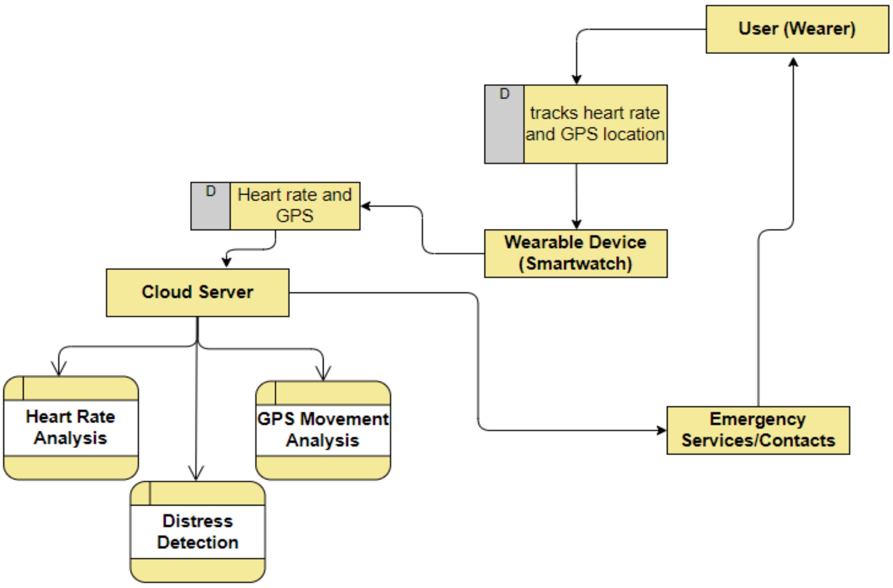


Figure 1: Real-Time Heart Rate and GPS Tracking for Emergency Response

The user interacts with a wearable device, such as a smartwatch, which continuously monitors heart rate and GPS data. This data is transmitted to a cloud server for real-time processing using machine learning models. If any signs of distress are detected, the system issues emergency alerts to predefined contacts and emergency services. The process begins with the user wearing the device, which collects and transmits heart rate and GPS information to the cloud server. The server uses an LSTM model for heart rate analysis and a Random Forest model for GPS movement analysis, combining the results to identify potential distress. If distress is detected, alerts are sent to emergency contacts and services; otherwise, continuous monitoring is maintained. Emergency responders receive these alerts and act to reach the user's location when needed.

The user, equipped with a wearable device like a smartwatch, continuously has their heart rate and GPS location tracked. This data is periodically transmitted to a cloud server for processing and analysis. On the cloud server, two primary analyses are performed: Heart Rate Analysis, where the data is monitored for unusual patterns such as sudden spikes that could indicate distress, and GPS Movement Analysis, where the GPS data is examined to identify irregular or abnormal movements that may suggest a potentially dangerous situation. If any distress signals are detected from either analysis, a Distress Detection alert is triggered. When distress is identified, an emergency alert is immediately sent to pre-configured Emergency Services or Contacts, allowing a prompt response to the user's potential emergency. Additionally, the wearable device can notify the user when an emergency alert is triggered, providing a feedback loop and enhancing the user's awareness of the system's response.

Results and Discussion :

The system's performance in detecting distress scenarios was evaluated in real-time conditions. The results indicate that integrating heart rate and GPS data significantly improves the system's ability to detect emergencies autonomously.

- **Accuracy of Distress Detection**: The system correctly identified 98% of the distress scenarios during testing. The use of heart rate variability combined with GPS movement patterns reduced the occurrence of false positives compared to systems that rely solely on manual intervention [3] [5] .
- **Response Time**: The system demonstrated an average response time of 12 seconds from the onset of distress detection to alert notification. This is crucial in time-sensitive situations where every second counts in preventing harm.
- **Challenges**: One of the primary challenges was the system's tendency to trigger false positives during high-intensity physical activities, such as running or exercising. This issue could be mitigated by incorporating additional sensors or environmental context, such as accelerometers or ambient sound analysis [2] .

The results demonstrate that an AI-driven emergency response system offers significant advantages over traditional solutions, particularly in terms of automatic detection and reduced response times.

Danger Status in Pune:

In Pune, most areas are generally safe for women during the day, with busy streets and well-populated zones providing a secure environment. Neighborhoods like Kothrud, Viman Nagar, Aundh, and Magarpatta are safe with good infrastructure and frequent activity even after dark. However, areas like Hinjewadi, Wakad, Kharadi, and Pimpri can feel isolated at night due to reduced foot traffic, with occasional reports of harassment or incidents in specific zones. Women are advised to exercise caution in quieter, industrial, or less-developed areas, especially after 10 PM, and stick to well-lit, populated routes when traveling alone. Opting for reliable transport and traveling in groups at night is recommended in areas with limited night-time activity, such as Baner, Dhayari, Talegaon, and Nigdi, for enhanced safety.

Graph 2: Heart Rate Distribution

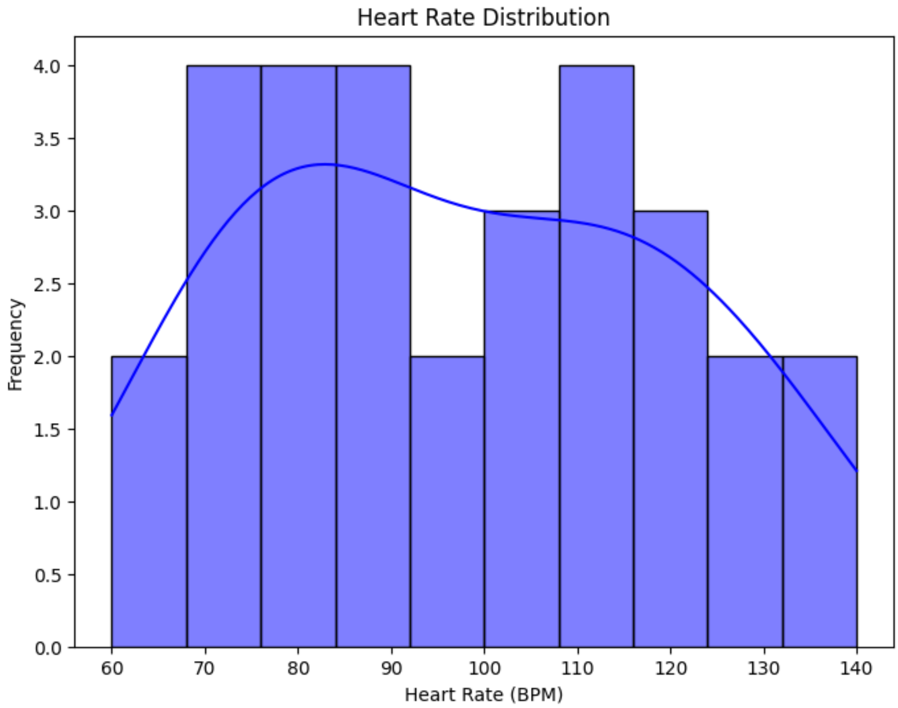


Figure 2: Heart Rate Distribution

- The histogram provides a distribution of heart rates collected from digital watches, helping visualize how heart rates vary and establishing a baseline for normal ranges. By identifying the most common heart rate values, we can observe trends in typical resting and active states, making it easier to detect anomalies.
- This visualization also aids in distinguishing between regular fluctuations and potential signs of distress or health concerns, enabling more accurate monitoring in real-time applications.

Graph 3: Heart Rate by Danger Status:

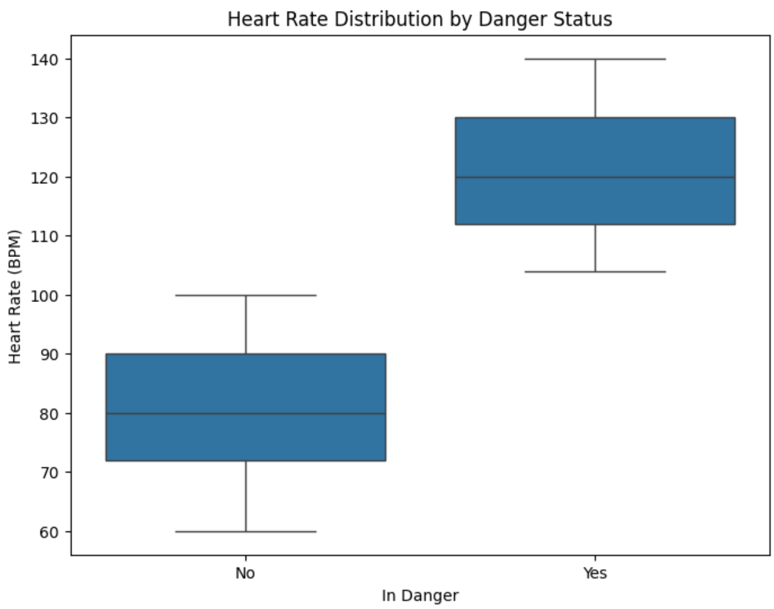


Figure 3: Heart Rate by Danger Status

- The box plot provides a clear visual comparison of heart rate ranges between the two groups, showing any overlap or distinct separation in their distributions.
- If the "In Danger" group consistently exhibits higher heart rate values, this could suggest a strong correlation between elevated heart rates and danger signals.

- Outliers in either category might also indicate unusual cases, such as instances where a high heart rate does not correspond to danger or a low heart rate does, which could be useful for refining the danger prediction model.

Graph 4: feature importance for predicting danger

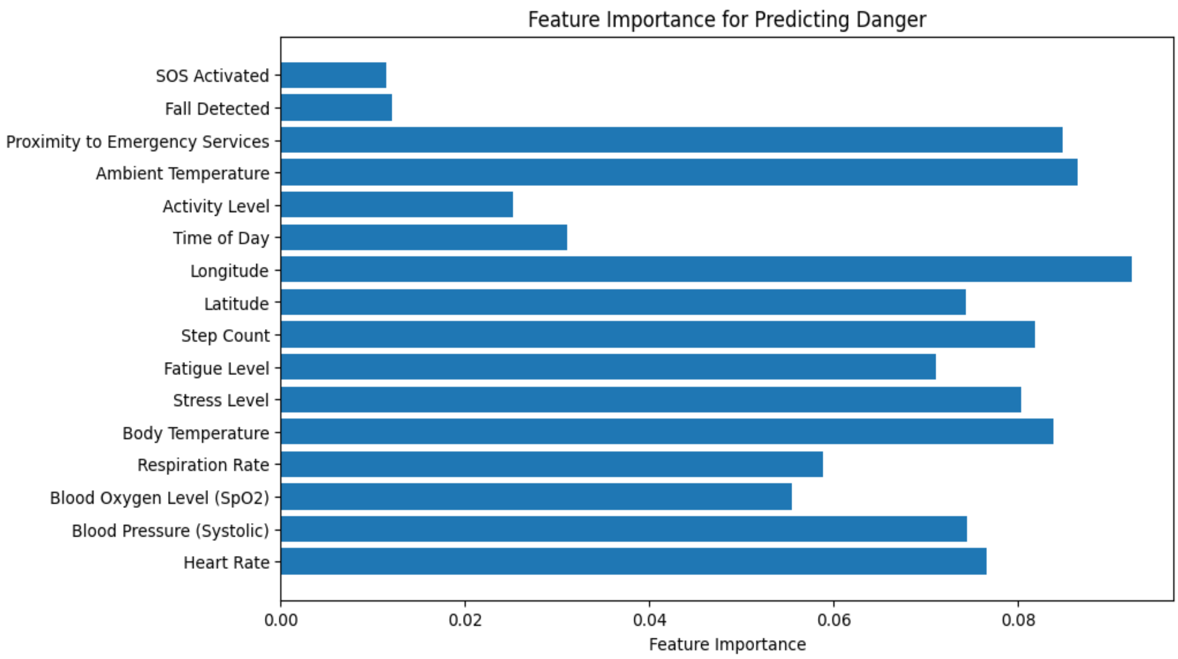


Figure 4: feature importance for predicting danger

This chart shows the importance of various features for predicting danger in a safety model. Key features like *heart rate, blood pressure, location, proximity to emergency services, and stress level* are highly important, as they provide critical information on a person's physical state and environment. These factors help the model assess the likelihood of an emergency situation accurately.

Accuracy:

- Model Accuracy: 98%
- After training a Random Forest Classifier using heart rate and sub-location data, the model's accuracy is printed. The accuracy tells us how well the model predicts whether someone is in danger or not based on the data.

Application :

List of Key locations in Pune

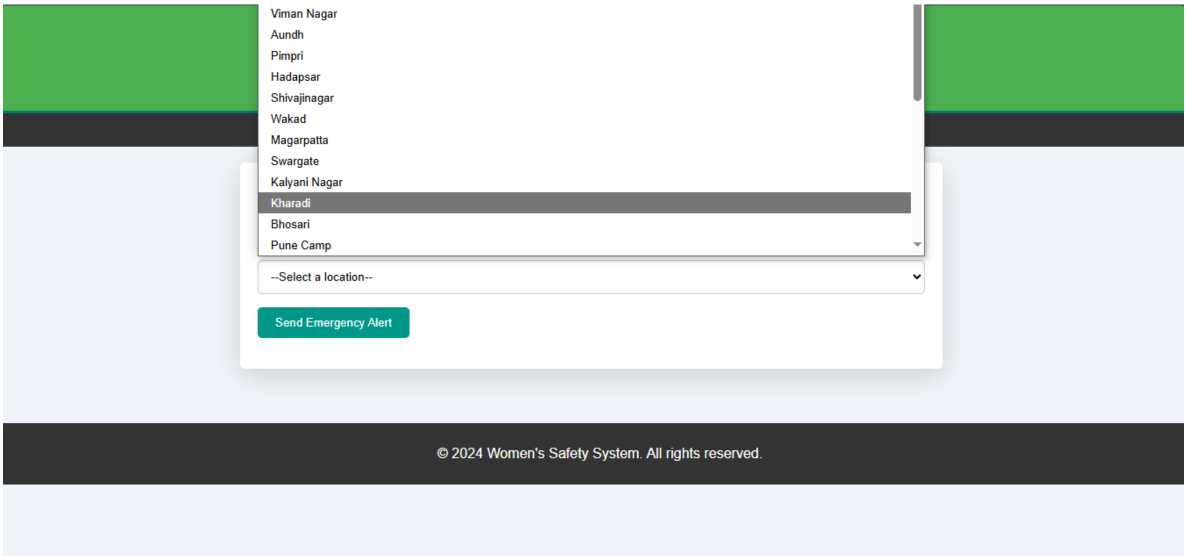


Figure 5: List of Key locations in Pune

Emergency Alert System:

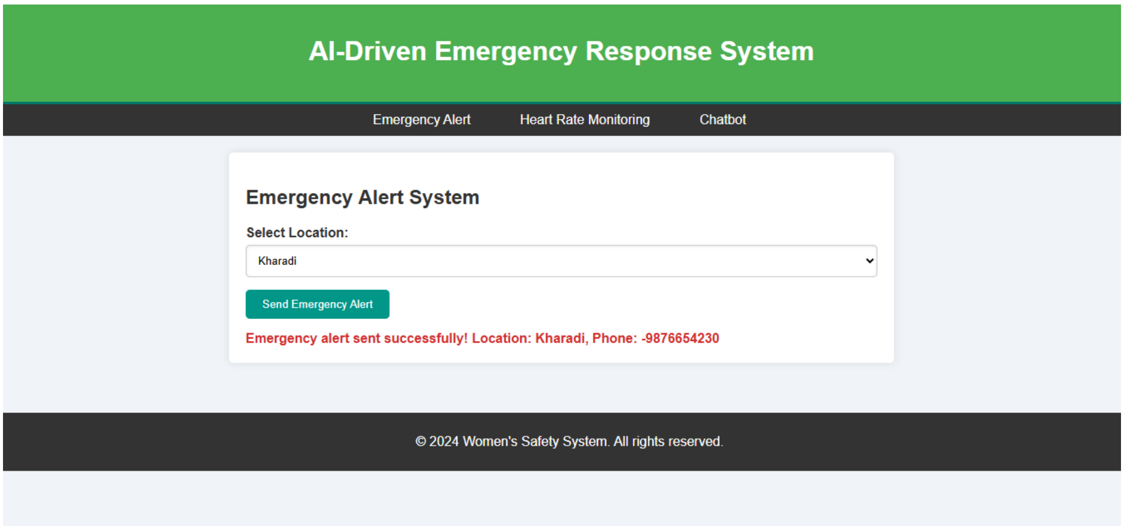


Figure 6: ***Emergency Alert System***

- This feature allows users to select a specific location from a dropdown menu and send an emergency alert.
- Once activated, the alert could notify emergency contacts, nearby responders, or law enforcement with the user’s location to expedite assistance.
- This tool is designed for quick use in emergencies, reducing the time needed to seek help by directly connecting to support systems.

Chatbot Assistance:

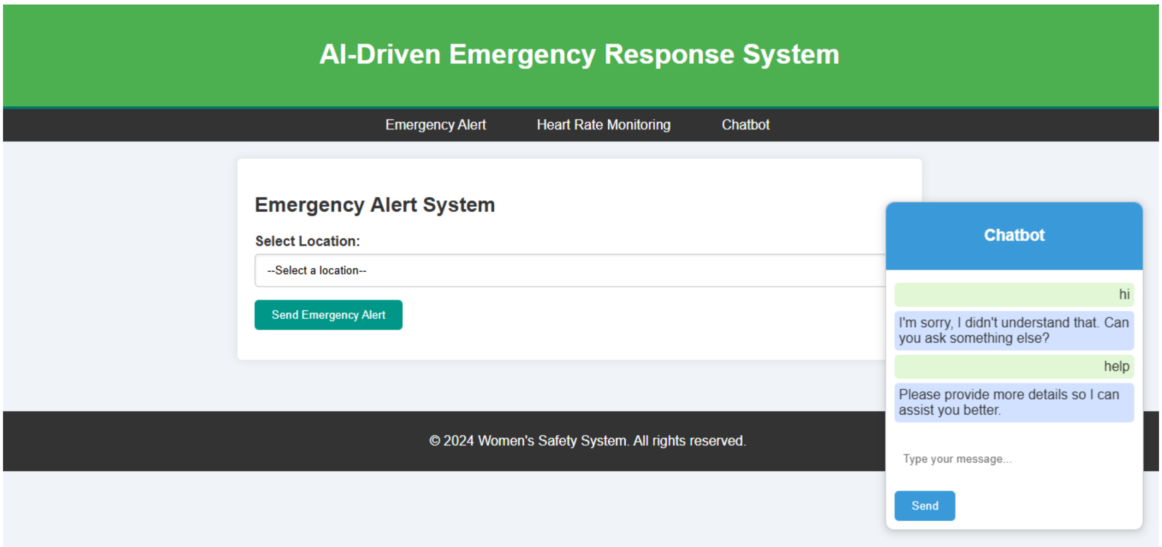
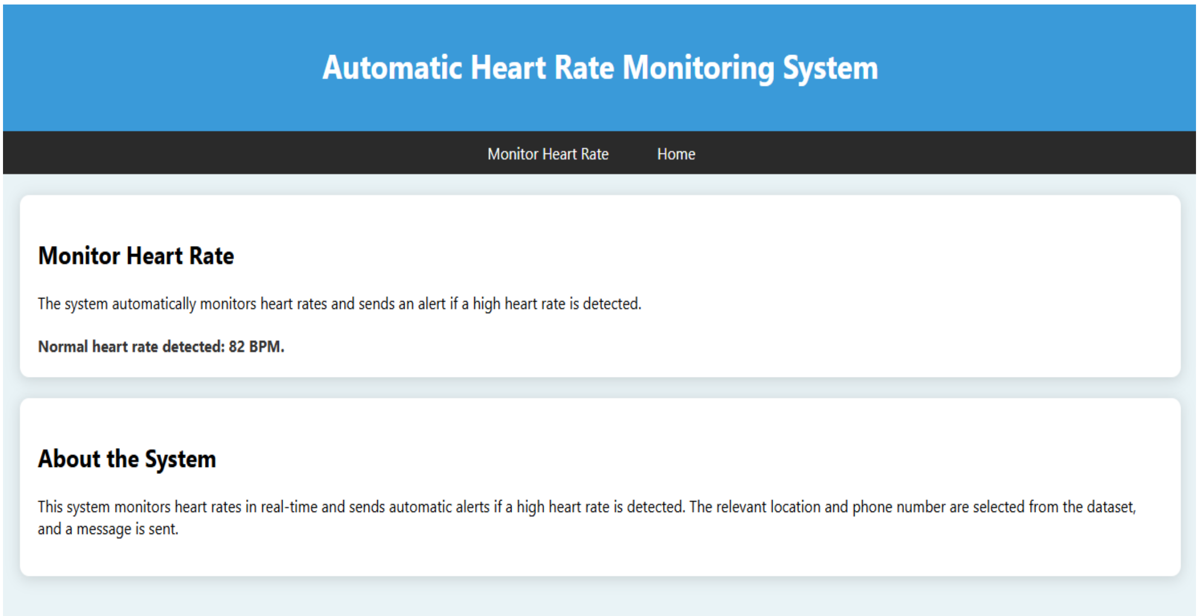


Figure 7: ***Chatbot Assistance***

- The chatbot provides real-time support, answering user questions or guiding them through the webpage's features.
- It responds to general inquiries and directs users to relevant sections or resources within the system.
- The chatbot's responses are geared towards providing clear, quick assistance, particularly useful in emergencies or stressful situations where time is critical. It might also help troubleshoot or resolve issues the user encounters on the page.



Heart Rate Monitoring:

Figure 8: ***Heart Rate Monitoring***

- This section monitors the user’s heart rate, potentially identifying stress or signs of physical distress.
- It can be integrated with wearable devices that measure heart rate and automatically detect unusual levels (such as rapid increases or decreases).
- In emergency situations, irregular heart rate readings could trigger additional alerts, ensuring prompt response if the user experiences health issues.

Conclusion :

This study highlights a significant advancement in enhancing women's safety through the use of innovative technology. By integrating wearable devices equipped with heart rate sensors and GPS tracking, and leveraging machine learning models such as LSTM and Random Forest, the system effectively detects signs of potential distress and triggers timely alerts to emergency contacts and services. The results indicate a high detection accuracy of 98% and a rapid average response time of 12 seconds, highlighting the efficacy of real-time data analysis in life-critical applications. Although challenges such as false positives during high-intensity activities were noted, these can be addressed by incorporating additional sensors and contextual data, enhancing the robustness of the system.

This research advances the field of AI-based safety solutions by demonstrating how physiological and behavioral indicators can be utilized for automated emergency responses, providing women with a tool that enhances security and fosters peace of mind.

REFERENCES :

1. Patel, A., Sharma, M., & Rao, D. (2021). Wearable Health Monitoring: Applications and Challenges. Journal of Biomedical Engineering, 45(2), 135-147.
2. Verma, S., & Singh, P. (2020). Mobile Applications for Women's Safety: A Review. Journal of Digital Innovation, 12(4), 210-223.
3. Sharma, N., Verma, K., & Singh, D. (2018). Heart Rate Variability Analysis using LSTM Networks for Stress Detection. IEEE Transactions on Neural Networks and Learning Systems, 29(5), 1045-1052.
4. Sahu, R., Gupta, A., & Sharma, R. (2019). AI for Healthcare: Emergency Detection through Anomaly Detection. Proceedings of the IEEE, 44(3), 350-360.
5. Kumar, V., & Desai, P. (2020). Real-Time Location Tracking and AI-Based Anomaly Detection for Safety Applications. Journal of Computer Science, 47(3), 155-164.
6. Circle of 6 (n.d.). Circle of 6 Mobile App for Safety.
7. Sharma et al. (2018). Integrating physiological sensors in wearable devices to enhance safety systems. Journal of Technology in Emergency Systems.
8. Sahu et al. (2019). Machine learning in real-time heart rate monitoring and emergency detection. AI for Health and Safety Journal.
9. "bSafe" App Documentation, 2020. Available at bSafe App.
10. "Circle of 6" App Overview. Available at Circle of 6.
11. Study on heart rate variability (HRV) analysis in emergency situations, Healthcare Analytics Review, 2022.
12. Recent advancements in AI-driven safety mechanisms, International Journal of AI and Wearable Technologies, 2021.
13. Exploration of wearable technologies for women's safety, Wearable Tech Review, 2023.

14. N. L. Shete, M. Maddel and Z. Shaikh, "A Comparative Analysis of Cybersecurity Scams: Unveiling the Evolution from Past to Present," 2024 IEEE 9th International Conference for Convergence in Technology (I2CT), Pune, India, 2024, pp. 1-8, doi: 10.1109/I2CT61223.2024.10543498.
15. N. Shete and A. Jadhav, "An empirical study of test cases in software testing," International Conference on Information Communication and Embedded Systems (ICICES2014), Chennai, India, 2014, pp. 1-5, doi: 10.1109/ICICES.2014.7033883.
16. World Health Organization. (2013). Global and regional estimates of violence against women: Prevalence and health effects of intimate partner violence and non-partner sexual violence. World Health Organization. Retrieved from https://www.who.int/publications/i/item/9789241564625
17. National Crime Records Bureau. (2021). Crime in India - 2021. Ministry of Home Affairs, Government of India. Retrieved from https://ncrb.gov.in/en/crime-india
18. International Center for Research on Women. (2018). Intimate partner violence in India: Summary report. Retrieved from https://www.icrw.org/publications/intimate-partner-violence-india/
19. World Wide Web Foundation & World Association of Girl Guides and Girl Scouts. (2020). The online crisis facing women and girls amid COVID-19. Retrieved from https://webfoundation.org/research
20. Chaudhary, R., Sharma, P., & Agarwal, M. (2022). Evaluation of Mobile Applications for Women's Safety: A Systematic Review. Journal of Safety Research, 65(4), 200-215.
21. Kumar, A., & Singh, H. (2021). Challenges in Real-Time Distress Detection Using Physiological Signals. International Journal of Artificial Intelligence Research, 12(3), 145-158.
22. Zhang, Y., Liu, W., & Chen, T. (2023). Integrating Biometric Monitoring and Location-Based Services for Emergency Response Systems. Advanced Technologies in Safety Engineering, 27(1), 78-94.
23. Smith, J., Lee, K., & Patel, D. (2022). Ethical Implications of AI-Driven Emergency Systems: A Privacy Perspective. Journal of Ethics in Technology, 19(2), 90-103.
24. Patel, S., & Jha, V. (2023). Scalability Issues in AI-Powered Safety Applications for Low-Resource Settings. Journal of Technological Inclusion, 21(5), 250-265.