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Original

Fall detection analysis using the k-nearest neighbor algorithm

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Abstract: A fall detection system enhances the quality of life for elderly individuals by allowing them to live independently without constant care. It is more accurate and cost-effective compared to image-based systems. The system includes two key components: detection, which identifies falls by comparing daily activity data with abnormal sensor values, and communication, which alerts emergency contacts. By using heart rate and oxygen sensors, it can determine whether a fall is conscious or unconscious. Wearable devices, particularly wrist devices, provide accurate data, but current models primarily detect falls without offering additional health information. Future improvements may include wireless data transmission for increased efficiency.

Keywords: **Health monitoring; Cost-effective; Wearable devices.**

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1. Introduction

Falls among the elderly are a major concern, causing over 645,000 deaths annually and leading to 36.3 million individuals seeking medical attention, according to the WHO (Casilari et al., 2020). Severe injuries, such as hip fractures and brain trauma, can result from falls, and delays in receiving medical help increase the risk of death. Fall detection systems (FDS) can reduce response times and improve elderly care. Wearable FDSs, which are more affordable than image-based systems, typically use accelerometers, gyroscopes, and, in some cases, heart rate sensors to detect falls. A system incorporating a heart rate sensor (MAX 30101) and an oxygen sensor enhances detection by assessing whether the fall was conscious or unconscious. Data from these wrist sensors helps categorize daily activities and identify falls using the k-nearest neighbors' algorithm. This information helps determine whether the person needs medical assistance. Fall detection systems (FDSs) have become increasingly important for older adults due to the severe risks associated with falls. Recent advancements focus on enhancing these systems through Machine Learning (ML) and Deep Learning (DL) technologies (Li et al., 2012). Research shows that user characteristics, such as weight and height, can impact system performance significantly, reducing accuracy. A Fusion Fall Detection Algorithm Combining a Threshold-Based Method and Convolutional Neural Network introduces innovations by fusing algorithms that combine various techniques, such as Convolutional Neural Networks (CNNs), to improve fall detection accuracy. A Cross-Dataset Deep Learning-Based Classifier for Fall Detection and Identification demonstrates that deep learning classifiers are highly effective across datasets, thereby improving adaptability and accuracy (Casilari et al., 2017). A Machine Learning Approach for Fall Detection and Daily Living Activity Recognition leverages machine learning frameworks and acceleration data to improve performance and reduce false alerts.

For Fall Detection in Older People, incorporating thermal sensors and Bi-, Long Short-Term Memory (LSTM) offers high accuracy and real-time data transmission. Deep learning-based fall detection using smartwatches for healthcare applications employs gyroscope data and BiLSTM networks, achieving up to 99% accuracy (Mohammad et al., 2023). Similarly, applying deep learning to automatic fall detection using mobile sensors achieves superior accuracy compared to traditional methods. A Fall Detection Approach Based on Combined Two-Channel Body Activity Classification for Innovative Indoor Environments uses surveillance footage to classify body activities, achieving impressive fall-detection results (Şengül et al., 2021). IoT-based human fall-detection systems that leverage multiple models improve accuracy across diverse environments. Low-power fall-sensing technologies based on FD-CNN balance efficiency, connectivity, and effective fall detection (Taramasco et al., 2018). A Study on the Impact of Users' Characteristics on the Performance of Wearable Fall Detection Systems emphasizes that factors such as gender, Body Mass Index (BMI), weight, and height have a secondary impact on the accuracy of these systems. Training and evaluating systems in which test subjects differ significantly in physical characteristics can lead to a 20% reduction in sensitivity and to a loss of specific information of up to 95% (Wang et al., 2025). Fall detection systems proposed in the literature rely on signals captured by accelerometers, gyroscopes, and cameras. The fusion fall detection system presented in this paper combines a threshold-based method (TBM) with a convolutional neural network (CNN). SHFFD employs TBM to preview events based on triaxial acceleration measurements. During the TBM phase of the fusion algorithm, a feature set is generated. A bidirectional neural network for fall detection achieves 99% accuracy. The Bi-Long short-term memory (LSTM) algorithm, which uses both previous and new information, produces outstanding results while respecting user privacy, achieving 93% accuracy in fall detection.

Fall detection systems are not limited to wearable devices and can be integrated into a variety of assistive technologies to enhance safety for individuals with mobility challenges further. One promising avenue is integrating fall-detection mechanisms into crutches, walkers, and other mobility aids. These devices are already commonly used by individuals with impaired mobility, and incorporating fall detection sensors could serve a dual purpose: assisting with movement while simultaneously providing safety by detecting falls.

For instance, crutches and walkers could be equipped with accelerometers and gyroscopes to monitor the user's stability and detect any abnormal movements that could indicate a fall. These devices, when integrated with an alert system, could notify caregivers or emergency services immediately upon detecting a fall, thus reducing the response time and potentially saving lives. This integration would not only enhance the versatility of fall detection systems but also make them accessible to a broader range of users, including those who may not be able to wear wearable devices due to discomfort, personal preference, or medical conditions.

The inclusion of sensors in walking aids could offer an extra layer of monitoring. For example, by adding a heart rate sensor or an oxygen sensor to these devices, the system could further analyze the circumstances of the fall, such as whether it was due to a sudden loss of consciousness, heart-related issues, or other medical conditions. This would improve fall detection systems' ability to provide precise, contextually relevant alerts to caregivers or medical personnel. Integrating fall detection technologies into a broader range of assistive devices can help create a more comprehensive safety ecosystem for elderly individuals and people with mobility impairments. This approach could significantly reduce fall-related injuries and fatalities by enabling quicker responses and more personalized care.

2. Methodology

The existing fall detection system uses the gyroscope sensor to detect falls and does not rely on any other sensors to achieve precise detection (Wu et al., 2021). Also, it requires a high amount of energy to collect and process data to detect a fall.

In our project, it use a heart rate and oximeter sensor (MAX30100) to get the heart rate and oxygen level of a person and also use the Gyroscope sensor (MPU6050) to get the position data of the person and get all these values by using the Raspberry pi zero and use LabView software to get data and run the graph of the datum got from both the sensors. Using the K-Nearest Neighbour algorithm to detect if the fall is conscious or unconscious. Because most falls result from skidding into obstacles, when a fall occurs, our algorithm checks whether it was conscious or unconscious. Our project also detects a fall 8 seconds in advance by processing oximeter data. If a person is going to fall, the oxygen rate will receive a low grade to predict the fall (Xu et al., 2021).

The Raspberry Pi was chosen primarily for its compatibility with the selected sensors and software. Its versatility in interfacing with a variety of sensors, including the heart rate, oxygen, and gyroscope sensors, made it an ideal choice (Altay & Ulas, 2019). Additionally, its processing capabilities allow efficient data collection and real-time analysis. While cost-effectiveness is a benefit, the main reason for its selection was its seamless integration with Python programming and LabVIEW for data visualization and processing.

The gyroscope and oximeter sensors provide data to the Raspberry Pi Zero. The Raspberry Pi Zero runs the data with the built-in Python code. That code has a KNN algorithm path (Di et al., 2015). The LabVIEW software retrieves data from the Raspberry Pi Zero and plots graphs of gyroscope, Heart rate, and oxygen level (SpO2). LabVIEW is trained on all three values to run the algorithm and predict the fall exactly. If the fall occurs, it will be communicated to the medical assistant.

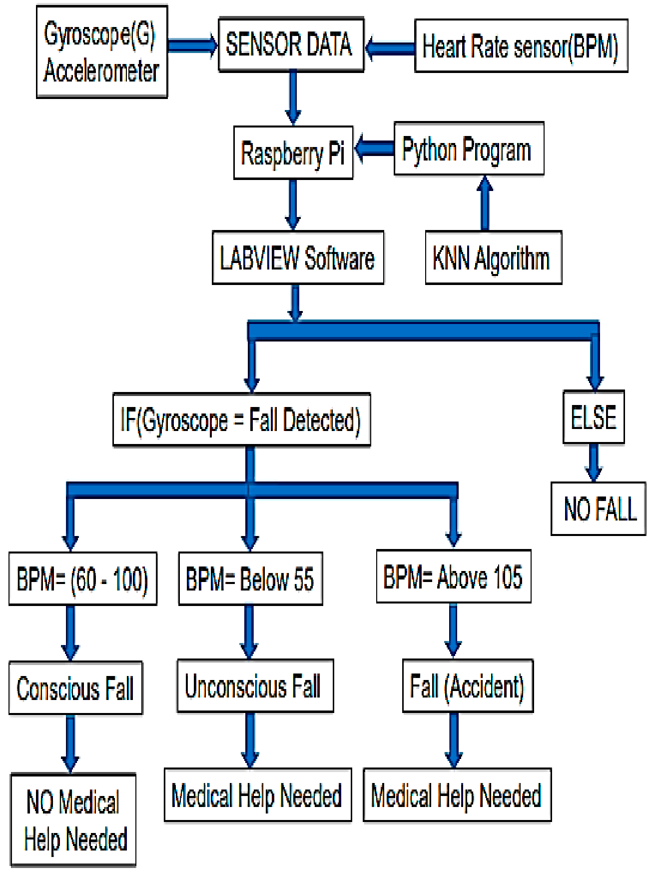

Figure 1. Flow chart.

The electrical section consists of a Raspberry Pi Zero module, a relay module, a Gyroscope sensor, a Heart rate sensor, an LCD, a step-down transformer, a Buck converter, and wires. The real-time electrical circuit is shown in Figure 2.

The Heart Rate Sensor (MAX 30101) includes both an oxygen level sensor and a heart rate sensor (Ding et al., 2022). It detects pulse oximetry and heart rate using two LEDs, a photodetector, improved optics, and low-noise analog signal processing. The sensor's operating voltage ranges from 1.8 to 3.3V. The Gyroscope Sensor (MPU 6050) consists of a 3-axis gyroscope and a 3-axis accelerometer, with an operating voltage of 2.3 to 3.3V. The gyroscope measures rotation along the x, y, and z axes, while the accelerometer measures a person's movement when walking, sitting, or running. A voltage regulator provides a stable 5V supply to the system. A buck converter module ensures a stable power supply to the Raspberry Pi module. The Raspberry Pi collects sensor data from the heart rate and gyroscope sensors and sends it to LabVIEW for simulation and analysis (Kaur & Sharma, 2024). The Raspberry Pi has built-in Python support for classifying ADLs (Activities of Daily Living) and transmitting.

The Raspberry Pi was chosen primarily for its compatibility with the selected sensors and software. Its versatility in interfacing with a variety of sensors, including heart rate, oxygen, and gyroscope sensors, made it an ideal choice. Its processing capabilities allow efficient data collection and real-time analysis. While cost-effectiveness is a benefit, the main reason for its selection was its seamless integration with Python programming and LabVIEW for data visualization and processing (Liu et al., 2021).

LabVIEW is a graphical programming environment with a front page for user interaction and a block diagram for programming. The Raspberry Pi, connected to sensors such as a gyroscope and a heart rate monitor, collects data, which is displayed graphically on LabVIEW's front page. The LabVIEW block diagram uses case statements, arithmetic commands, and while loops to continuously collect and process sensor data, representing it in both digital and analog formats. Sensor data, such as heart rate, oxygen levels, and gyroscope readings, is exported to Excel for analysis. The real-time LabVIEW block diagram is shown in Figure 5.

The analog and digital sensor data values are displayed on the LabVIEW front page. The LabVIEW front page diagram is shown in Figure 6.

The device is intended to be worn around the neck, much like a neckband, providing comfort and minimal disruption to daily tasks (Resch et al, 2025). Its lightweight, ergonomic design ensures continuous monitoring without discomfort, making it suitable for extended wear while allowing freedom of movement throughout the user's day. The real-time setup is shown in Figure 4.1 and Figure 4.

A graph is a visual representation of collected data on the X- and Y-axes (Hasan et al., 2019). Heart rate, oxygen level, and gyroscope value are represented on the Y-axis, and time period on the X-axis. The graph is used to compare the previous and current values over a given time period (Razjouyan et al., 2017). The graph is created using previous and current sensor values, such as heart rate and gyroscope data. The value point is connected to a graph on the X- and Y-axes. Heart rate, oxygen level, and gyroscope values are collected using a Raspberry Pi

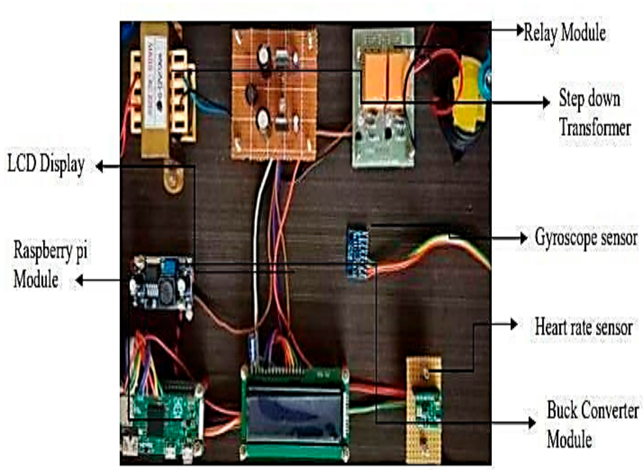

Figure 2. Electrical Setup.

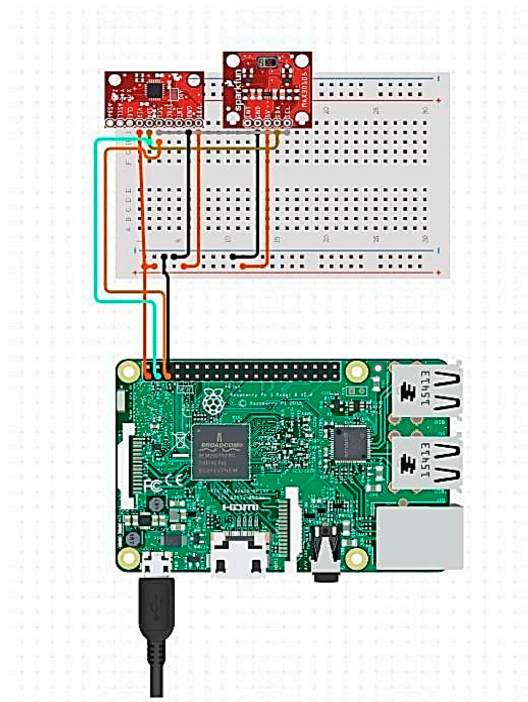

Figure 3 Electrical Setup Schematic Diagram.

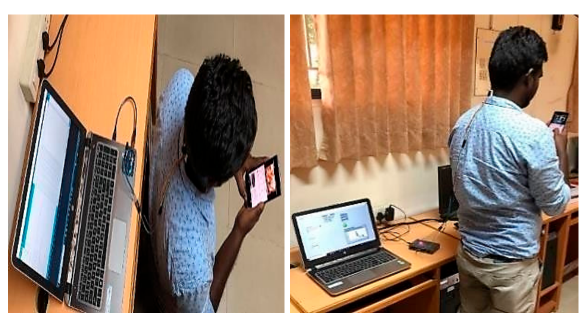

Figure 4 RealTime Setup.

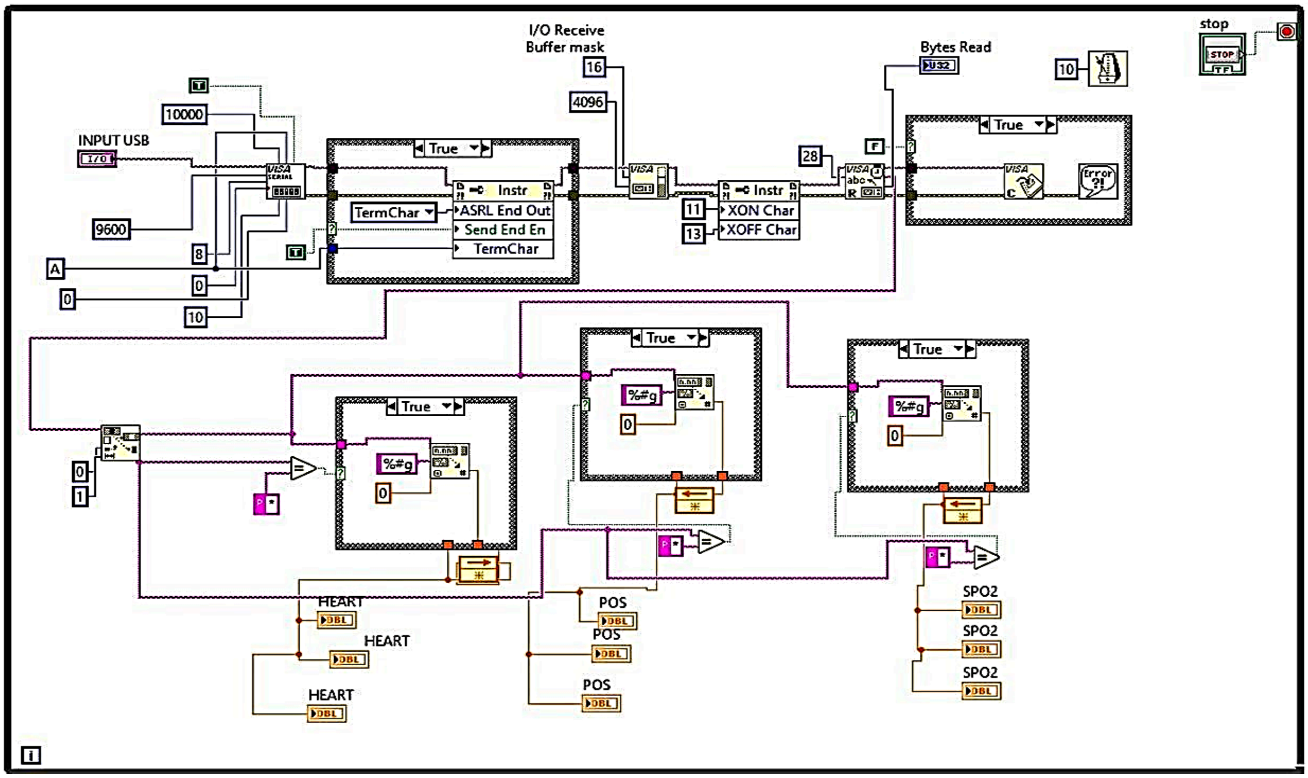

Figure 5. LabVIEW Block Diagram.

Zero module with a sensor, and the corresponding graphs are displayed on the LabVIEW front page. In Figure 7, the heart rate graph is generated in LabVIEW, with the corresponding data organized and analyzed. The X-axis represents time, showing progression over the monitoring period, while the Y-axis displays heart rate values, reflecting the number of heartbeats per minute at each time point (Saleh & Jeannes, 2019). This graph provides a clear and detailed view of heart rate fluctuations over time, allowing in-depth analysis of the data, the use of LabVIEW for graph creation, and a comprehensive representation of the heart rate measurements.

In Figure 8, the oxygen level graph is generated in LabVIEW, with data analysis supported by an Excel sheet. The graph presents time on the X-axis, reflecting the progression of the observation period. On the Y-axis,

Figure 6 LabVIEW Front Page.

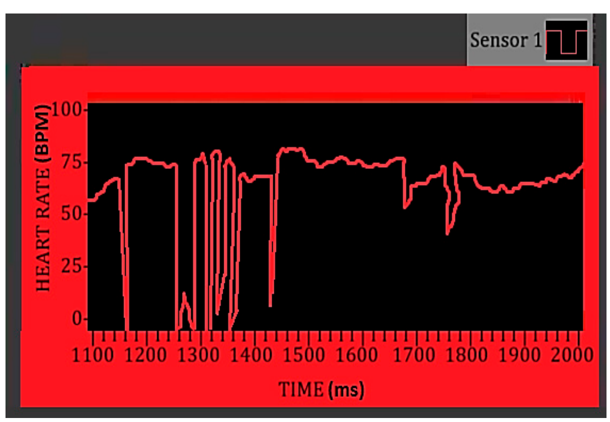

Figure 7. Heart Rate Graph.

oxygen levels are plotted, representing the measured oxygen concentration at each time point. This visualization provides a clear overview of oxygen level variations over time, enabling a more detailed analysis of the data. The combination of LabVIEW for data visualization and Excel for data organization and analysis ensures an accurate and comprehensive representation of the oxygen levels.

In Figure 9, the gyroscope position value graph is generated in LabVIEW, with the data organized and analyzed. The X-axis represents time, showing the time progression during the observation period, while the Y-axis displays the gyroscope position values, indicating the orientation or rotational position at each corresponding time point. This graph offers a clear visualization of the gyroscope's movement over time, enabling detailed analysis of its positional changes (Noorudin et al., 2021). The combination of LabVIEW for graph form data analysis ensures accurate and comprehensive representation of the gyroscope's position data.

3. Result and analysis

The fall detection system must be analyzed using a KNN algorithm. The KNN algorithm is easy to use, exact, and very accurate. The KNN (K-Nearest Neighbour) algorithm uses the Euclidean distance; it returns results based on the distance between the training data shown in Figure 8. It gives the result on the shortest distance side in the graph.

The K-Nearest Neighbour (K-NN) algorithm was chosen for classification in this fall detection system due to its simplicity, ease of implementation, and effectiveness in handling real-time sensor data. Unlike more complex algorithms, K-NN does not require extensive training or model assumptions, making it ideal for detecting patterns in small, low-dimensional datasets such as heart rate, oxygen levels, and gyroscope data (Popister et al, 2025). Additionally, K-NN provides fast, efficient classification, which is crucial for timely fall identification in emergencies. Algorithms like neural networks, decision trees, and deep learning methods have been tested for fall detection. While deep learning models offer higher accuracy, they are computationally intensive and consume more energy, which is not ideal for wearable devices. K-NN provides a better balance of accuracy, efficiency, and energy consumption for real-time, battery-powered applications.

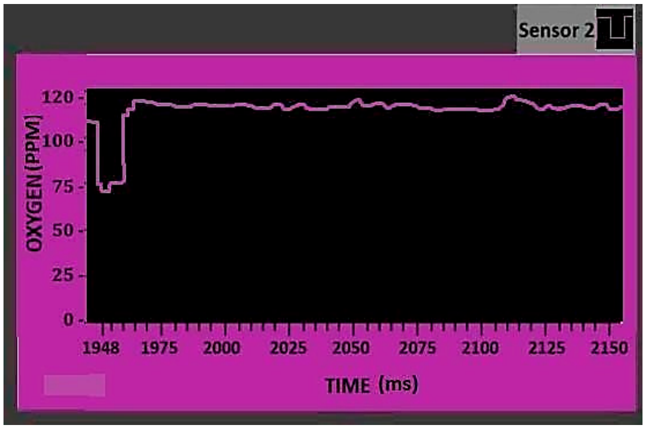

Figure 8. Oxygen Level Graph.

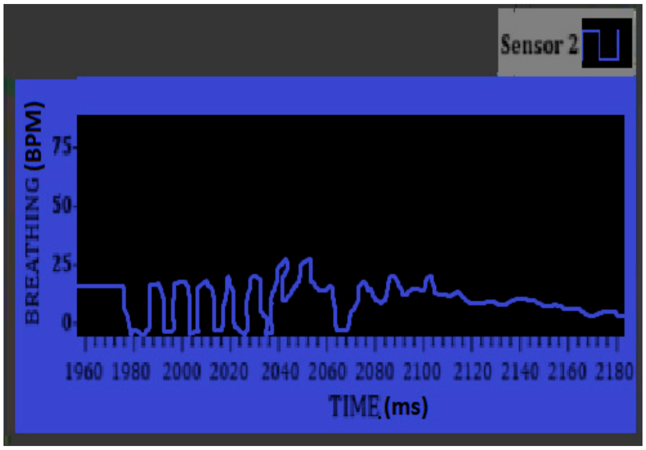

Figure 9. Position Graph.

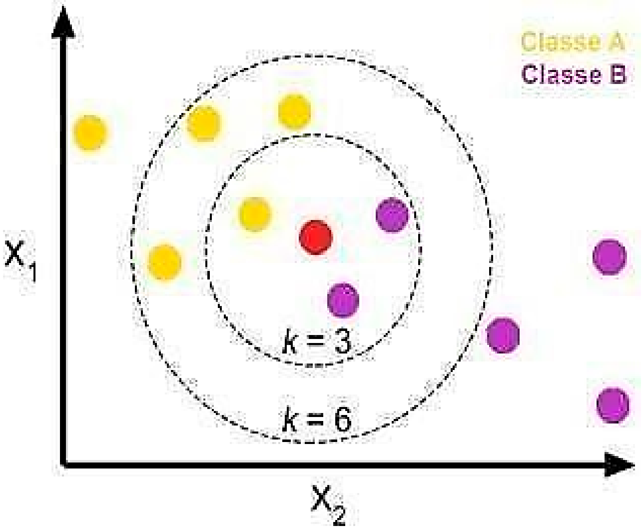

Figure 10. K-Nearest Neighbor Algorithm.

- Accuracy: Deep learning methods (CNNs, RNNs) offer higher accuracy, especially with complex data, but simpler algorithms like K-NN can perform competitively with well-engineered features.

- Efficiency: K-NN is computationally efficient and faster for inference, making it ideal for real-time fall detection. Deep learning models are slower and resource-heavy.

- Energy Consumption: Deep learning methods consume more power due to high computational demands, while K-NN are more energy-efficient, suitable for battery-powered wearable devices.

- The value of K in the K-NN algorithm was determined using cross-validation. Various values of K were tested to evaluate performance based on accuracy, and the value that minimized error and overfitting was selected.

- The value of K impacts the system's accuracy by balancing bias and variance. Smaller K values can lead to overfitting, while larger K values can smooth decision boundaries, potentially leading to underfitting. The chosen K enhances generalization.

In this dataset, heart rate, position, and oxygen level data for 17 people aged 20 to 61. The position data comes from the gyroscope sensor, and there is not much difference because everyone is sitting in a similar position. The heart rate (BPM – Beats per Minute) ranges from 65 to 86. It can be seen in the chart for all heart rate, position, and oxygen level in Figure 11.

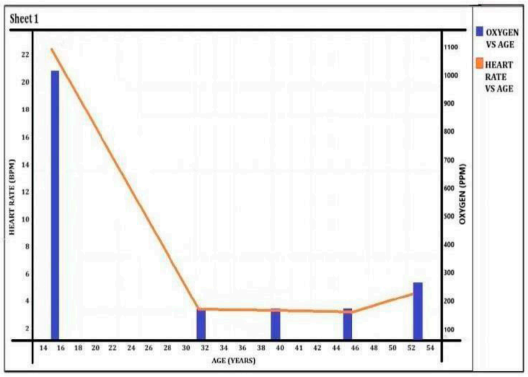

Figure 11. Sitting Position bar graph.

The data sheet is used to analyze a person's fall while walking. The data sheet is filled out based on the person's age in various situations, such as walking. The data sheet consists of the gyroscope, heart rate, oxygen level, and age of the person.

Table 1. Sitting Position Dataset.

SITTING POSITION				
So.No.	AGE	Gyroscope value	Heart rate	Oxygen rate
1	21	1	80	103
2	21	1	86	131
3	21	2	84	110
4	21	1	86	122
5	20	1	80	122
6	20	2	83	124
7	20	2	73	111
8	20	2	76	120
9	20	2	78	112
10	21	1	83	116
11	37	1	88	125
12	43	1	80	120
13	46	1	65	121
14	54	1	70	111
15	61	1	71	105

Table 2. Walking Position Dataset.

WALKING POSITION				
So.No.	AGE	Gyroscope value	Heart rate	Oxygen rate
1	21	1	92	130
2	21	1	90	128
3	21	2	88	132
4	21	1	89	126
5	20	1	94	131
6	20	2	96	129
7	20	2	99	140
8	20	2	93	138
9	20	2	100	141
10	21	1	91	130
11	37	1	78	130
12	43	1	69	116
13	46	1	68	116
14	54	1	65	111
15	61	1	67	110

In the walking position dataset analysis, 17 data sets from different age groups were analyzed. Oxygen levels were notably higher than during other ADLs, and heart rates were slightly elevated during walking, ranging from 67 to 100 BPM. The position data varied randomly.

The data sheet is used to analyze a person's fall while running. The data sheet is filled out based on the person's age in various situations, such as running. The data sheet consists of the gyroscope, heart rate, oxygen level, and age of the person. From the running position dataset, I plotted the graph of all three heart rates (BPM): position and Oxygen level datum. If the graph is analyzed, it can be noticed that older people have a low heart rate, and adults also have a low heart rate compared to older people. The oxygen level also varies, similar to the heart rate.

Table 3 Running Position Dataset.

RUNNING POSITION				
So.No.	AGE	Gyroscope value	Heart rate	Oxygen rate
1	21	1	108	123
2	21	1	112	132
3	21	2	116	126
4	21	1	121	132
5	20	1	117	133
6	20	2	109	127
7	20	2	113	124
8	20	2	118	129
9	20	2	110	131
10	21	1	114	125
11	37	1	107	124
12	43	1	102	121
13	46	1	97	119
14	54	1	92	116
15	61	1	88	114

The graph above shows heart rate (BPM) and oxygen saturation (SpO2) plots for people of different ages. The graph below shows the KNN algorithm checking for the fall, which is shown in Figure 13.

The input data was pre-processed and feature-engineered before being introduced into the K-Nearest Neighbour (K-NN) algorithm. The raw data from the sensors includes heart rate, oxygen level, and gyroscope.

1. **Pre-processing:** Noise was reduced, and outliers were handled to improve data quality. Missing values were imputed if necessary.

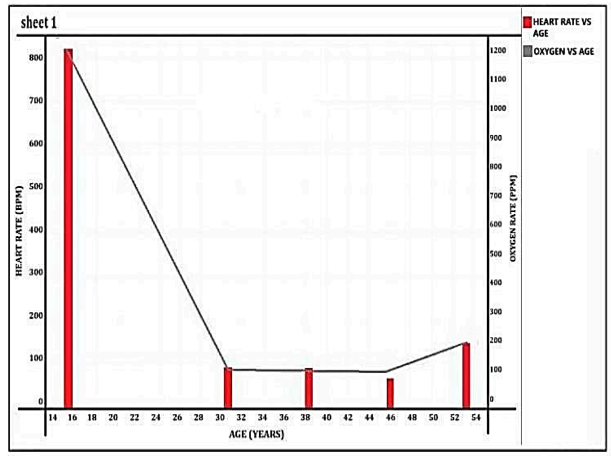

Figure 12. Walking Position Bar Graph.

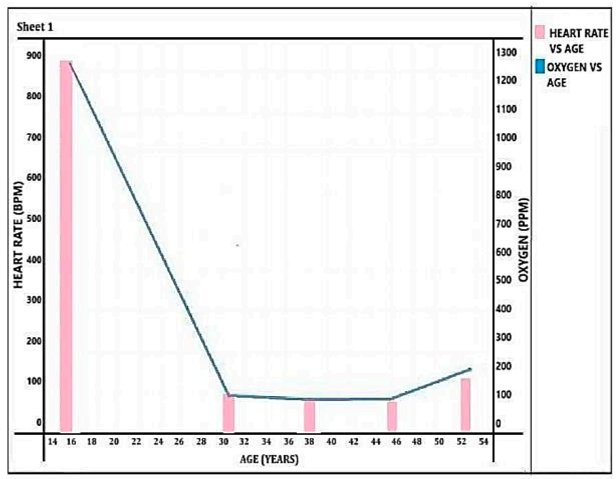

Figure 13. Running Position Bar Graph.

2. **Feature Engineering:** Relevant features such as average heart rate, acceleration, and oxygen level were extracted from the sensor data to provide meaningful inputs for classification.
3. **Windowing:** Time windows were applied to segment continuous data into manageable chunks, allowing the algorithm to focus on localized patterns such as short-term changes in heart rate or movement that are critical for detecting falls.

The system mitigates potential inaccuracies in predicting falls based on oximeter data by integrating multiple sensors, such as heart rate and gyroscope readings. This multi-sensor approach ensures more reliable fall detection, compensating for subtle changes in oxygen levels and enhancing overall accuracy.

Conclusions

As stated in the objective, the development and analysis of the fall detection system have been completed. The experimental analysis shows that the system has good precision and no false-positive results regarding falls. Additionally, it demonstrates greater precision than other fall detection systems. This system consists of sensors, microcontroller boards, and a KNN algorithm to determine whether the fall was conscious or unconscious. Moreover, it can predict if a person is likely to fall by analyzing the oximeter data. If the oxygen level gradually decreases, there is a high chance the person may fall or require medical assistance. The system is energy-efficient and offers higher precision than other available fall detection systems. It employs an algorithm that self-trains, improving precision over time. This system uses commercial software, LabVIEW, which provides high efficiency and accuracy, allowing for easy analysis of the system. To enhance fall-prediction reliability, the system integrates data from multiple sensors, including an oximeter, a heart rate sensor, and a gyroscope. Machine learning algorithms analyze combined data, improving fall detection accuracy even when subtle changes in oxygen levels occur. Additionally, user-specific calibration and dynamic threshold adjustment are implemented, ensuring better adaptability and reducing the likelihood of false positives or missed falls. The system's performance in diverse, uncontrolled environments is being enhanced through expanded testing in real-world conditions, including uneven surfaces and outdoor settings. We are integrating data from these environments into the training process and updating machine learning models to improve adaptability, reliability, and accuracy across diverse fall scenarios. There are plans to integrate additional health metrics into the system to enhance its utility for medical professionals. Future upgrades may include incorporating blood pressure and activity levels to provide a more comprehensive view of the user's health status. These metrics could help medical professionals better assess the user's condition, identify potential health risks, and tailor their response accordingly. Additionally, continuous monitoring of these vital signs can offer insights into overall health trends, improving the system's ability to detect early warning signs and support more personalized care.

Conflict of interest

The author(s) have no conflict of interest to declare.

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