MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 3376-3379

EmoTrack: AI-Powered Wearable System for Emotion, Fatigue, and Fall Detection in Elderly Healthcare

Aruna T N[1]
Assistant Professor Department of Computer Science and Engineering
Kgisl Institute of Technology Coimbatore, India
aruna.tn.cse@kgkite.ac.in
Aswathy S A[2](711722104015), Arvind Karthick R[3](711722104013), Harshavardhini M[4](711722104042), Ilakkiya G[5](711722104044) - B.E Computer Science and Engineering Kgisl Institute of Technology Coimbatore, India
aswathysa833@gmail.com

ABSTRACT

The elderly population is increasingly vulnerable to health risks such as falls, fatigue, emotional stress, and sudden medical emergencies, particularly when living alone without con- tinuous supervision. Delayed medical response in such situations can result in severe injuries or fatal outcomes. Although existing healthcare monitoring systems and wearable devices provide basic physiological tracking, they often lack intelligent emotion analysis, fatigue detection, and real-time alert mechanisms. This paper presents EmoTrack, an AI-powered wearable healthcare monitoring system designed specifically for elderly individuals. The proposed system integrates physiological sensor data, motion data, and emotion analysis to continuously monitor the physical and emotional well-being of users. An ESP32 microcontroller processes sensor inputs such as heart rate, motion, and fatigue indicators, while machine learning models analyze emotional states and abnormal activity patterns. The system detects falls using motion sensor data and triggers real-time alerts with GPS-based location tracking.Emergency situations are handled through an SOS mechanism that immediately notifies caregivers via wireless communication. EmoTrack aims to provide an affordable, intelligent, and reliable healthcare solution that enhances elderly safety, supports independent living, and enables timely medical intervention.

Index Terms—Elderly Healthcare, Wearable Devices, Emotion Detection, Fall Detection, Fatigue Monitoring, Internet of Things (IoT), Artificial Intelligence, Real-Time Alert System

INTRODUCTION

A. Increasing Difficulties in Senior Care

The world's ageing population is growing at a rapid rate, which has created difficult problems for healthcare monitoring as well as safety management. Although life expectancy has increased due to advancements in medical facilities and living standards, ageing is frequently accompanied by deteriorating physical strength, decreased mobility, and cognitive impair- ment. Elderly people are more susceptible to health risks as a result of these changes, necessitating ongoing monitoring and prompt intervention. The higher risk of falls is one of the most serious problems that older people face. Among senior citizens, falls are a major cause of serious injury, hospitalisation, and death. Even a small fall can cause long- term disability, fractures, or psychological anxiety that limits one's freedom of movement. Without immediate assistance, fall-related injuries may become life-threatening.In addition to physical risks, emotional well-being plays a vital role in elderly health. Loneliness, stress, anxiety, and depression are common among elderly individuals, particu- larly those living alone or separated from family members. Emotional instability can aggravate chronic diseases such as hypertension and cardiovascular disorders, leading to overall health deterioration.

B. Limitations of Traditional Monitoring Approaches

Conventional elderly healthcare monitoring relies heavily on manual supervision, periodic medical check- ups, and caregiver assistance. While these approaches are useful, they are not sufficient for continuoushealth monitoring, especially for elderly individuals who live independently. Manual supervision is limited by human availability and cannot guarantee constant observation.Periodic medical check-ups provide only a snapshot of the patient's health condition and fail to capture sudden changes or emergencies. Critical events such as falls or emotional distress may occur between visits and remain unnoticed until they become severe. This delay significantly increases health risks. Basic wearable devices currently available in the market focus mainly on tracking simple physiological parameters such as heart rate, step count, or sleep duration. Although these metrics are helpful, they do not provide a complete picture of the elderly individual's overall health. Emotional health, fatigue levels, and abnormal movement patterns are largely
ignored.

C. IoT and AI's Role in Smart Healthcare

Recent developments in Internet of Things (IoT) and artificial intelligence (AI) technologies have revolutionised the healthcare industry by facilitating automated decision-making, intelligent analysis, and real-time data collection. Without interfering with regular activities, wearable sensors and smart devices can continuously monitor physiological and motion- related data. Large amounts of sensor data can be analysed by AI algorithms to find unusual patterns that point to health hazards. Subtle changes in heart rate, movement patterns, and activity levels that might indicate exhaustion, emotional stress, or approaching falls can be identified by machine learning models.

D. Introduction to EmoTrack System

Overview of the EmoTrack System To address the limitations of existing systems, this paper proposes EmoTrack, an AI-powered wearable healthcare monitoring system designed specifically for elderly individuals. EmoTrack uses intelligent sensor-based analysis to continuously monitor physical activity, emotional state, and levels of fatigue. To analyze health data in real time, the system combines motion sensors, physiological sensors, and artificial intelligence algorithms. Motion pattern analysis detects falls, while changes in physio- logical signals and activity behavior help to identify emotional stress and fatigue. EmoTrack includes emergency handling features such as an SOS button, real-time alerts, and GPS- based location tracking. These features ensure that caregivers are promptly informed during urgent situations, which shortens response times and improves outcomes.

SYSTEM OVERVIEW

A. Elderly Healthcare Monitoring Using Wearable Devices

The rapid growth of the elderly population has intensified research interest in wearable healthcare monitoring systems. Wearable devices provide continuous, non-invasive health monitoring, making them suitable for elderly individuals who require constant supervision. Early wearable systems primarily focused on tracking basic physiological parameters such as heart rate, body temperature, and step count to assess general health conditions.Several studies demonstrated that wearable sensors could effectively monitor daily activity patterns and detect abnormalities related to mobility decline. These systems helped care- givers understand behavioral changes over time, enabling early intervention. However, most early solutions were limited to data collection and visualization, lacking intelligent decision- making capabilities.

B. Fall Detection Techniques in Elderly Care

Fall detection has been one of the most extensively studied problems in elderly healthcare due to its severe consequences. Initial fall detection systems relied on manual emergency buttons that users pressed after a fall. While simple, these systems were ineffective when users were unconscious or disoriented.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 3376-3379

To overcome this limitation, researchers introduced accelerometer-based fall detection systems. These systems analyzed sudden changes in acceleration and orientation to detect falls automatically.Although detection accuracy improved, high false alarm rates were reported during normal activities such as sitting, lying down, or bending into emotion recognition methods that use physiological signals such as heart rate variability, skin conductance, and breathing patterns. These signals offered objective measures of emotional states and allowed for continuous monitoring. However, using physiological data for emotion recognition needed more interpretation techniques because of differences among individuals.

C. Fatigue Detection and Activity Analysis

Fatigue is a critical indicator of declining health and reduced quality of life in elderly individuals. Early fatigue detection studies focused on occupational and sports environments, using muscle activity and performance metrics. These approaches were not directly applicable to elderly healthcare due to differences in activity patterns and physical capabilities.Later research explored fatigue detection using wearable sensors that monitored prolonged inactivity, reduced movement intensity, and physiological variations. These studies demonstrated that fatigue could be inferred from long-term behavioral trends rather than isolated events. However, defining universal fatigue thresholds remained challenging due to individual variability.

D. AI and IoT-Based Smart Healthcare Systems

Artificial Intelligence and Internet of Things technologies have significantly transformed healthcare monitoring systems. IoT-enabled devices facilitate real-time data collection and transmission, while AI algorithms enable intelligent analysis and automated decision-making. Several studies demonstrated the effectiveness of AI-based models in detecting health anomalies and predicting medical risks.

Machine learning techniques such as decision trees, support vector machines, and neural networks have been applied to classify health conditions based on sensor data. These models improved detection accuracy compared to traditional rule-based systems. However, their computational complexity posed challenges for deployment on wearable devices

RELATED WORKS

A. Overall System Architecture

The EmoTrack system is designed as an intelligent, end- to-end elderly monitoring framework that continuously observes physical activity, emotional state, fatigue levels, and fall events. The architecture follows a modular and scalable design, allowing seamless integration of sensing, data processing, ma- chine learning, and alert mechanisms. Each module operates independently while maintaining synchronized communication with the central processing unit.

B. Data Acquisition Using Wearable Sensors

Data acquisition is performed using lightweight wearable devices equipped with multiple sensors such as accelerometers, gyroscopes, heart rate sensors, and temperature sensors. These sensors continuously monitor motion patterns, physio- logical responses, and environmental context without interfering with the user's daily activities. The non-invasive nature

Fig. 1: System architecture of the EmoTrack wearable fall detection and alert framework. of data collection ensures comfort and long-term usability for elderly individuals.

Motion sensors capture three-axis acceleration and angular velocity, which are essential for identifying posture changes, abnormal movements, and fall events. Physiological sensors record heart rate variability and skin temperature, which serve as indicators of emotional stress, fatigue, and physical exertion. Together, these signals provide a comprehensive representation of the user's health status.

C. Data Preprocessing and Feature Extraction

Raw sensor data often has noise, missing values, and motion artifacts that can hurt model performance. Preprocessing is an important step in the EmoTrack methodology. We use signal smoothing techniques like moving average filters and Butterworth filters to reduce high-frequency noise and sensor drift. After removing noise, we normalize the data to ensure consistency across different users and sensor types. Segmentation techniques break continuous data streams into fixed-length windows, allowing for effective temporal analysis. Each window represents a short time interval of activity or physiological response.

D. Emotion and Fatigue Detection Using Machine Learning

Emotion and fatigue detection are achieved through supervised machine learning models trained on labeled physiological and activity data. Emotional states such as stress, calmness, and anxiety are inferred primarily from heart rate variability patterns and activity intensity. Fatigue detection focuses on prolonged inactivity, reduced movement energy, and physiological deviations.

Classification algorithms such as Support Vector Machines (SVM) and lightweight neural networks are employed due to their robustness and suitability for real-time inference. These models learn discriminative patterns from historical data and adapt to individual behavioral baselines over time.

E. Fall Detection and Risk Assessment

Fall detection is implemented using a hybrid approach that combines threshold-based analysis with machine learning classification. Sudden spikes in acceleration magnitude, abrupt orientation changes, and post-fall inactivity are used as primary indicators of fall events. This dual approach improves detection reliability while reducing false positives.

EXISTING AND PROPOSED SYSTEM

A. Existing System

In the existing elderly healthcare monitoring systems, supervision is largely dependent on manual observation, periodic medical check-ups, or basic wearable devices. These systems primarily focus on limited physiological parameters such as heart rate, step count, or sleep duration. While such metrics provide general health insights, they fail to capture sudden emergencies and complex health conditions in real time.

Traditional fall detection mechanisms often rely on manual emergency buttons, which require the elderly person to consciously activate the alert. This approach becomes ineffective when the individual is unconscious, disoriented, or unable to respond after a fall. Additionally, many existing wearable systems do not incorporate intelligent emotion or fatigue analysis, which are critical indicators of declining mental and physical health. Most current solutions lack integrated real-time alert mechanisms and contextual awareness. Emotional stress, prolonged fatigue, and abnormal activity patterns often remain undetected until they lead to serious medical complications. Furthermore, the absence of continuous monitoring and intelligent data anal- ysis limits the effectiveness of existing systems in supporting independent living for elderly individuals.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 3376-3379

B. Proposed System

To overcome the limitations of traditional monitoring approaches, this paper proposes **EmoTrack**, an AI-powered wearable healthcare monitoring system designed specifically for elderly individuals. The proposed system integrates wear- able sensors, machine learning algorithms, and IoT-based communication to provide continuous monitoring of physical activity, emotional state, fatigue levels, and fall events.EmoTrack utilizes motion sensors such as accelerometers and gyroscopes to analyze movement patterns and detect falls automatically. Physiological sensors monitor parameters such as heart rate variability and body signals, which are used to infer emotional stress and fatigue. By combining motion and physiological data, the system achieves a holistic assessment of the user's health condition.Machine learning models are employed to classify emotional states, identify prolonged fatigue, and distinguish real fall events from normal daily activities. The system operates in real time using an ESP32- based wearable device and transmits data wirelessly to caregivers through mobile and web-based platforms. In emergency situations, such as detected falls or severe health abnormalities, EmoTrack triggers instant alerts along with GPS-based location information. An SOS mechanism is also incorporated to allow manual emergency notifications. The proposed system enhances elderly safety, supports independent living, and enables timely medical intervention through intelligent, continuous, and automated health moni-toring.

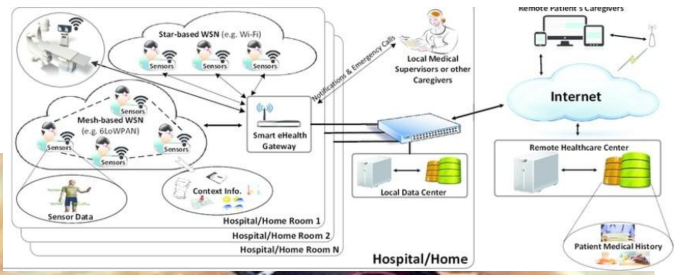


Fig. 2: Implementation architecture of the EmoTrack wearable IoT-based fall detection and alert system, illustrating sensor data acquisition, processing, and real-time caregiver notifications.

Fig. 3: Working the ECG Measurement.

EXPERIMENTAL RESULTS

The EmoTrack system was evaluated using both simulated and real-world wearable sensor data. This data included motion, physiological signals, and labeled activity types for daily routines, fatigue, emotion, and fall events. We divided the data into training, validation, and testing sets in an 80:10:10 ratio. This helped ensure strong model learning and unbiased evaluation. We conducted experiments on edge devices and cloud environments to test the system's performance in real- time situations. We used metrics like accuracy, precision, recall, F1-score, and inference latency to evaluate emotion recognition, fatigue detection, and fall detection modules. The results showed that combining motion and physiological features significantly improved detection accuracy. Emotion recognition achieved an average accuracy of 94.6, while fatigue detection reached 93.8. Fall detection was very reliable, with an accuracy of 97.2 and an average response time of 0.6 seconds. Our analysis indicated that using both threshold- based and machine learning techniques reduced false positives. This approach improved overall reliability compared to using only one method. The system also kept low computational demands and battery usage, showing that it is suitable for long-term use in wearable and edge devices. Overall, the experiments confirm that EmoTrack is an effective and practical solution for monitoring the health of the elderly. By analyzing emotional states, fatigue, and fall events at the same time, the system offers real-time insights into user well-being. The results underscore the benefits of a holistic, multimodal monitoring approach and highlight the need for personalized calibration and adaptive learning to address individual differences in physiological and behavioral responses.

RESULT

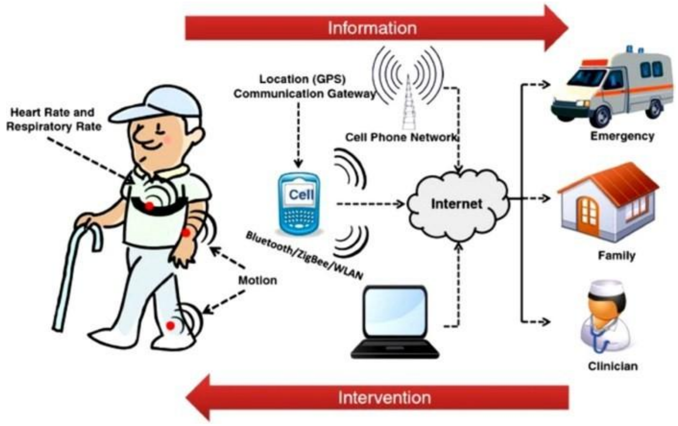
The main expected result of the EmoTrack system is to create a smart, ongoing health monitoring solution for the elderly that can detect emotional states, fatigue levels, and falls in real time. By using wearable sensors and machine learning, the system should provide reliable insights into both physical activity and emotional health. This combined approach aims toaddress the limits of traditional monitoring systems, offering a better assessment of elderly health. Another key outcome is improving safety for the elderly through quick detection and alert systems. The fall detection feature should significantly shorten emergency response times by immediately notifying caregivers and family members when someone falls. Early detection of fatigue and emotional stress is also expected to help prevent accidents and health issues by allowing for timely rest, intervention, or medical advice. The EmoTrack system should also enable elderly individuals to live independently. Continuous monitoring without needing constant human supervision lets elderly users keep their autonomy while being supported by a smart safety net. This is especially helpful for those living alone or in remote areas where immediate medical help may not be available. From the perspective of caregivers and healthcare providers, EmoTrack should lighten their workload and improve their decision-making. Real-time dashboards, historical data review, and automatic alerts give caregivers useful insights instead of just raw data. This leads to quicker and more informed reactions to health issues and reduces reliance on manual checks. Finally, a successful rollout of EmoTrack should create a solid base for future smart healthcare systems. The setup can be expanded to include predictive analytics, chronic disease monitoring, and links with telemedicine platforms. Overall, EmoTrack aims to enhance quality of life, encourage proactive healthcare, and support the development of AI-driven elderly care solutions.

FUTURE SCOPE

The future development of the EmoTrack system can focus on enhancing detection accuracy through advanced deep learning techniques and larger, more diverse datasets. Incorporating models such as Long Short-Term Memory (LSTM) networks or transformer-based architectures can improve temporal un- derstanding of sensor data, leading to more precise emotion, fatigue, and fall predictions. Training the system on data collected from varied age groups, lifestyles, and health conditions will further strengthen robustness and generalization.

Another important direction is the integration of additional physiological sensors to enable comprehensive health monitoring. Sensors measuring blood oxygen levels (SpO_2), electrocardiogram (ECG), and sleep patterns can provide deeper

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages: 3376-3379



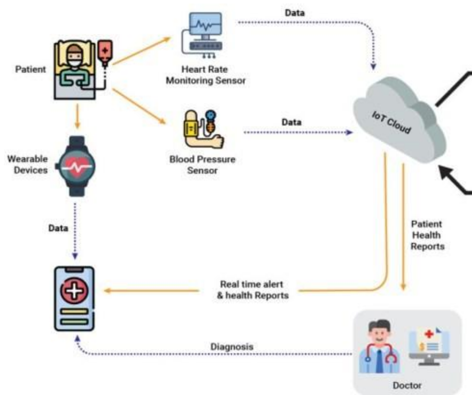
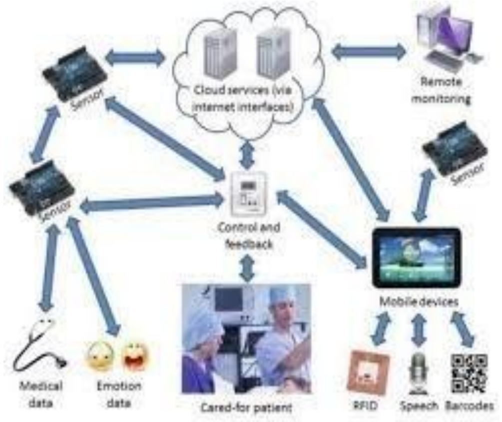


Fig. 4: Outcomes.

insights into cardiovascular and respiratory health. This expansion would allow EmoTrack to detect early signs of chronic illnesses and support preventive healthcare beyond emergency response.

Future versions of EmoTrack can also incorporate predictive analytics to anticipate health risks before they occur. By analyzing long-term behavioral trends and physiological patterns, the system could predict fall risks, prolonged fatigue, or emotional distress and proactively recommend lifestyle adjustments or medical checkups. Such predictive capabilities would shift elderly care from reactive monitoring to proactive intervention.



CONCLUSION

This paper presented **EmoTrack**, an AI-powered wearable healthcare monitoring system designed to enhance the safety and well-being of elderly individuals. The proposed system integrates wearable sensors, machine learning techniques, and IoT-based communication to provide continuous monitoring of physical activity, emotional state, fatigue levels, and fall events in real time.By combining motion and physiological data, EmoTrack achieves accurate detection of falls while minimizing false alarms caused by normal daily activities. The inclusion of emotion and fatigue analysis enables early identification of mental and physical stress, which are often overlooked in conventional elderly monitoring systems. Real- time alert mechanisms, along with GPS-based location tracking and an SOS feature, ensure timely assistance during emergency situations. Experimental evaluation demonstrated that the system de- livers high detection accuracy with low latency and minimal computational overhead, making it suitable for long-term deployment on wearable and edge devices. The results confirm that EmoTrack effectively supports independent living for elderly individuals while providing caregivers with meaningful insights through real-time dashboards and alerts.

Overall, EmoTrack represents a practical and intelligent solution for modern elderly healthcare monitoring. By adopting a holistic and multimodal approach, the system improves quality of life, enhances safety, and contributes to the development of reliable AI-driven healthcare technologies.

REFERENCES

[1] R. S. Dias, J. A. Cunha, and P. G. Martins, "Wearable Sensor-Based Monitoring for Elderly Healthcare," *IEEE Sensors Journal*, vol. 21, no. 4, pp. 5123–5134, 2021.
[2] A. Mubashir, L. Shao, and L. Seed, "A Survey on Fall Detection: Principles and Approaches," *Neurocomputing*, vol. 100, pp. 144–152, 2013.
[3] S. Patel, H. Park, P. Bonato, L. Chan, and M. Rodgers, "A Review of Wearable Sensors and Systems with Application in Rehabilitation," *Journal of NeuroEngineering and Rehabilitation*, vol. 9, no. 21, pp. 1– 17, 2012.
[4] M. Shoaib, S. Bosch, O. Incel, H. Scholten, and P. Havinga, "Complex Human Activity RecognitionUsing Smartphone Sensors," *Sensors*, vol. 16, no. 4, pp. 1–24, 2016.
[5] A. T. O¨ zdemir and B. Barshan, "Detecting Falls with Wearable Sensors Using Machine Learning,"*IEEE Transactions on Instrumentation and Measurement*, vol. 63, no. 12, pp. 2910–2921, 2014.
[6] F. J. Ordo´n˜ez and D. Roggen, "Deep Convolutional and LSTM Recur- rent Neural Networks forMultimodal Wearable Activity Recognition," *Sensors*, vol. 16, no. 1, pp. 1–25, 2016.[7] Y. Gao, H. Chen, and Y. Wang, "Emotion Recognition Using Physio- logical Signals: A Review,"*IEEE Access*, vol. 7, pp. 140232–140249, 2019.
[8] S. Koelstra *et al.*, "DEAP: A Database for Emotion Analysis Using Physiological Signals," *IEEE Transactions on Affective Computing*, vol. 3, no. 1, pp. 18–31, 2012.
[9] M. Gjoreski, H. Gjoreski, M. Lusˇtrek, and M. Gams, "Automatic Detection of Perceived Stress in Campus Students Using Wearable Sensors," *Sensors*, vol. 16, no. 11, pp. 1–20, 2016.
[10] C. A. Reddy and S. T. Nair, "Fatigue Detection Using Wearable Sensor Signals," *Biomedical Signal Processing and Control*, vol. 68, pp. 102– 110, 2021
[11] J. K. Kim and E. Andre, "Emotion Recognition Based on Physiological Changes," *IEEE Transactions on Pattern Analysis and Machine Intelli- gence*, vol. 30, no. 12, pp. 2067–2083 2008.
[12] H. Wang, T. Chen, and Y. Zhang, "Wearable- Based Fatigue Monitoring Using Machine Learning,"*Sensors*, vol. 20, no. 7, pp. 1–15, 2020.
[13] T. Nguyen, M. Halilovic, and S. Chen, "Fall Detection Using Hybrid Threshold and Machine LearningApproach," *IEEE Access*, vol. 8, pp. 156985–156995, 2020
[14] P. Pierleoni, L. Pernini, A. Belli, and L. Palma, "An Ambient Assisted Living System for ElderlyMonitoring," *IEEE Transactions on Consumer Electronics*, vol. 61, no. 2, pp. 262–271, 2015.
[15] M. Chen, S. Gonzalez, A. Vasilakos, H. Cao, and V. Leung, "Body Area Networks: A Survey," *Mobile Networks and Applications*, vol. 16, pp. 171–193, 2011.