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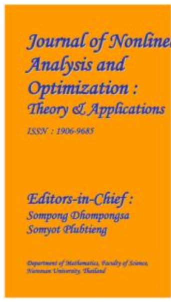

WEARABLE HEALTH MONITORING FOR SENIOR CITIZENS

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Abstract—
Wearable technology advancements are paving the way for integrating intelligent systems into everyday objects for improved well-being. This paper proposes the design, development, and implementation of smart shoes equipped with sensors for health monitoring and activity tracking, seamlessly integrating into users' daily lives. The smart shoe system utilizes accelerometers, gyroscopes, and force-sensitive resistors (FSRs) to capture motion data and pressure distribution. An ESP32 microcontroller processes the data and transmits it wirelessly to a mobile application for visualization and analysis. Additionally, local storage and processing enable long-term data storage and trend analysis. The paper elaborates on the hardware and software architecture, including sensor integration, data processing algorithms, and communication protocols. A user-friendly mobile application provides personalized feedback and insights based on collected data, allowing users to track fitness goals, monitor gait patterns, and prevent potential injuries. Extensive real-world testing and user feedback demonstrate the system's effectiveness in accurately tracking activities, monitoring vital signs, and providing valuable insights for improved health and fitness. The paper explores the potential applications of smart shoes in healthcare, sports performance monitoring, and rehabilitation. While discussing limitations and future directions, the paper emphasizes the promise of smart shoes for fostering proactive health management and enhancing well-being.

Keywords—
Smart shoes, Health monitoring, Activity tracking, Sensor integration, Motion data, ESP32 Microcontroller, Mobile application, Cloud-based storage.

I. INTRODUCTION

Research explores the effectiveness of wearable health monitoring systems (WHMS) in mitigating fall risks and promoting independence in senior citizens [1]. WHMS uses advanced sensor technology, intelligent algorithms, and communication platforms to create a comprehensive health monitoring network. These sensors capture real-time movement data, providing a detailed picture of the wearer's activity and gait patterns [2]. Machine learning algorithms trained on platforms like Edge Impulse analyze this data to identify potential fall risks with high accuracy [3]. This proactive approach reduces the likelihood of falls. WHMS often integrates with communication platforms like Twilio, allowing immediate alerts to designated caregivers upon fall detection [4]. This ensures prompt intervention and minimizes potential health consequences for the fallen individuals. Figure 1 illustrates the components of this system, which includes FSR, gyroscope, accelerometer sensors embedded within the smart shoe and connected to an ESP-32 controller. Sensor data is transmitted to local storage and then processed by a machine learning model, trained using algorithms such as K-Nearest Neighbours (KNN) classifier in edge impulse. Upon successful training and evaluating its performance, the model is deployed for use. This promotes security and empowers seniors to maintain their independence. The research aims to demonstrate the effectiveness of WHMS by evaluating fall detection algorithms, caregiver notification timeliness, and the overall impact on senior well-being [5]. The investigation of the synergy between advanced sensors, intelligent algorithms, and communication platforms will provide valuable insights into the potential of this technology to revolutionize senior care and improve their quality of life [6].

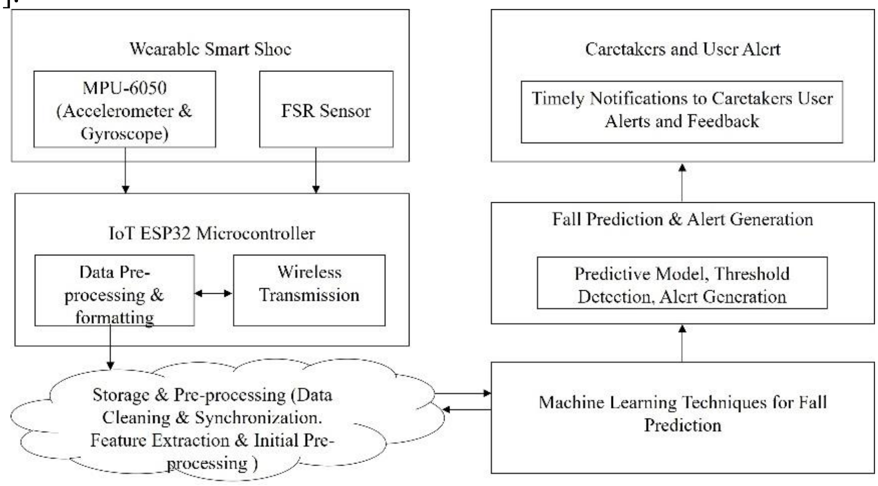

Fig 1: Block diagram of IoT Enabled Architecture for Smart Shoe

For edge devices, which have limited processing power and frequently operate without a constant internet connection, Edge Impulse is a software platform for developing, training, and deploying machine learning models. It simplifies the process by offering a user-friendly interface for data collection, model training, and deployment. Edge Impulse allows users to easily collect sensor data from various devices, optimizes model training on collected data, and helps deploy the trained model onto the target edge device. It supports various sensors and integrates with popular development boards, making it a versatile tool for a wide range of machine-learning projects on edge devices [7].

Communication Platform as a Service (CPaaS) platforms like Twilio provide developers with a range of tools and functionalities for real-time communication, including SMS, phone calls, and video calls. These platforms are scalable and flexible, allowing applications to send and receive messages or calls instantly [8]. Developers can customize communication features using APIs based on specific application needs. CPaaS platforms often integrate with existing business systems, providing a unified communication experience. Twilio offers a developer-friendly interface and documentation, allowing developers to integrate communication features into their applications. It also provides access to a global network of phone numbers and carriers. Security is a major concern with these platforms [9].

II. LITERATURE SURVEY

Gait monitoring through the Internet of Things (IoT) has become a crucial area of research due to the increasing need for effective solutions in elder care [10]. This survey explores relevant studies on using gait analysis and machine learning for fall prediction and health monitoring among senior citizens. Several studies by Achanta et al. (2019, 2021) investigate the potential of gait analysis for fall prediction, proposing a novel approach utilizing advanced gait analysis techniques for physically challenged individuals [11-12]. They explore deep learning for fall prediction based on gait analysis, demonstrating promising results for improving prediction accuracy. It also explores the integration of wearable sensors for gait analysis using IoT platforms. Achanta et al. (2020) [13] devise a wireless IoT setup for gait detection using FSR sensors and wearable IoT devices, aligning with the development of smart shoe systems. Murthy et al. (2020) highlight the potential of machine learning in healthcare by proposing a model that utilizes machine learning for gait analysis in diagnosing cardiovascular diseases [14]. Researchers propose alternative approaches and advanced techniques, including virtual reality for gait analysis and deep neural networks for individual recognition. Studies by Ahammad et al. (2023) and Kumari et al. (2021) showcase the potential of deep learning and machine learning for health monitoring applications, focusing on spinal cord detection in MRI images and heart arrhythmia detection [15]. Murthy et al. (2019) demonstrate machine learning for data processing by applying random forest machine learning methods for image compression [16-18]. These studies provide a strong foundation for developing a smart shoe system for gait monitoring and fall prediction in senior care, promoting safety and independence among the elderly population. The research investigates the use of the K-Nearest Neighbours (KNN) algorithm in a smart shoe system for gait analysis and fall detection [19]. The system uses sensors like accelerometers, gyroscopes, and force-sensitive resistors to collect data on the wearer's gait patterns. Apply the KNN algorithm to a training dataset that labels "slip", "stand" and "other" events. It analyses the similarity of the new sensor data to the training dataset, identifying the k nearest neighbours and predicting the class label for the new data point. Predict a fall event if the majority of nearest neighbours indicate a fall. KNN offers advantages such as simplicity, non-parametricity, and interpretability, making it suitable for real-time applications. Future research could explore advanced machine learning algorithms like deep learning, sensor fusion, feature engineering, and real-time processing and alerting systems [20].

III.METHODOLOGY AND WORKING

Hardware description

The ESP32-C3 microcontroller is a key component in a smart shoe system for elder care, providing wireless capabilities and data transmission. It interacts with sensors like the MPU6050 and FSR, using GPIO pins for data exchange and an SPI interface for readings. The microcontroller processes raw sensor data, potentially performing calculations or analysis. It has a built-in flash memory and an analog-to-digital converter for accurate measurement. Operating at 3.3V and handling input voltages of 7–12V, it has a 160MHz processing power and 16 digital input/output pins. The FSR (Force-Sensitive Resistor) sensor is a crucial component in smart shoe systems, measuring pressure applied to the wearer's foot. It acts as a pressure-sensitive resistor, allowing it to measure pressure distribution across the sole of the shoe as the wearer walks and the working model can be seen in figure 2. The sensor provides an analog output signal corresponding to the applied pressure, which is then fed to the ESP32-C3 microcontroller for processing. By monitoring variations in pressure distribution between the left and right shoes during walking, the system can potentially identify abnormalities in gait patterns, potentially indicating potential health issues or gait imbalances. The FSR sensor is easily customizable and offers affordability, making it an ideal choice for the smart shoe system. The specific model used is a square sensor with a diameter of 44.45 mm and a pressure handling range of 100 grams to 10 kilograms. The sensor is likely integrated within the shoe itself, strategically placed to capture pressure data from the wearer's foot as shown in figure 3. The Arduino IDE is used for code development, allowing for the processing of sensor data, including the FSR sensor output, in the Arduino programming language. Standard libraries within the Arduino IDE facilitate communication with the FSR sensor and other components.

Fig 2: Working model of smart shoe

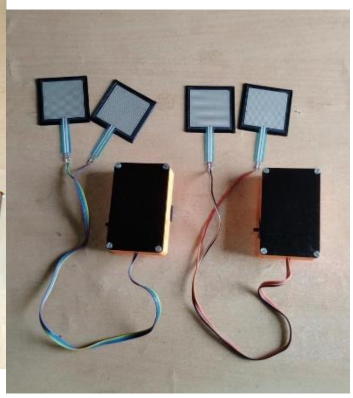

Fig 3: Integration of FSR sensors

Software Description

The smart shoe system uses libraries like Adafruit_MPU6050.h and *Adafruit_Sensor.h* for sensor communication and data transfer. *Wire.h* facilitates communication with I2C devices, while *WiFi.h* and *HTTPClient.h* provide Wi-Fi connectivity and HTTP communication. Sensor data from accelerometers, gyroscopes, and FSR sensors is collected and stored in local flash memory. The data is then transferred to a web browser for visualization or analysis. Manual copying and storage in Excel sheets are suggested as improvements. An automated data transfer and storage solution could be implemented. Data visualization helps understand sensor outputs and identify patterns. The K-Nearest Neighbours (KNN) algorithm is applied for fall detection based on the similarity between collected sensor data and training data points. The software components and data analysis methods contribute to the functionality of the smart shoe system, potentially enhancing elder care and promoting safety.

The methodology involves collecting sensor data from a smart shoe system using accelerometers, gyroscopes, and FSRs to track the wearer's movement patterns. The ESP32-C3 microcontroller stores the data locally during walking activities and potential fall events. Wi-Fi then transfers the data to a computer, where an Excel sheet displays it in figure 4. Edge Impulse, a software platform for developing machine-learning models for edge devices, performs data pre-processing and training. Based on the data, create a training dataset and label it as either "normal walking" or "fall event." Choose the KNN algorithm for fall detection, and train the KNN model on the training dataset. Data visualization helps understand sensor outputs and identify patterns related to walking or potential fall outputs represented in figure 5, figure 6, and figure 7. The evaluate the KNN model's performance on unseen data to gauge its effectiveness in real-world scenarios. Edge Impulse offers a user-friendly interface for collecting sensor data, training machine learning models on edge devices, and deploying them.

	A	B	C	D	E	F	G	H	I
1	Date	Acc-x (m/:	Acc-y (m/:	Acc-z (m/:	Gyro-x (ra	Gyro-y (ra	Gyro-z (ra	Front-fs (r	Rear-fs (raw)
2	26-01-2024	-5.12	-2.33	8.07	0	-0.02	0	4095	4095
3	26-01-2024	-5.01	-1.42	8.69	0.01	0.01	0.02	1101	4095
4	26-01-2024	-6.96	-1.75	7.66	-0.39	-4.07	-1.42	1335	4095
5	26-01-2024	-4.8	-2.73	8.16	0.1	0.13	0.09	3400	4095
6	26-01-2024	-9.03	0.54	2.22	-0.89	-1.42	0.42	412	4095
7	26-01-2024	-4.77	-2.9	7.94	0.02	-0.01	0.01	4095	4095
8	26-01-2024	-12.35	-8.97	9.16	-0.03	-2.57	-2.11	1310	4095
9	28-01-2024	-5.02	-2.62	8.09	0	0.01	0.02	4095	4095
10	28-01-2024	-10.24	-0.78	12.58	0.12	2.35	1.02	982	4095
11	28-01-2024	-5.54	-4.2	3.8	2.01	-3.08	-2.9	971	4095
12	28-01-2024	-4.91	-2.75	7.99	0.06	-0.01	0.07	4095	4095
13	29-01-2024	-6.51	-5.77	4.75	1.52	-3.78	-2.38	1117	4095
14	29-01-2024	-4.45	-7.13	9.22	-0.1	6.55	2.92	4095	3151
15	29-01-2024	-14.58	2.52	-3.93	0.63	-1.95	-0.87	1308	4095
16	29-01-2024	-7.37	-4.81	5.05	2.49	0.11	-3.7	320	4095

Fig 4: Excel sheet data of the left shoe collected from sensors

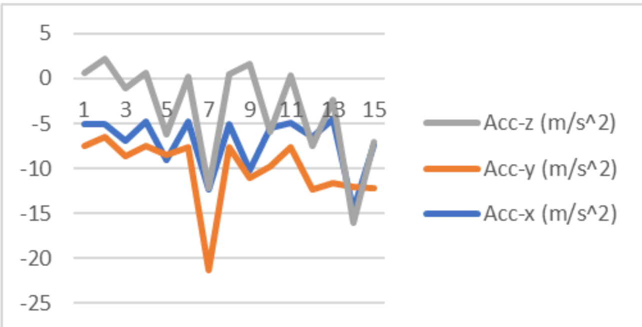

Fig 5: Graphical representation of accelerometer data values

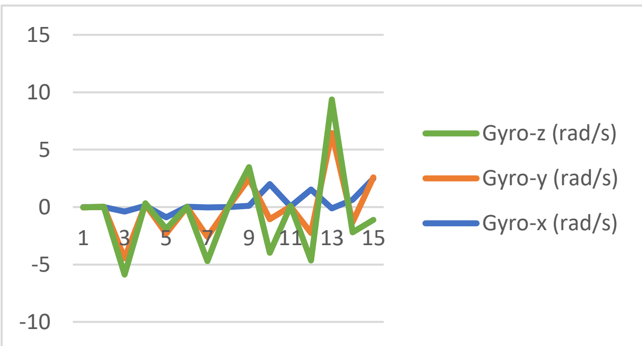

Fig 6: Graphical representation of gyroscope data values

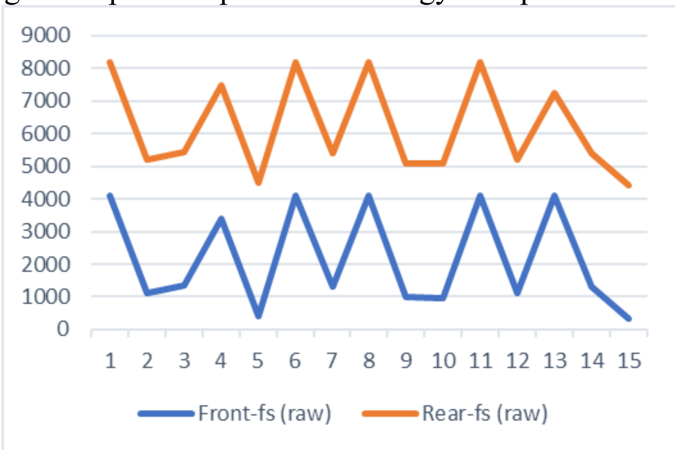

Fig 7: Graphical representation of FSR data values

IV. RESULTS AND DISCUSSION

The KNN classifier is a promising approach for fall detection in a smart shoe system, utilizing accelerometers, gyroscopes, and FSR sensors to capture motion data for continuous monitoring in figure 8 stand slip and other. Machine learning techniques enable fall prediction and trigger messages to caretakers upon detection. The KNN classifier is trained using regression and classification approaches within the KNN algorithm, suggesting the exploration of different methods for optimal performance in figure 9. Sensor data is categorized and labelled based on features related to movement patterns, and spectral analysis is performed on raw data to extract relevant features. Data visualization is used to identify potential differences between normal activities and falls. The KNN model's performance is evaluated using metrics like accuracy, precision, and recall. Future work could include incorporating additional sensors, using advanced machine learning algorithms, or improving data collection methods. Further discussion on the obtained results, limitations, and potential improvements would provide a more comprehensive understanding of the system's effectiveness.

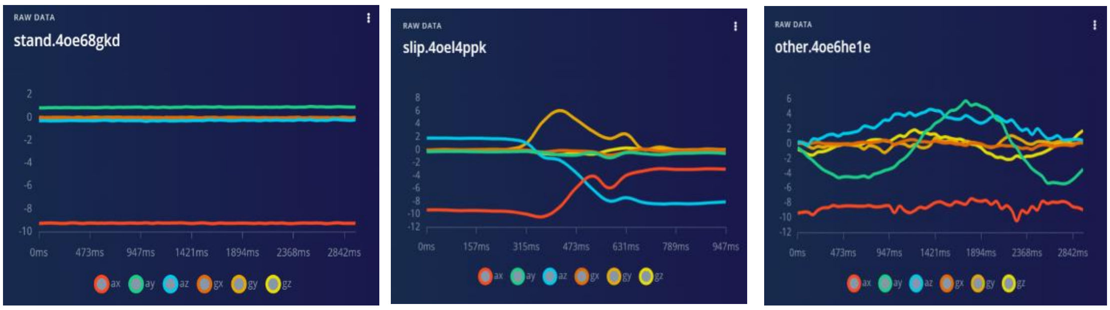

Fig 8: Graphical representation sensor data of Stand, Slip, and Other

Train the KNN classifier using labelled and feature-extracted data to identify normal and fall events. Metrics such as accuracy, precision, and recall evaluate its performance, gauging its effectiveness in classifying normal activities and falls. However, the text does not explicitly mention the performance metrics used for fall detection, such as accuracy 100, precision, recall, and the F1 score observed in Figure 9. The text also discusses the use of regression methods for KNN but lacks details on their results and comparison with classification. Further details on spectral analysis and feature importance would be valuable for understanding the most influential features in fall detection, which could be crucial for model optimization.

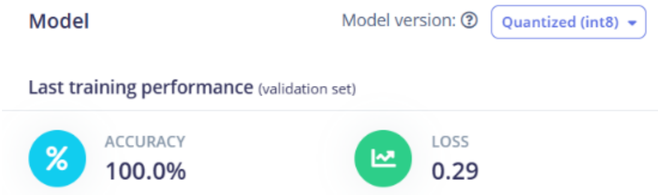

Fig 9: Accuracy performance model

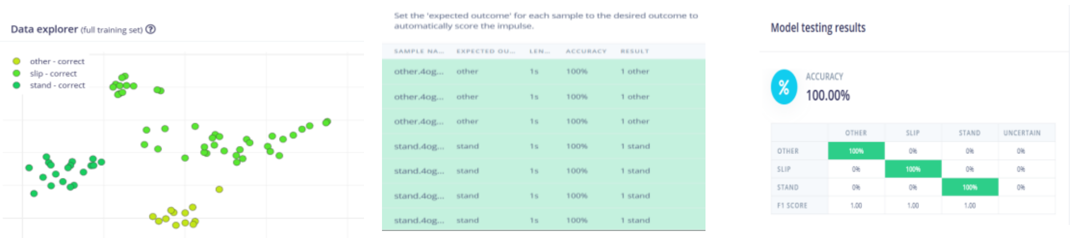

Fig 10: Representation of training model testing of KNN with different gait positions

When a fall detection model achieves 100% accuracy on training data, it may overfit and memorize specific patterns that it may not recognize in unseen data, potentially leading to missed falls in real-world scenarios represented in figure 10. The evaluation process is unclear, with missing metrics like accuracy, precision, recall, and F1 score. The text mentions using KNN with regression but does not elaborate on the results or compare them to classification. Recommendations for improvement include cross-validation techniques, training on a larger dataset, and using evaluation metrics like accuracy, precision, recall, and F1 score.

Fig 11: Representation of model training using a regression approach

The regression model for fall detection has limitations due to its use of numerical labels instead of categories. The test data used numerical labels, likely converted from categorical labels in figure 11. The regression model achieved a lower accuracy (77.78%) compared to the reported 100% accuracy for classification. This may be due to overfitting the training data. Recommend cross-validation techniques and a larger dataset to improve the accuracy of both classification and regression approaches in figure 12.

SAMPLE NAME	EXPEC...	LENGTH	ACCUR...	RESULT
other.4oga8j5e	0	1s	0%	-0.25
other.4oga7g...	0	1s	0%	-0.21
other.4oga74...	0	1s	100%	0.07
stand.4oga2plb	1	1s	100%	1.09
stand.4oga2htj	1	1s	0%	1.24
stand.4oga1ria	1	1s	100%	0.99
stand.4oga1e...	1	1s	0%	0.83

Fig 12: Test data results upon model testing for the regression model

The system uses a KNN model to analyse sensor data from accelerometers, gyroscopes, and FSR sensors in shoes to detect normal and abnormal walking patterns, potentially indicating a fall event. The system alerts caregivers via text message when it detects a fall, specifically identifying the side of the fall. This system offers benefits for elderly care, including timely intervention and assistance, potentially minimizing fall consequences. Continuous monitoring of gait patterns provides insights into the wearer's health and well-being, while real-time fall detection reduces fall-related injuries. The system offers peace of mind for caregivers and elders by providing a safety net and enabling remote monitoring. Twilio facilitates sending text message alerts upon fall detection in Figure 13.

- Fall down, caretaker alert, from right shoe

- Fall down, caretaker alert, from left shoe

Fig 13: Elderly person falls caretaker message from both the legs

V. CONCLUSION

The system uses a KNN model to analyse sensor data from accelerometers, gyroscopes, and FSR sensors in shoes to detect normal and abnormal walking patterns, potentially indicating a fall event. The system alerts caregivers via text message when it detects a fall, specifically identifying the side of the fall. This system offers benefits for elderly care, including timely intervention and assistance, potentially minimizing fall consequences. Continuous monitoring of gait patterns provides insights into the wearer's health and well-being, while real-time fall detection reduces fall-related injuries. The system offers peace of mind for caregivers and elders by providing a safety net and enabling remote monitoring. Twilio facilitates sending text message alerts upon fall detection.

VI. FUTURE SCOPE

Future research focuses on developing wearable health monitoring for seniors. Potential areas for exploration include enhanced fall detection algorithms, multi-sensor fusion, advanced activity recognition, real-time fall prevention, and smart home integration. Advanced fall detection algorithms could improve accuracy and robustness, while multi-sensor fusion could offer a comprehensive picture of an elder's health and well-being. The system could also recognize a broader range of activities beyond walking and falling, providing a more detailed picture of an elder's daily routine. Feedback or intervention mechanisms could achieve real-time fall prevention. It also integrates the smart shoe system with other smart home technologies to enhance senior safety and independence.

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