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A Low-Cost Wearable System to Detect Fall and Non-Fall Activities for Elderly Individuals

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***Abstract*—As the elderly population grows, the prevalence of age-related health conditions such as cardiovascular diseases, cognitive decline, and mobility impairment is also increased. Among these health conditions, falls are considered one of the greatest threats to elderly individuals. A low-cost wearable fall detection system is designed, with the purpose of monitoring and detecting their activities. Three master modules were constructed, with each consisting of an inertial sensor, a microcontroller, and a power supply circuit block. The data were collected using IMU MPU6050 and preprocessed using the MCU ESP32. Each master module is also supplied using a 3.7V 1S LiPo battery. 18 healthy subjects, consisting of 13 males and 5 females, agreed to volunteer for the experiments. They were instructed to do 8 different activities, including non-fall (stand still, sit-to-stand, walk, and sleep position) and fall events (forward fall, sideways fall, and backward fall). Overall, the system showed a good performance using the Multilayer Perceptron (MLP) algorithm with an accuracy of 95.3% across all activities. While misclassification happens between classes, our system is still able to distinguish between non-fall vs. fall events with 100% accuracy. Cost analysis was also conducted; the overall cost for the three master modules in our proposed system is $65.4. This is cheaper than commercial fall detection systems and other related research, and our proposed system can also be used continuously. The system will alert caregivers to the immediate attention of elderly individuals.**

***Index Terms*—Elderly Individuals, Fall Detection System, Low-cost, Multilayer Perceptron, Wearable Device**

I. INTRODUCTION

The rise of science and technology has significantly contributed to various sectors, particularly in healthcare. Devices constructed as prototypes are often designed for a variety of purposes, such as vital sign monitoring, early detection, and symptom identification [1]. These technological advancements have enabled more precise and continuous health monitoring that was previously unattainable. Research on healthcare topics was conducted on a variety of subjects, but one prominent area of its application is for elderly individuals. This is due to the shift in global population demographics towards older age groups, which is known as population ageing [2]. It is predicted that in 2050, the number of people aged 60 and above will exceed the number of adolescents aged 10–24 [3]. As the elderly population grows, the prevalence of age-related health conditions such as cardiovascular diseases, diabetes, cognitive decline, and mobility impairments also increases [4]. These conditions often require regular monitoring and long-term management of health. Among these health conditions, falls are considered one of the greatest threats to elderly individuals [5].

Fall-related injuries can be either fatal or non-fatal, although most are non-fatal [6]. The combination of multiple chronic conditions and increased fall risk makes it difficult for traditional healthcare systems to provide adequate care. Traditional healthcare systems themselves, which rely on periodic hospital visits and admissions, are increasing in number, which limits the ability to meet the needs of the expanding demographic of elderly individuals [7]. To address these challenges, caregivers often assist the elderly in their homes. These caregivers are usually family members, such as spouses, partners, or other relatives, who are typically unpaid with full responsibility for taking care of the elderly [8]. However, caregiving usually requires spending more time on the job, leading to various consequences, including impacts on mental and physical health, health behaviors, and broader family dynamics [9]. To overcome these challenges, solutions are needed that respect both elderly individuals and caregivers. One such solution is the development of fall detection systems, which aim to address these problems effectively.

Fall detection systems are implemented to alert medical personnel or caregivers to help when a fall occurs. These systems have been widely researched, with the addition of fall alert features being the most popular research area, and ongoing research continually improving them [10]. While fall detection systems cannot prevent falls, they play a crucial role in reducing complications by ensuring that fall victims receive immediate response and necessary assistance. Routine detection and notification of falls could significantly reduce the risk of long-term disabilities, hospitalization duration, and mortality rates [11]. Fall detection and the alert system need to be automated, as fall victims may be unable to activate an alarm themselves [12]. This is particularly crucial considering that many elderly individuals who fall may lose consciousness, experience confusion, or suffer injuries that limit their mobility and ability to call for help. The duration between a fall and receiving assistance is a critical factor in determining the severity of outcomes, which emphasizes the importance of an automatic fall detection system. A typical fall detection system includes a sensing component and an algorithm that is able to detect falls based on sensor readings. Modern sensing components are often attached to the human body, such as accelerometers, gyroscopes, and pressure sensors, making these systems wearable devices [13]. The user's orientations are continuously monitored by these sensors. When the sensor data indicates a sudden change consistent with a fall event, the system triggers an alert to designated caregivers or emergency services.

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However, wearable devices come with certain limitations. For instance, the users must wear them consistently for a long time, and if, in some cases, the device is removed, the system becomes ineffective. But, on the positive side, the advancements of Microelectromechanical Systems (MEMS) have significantly enhanced the development of tiny electronic sensors. These advancements in technology have made sensors more portable and cost-effective, contributing to the widespread adoption of wearable fall detection systems [14]. Tiny wearable sensors can be concealed under clothing or integrated into everyday accessories [15]. The use of cameras for a fall detection system has also been explored [16], [17]. However, camera-based fall detection approaches using cameras face several challenges, including occlusion, overlapping, cluttered backgrounds, noise, low illumination, and dynamic backgrounds [18]. Due to these limitations, implementing a camera for an outdoor fall detection system remains impractical.

In this paper, we present the development of a low-cost wearable fall detection system designed for elderly individuals. Inertial sensors were mainly used, with data collected using microcontrollers capable of wireless data transmission to our Single Board Computer (SBC). The system is designed with cost-effectiveness as a primary consideration. We tested our system by implementing a Multilayer Perceptron (MLP) algorithm to ensure that our system is capable of detecting fall and non-fall activities accurately.

II. Related Works

The safety and well-being of elderly individuals depend on the designed fall detection systems, which alert the caregivers to immediate attention. There are many ways to identify fall, one of them is using wearable inertial sensors to detect body orientation, which are processed later on a microcontroller. Several studies construct a wearable fall detection system using an Inertial Measurement Unit (IMU). Optimal performance in fall detection systems can be achieved through the careful selection of IMU sensors. Many researchers used MPU9250 [19], [20], [21], [22], and others can be found using IMU MPU6050 [23], [24], [25]. These two types of IMUs are widely used due to their portability, ease of use, and low power consumption. IMU MPU9250 combines a 3-axis accelerometer and a 3-axis gyroscope similar to IMU MPU6050, but with the addition of a 3-axis magnetometer, making it reliable for a fall detection system. Both sensors have proven effective in various research schemes, with the choice depending on the specific requirements of the application, cost, and power consumption.

The choice of microcontrollers in fall detection systems also varies, depending on the system's complexity, power consumption, and connectivity features. For instance, the use of Arduino Nano is employed in [26], Arduino Uno in [27], and ESP32 in [28], [29], [30]. These microcontrollers offer diverse features with different specifications. Arduino Nano and Uno are considered suitable for minimal data processing and offline data logging due to their limited computational power and connectivity features. In recent years, ESP32 has gained significant popularity due to its integrated Bluetooth and Wi-Fi capabilities, providing strong support for IoT applications. Both features enable us to create a system that provides real-time data transmission to caregivers and remote monitoring capabilities. Furthermore, the ESP32 dual-core processing architecture with large memory capacity can handle complex algorithms. This variety of features in the microcontroller, combined with different IMU types, enables us to create a reliable and efficient wearable fall detection system, which is one of the solutions for the elderly.

One of the critical challenges in the implementation of fall-detection systems is the high energy consumption of wearable devices. Wearable fall detection systems are typically powered by low-capacity batteries or a power bank. Bayar et al. [31] designed a fall detection system using MPU6050 with the power supplied using a power bank. While the power bank provides more efficient energy sources, it is bulky, and a bigger space requirement is needed. Escriba et al. [32] used a thin battery with a capacity of 30mAh, integrated with a 3D accelerometer and a GPS module. The system is able to function without recharge for 3 days in low-power mode and for 13 hours under continuous GPS tracking. In the fall detection system, continuous monitoring without frequent recharging is required to ensure both efficiency and user acceptance of the devices.

Beyond power considerations, the placement of wearable sensors significantly impacts detection accuracy. Different body locations, such as the waist, wrist, chest, or thigh, offer different results regarding fall-related movements. Several studies can be found placing IMU sensors in different locations. Iguchi et al. [33] placed the IMU sensors on the helmet. While the detection of falls can be effectively achieved with head-mounted IMUs, the use of a helmet may be considered uncomfortable for daily use among elderly individuals. Research [34], [35] placed the IMU on the waist of the user. Waist-mounted sensors are often preferred due to the most representative fall patterns that can be captured. De Quadros et al. [36] placed the IMU sensors on the wrist. Wrist placement is more convenient for elderly users but may lead to lower accuracy due to frequent arm movements unrelated to falls. Kulurkar et al. [37] placed the sensor on the combination of the waist, wrist, and thigh. This is similar to research by Alarifi and Alwadain [38] placed on the combination of the head, chest, waist, wrist, ankle, and thigh. The combination of multiple sensor placements offers the advantage of increased data availability, making the system more accurate.

A comprehensive summary of the reviewed studies is presented in Table I, which details fall detection systems with various sensors, microcontrollers, power supply types, sensor placements, and algorithms with the detection performance. In our proposed system, we design a wearable fall detection system using three modules placed on the waist, wrist, and thigh. Each module consists of IMUs, a microcontroller, and a power supply unit. IMU MPU6050 is used considering its cost, powered using 900mAh batteries. The data is preprocessed in ESP32 microcontrollers with Wi-Fi support, capable of sending

TABLE I. OVERVIEW OF WEARABLE FALL DETECTION SYSTEM STUDIES

Ref.	Microcontroller	Sensor *	Power Supply	Placement	Algorithm Type	Algorithm Performance **
Yan and Ou [19]	-	Ac, Gy, and Mag (MPU9250)	-	Waist	Thresholding	-
Lee et al. [21]	-	Ac and Gy (MPU9250)	-	Back	1D-CNN	Acc 92.0%
					2D-CNN	Acc 90.7%
					LSTM	Acc 94.4%
					Conv-LSTM	Acc 97.6%
Koo et al. [22]	-	Ac and Gy (MPU9250)	-	Waist	ANN	Acc 99.13%
Siwadamrongpong et al. [23]	Arduino	Ac, Gy (MPU6050), and EMG	-	Hip	RF	Acc 94.72%
Nutsathaporn et al. [24]	ESP8266	Ac and Gy (MPU6050)	Battery	Hip	-	-
Saadeh et al. [26]	Arduino (Nano)	Ac and Gy (MPU6050)	Battery (9V)	Thigh	SVM and Thresholding	Sens 98.6%, Spec 99.3%
Alejandro et al. [30]	ESP32	Ac and Gy (MPU6050)	Battery	Wrist	Thresholding	-
Bayar et al. [31]	ESP32	Ac and Gy (MPU6050)	Power Bank	Waist	ANN	Acc 88.29%
Yulastri et al. [35]	Arduino (Nano)	Ac, Gy (MPU6050), and GPS	Battery	Waist	Thresholding	-
Kulurkar et al. [37]	STM32 (Nucleo-L152RE)	Ac and Gy (LSM6DS0)	-	Waist, Wrist, Thigh	LSTM	Acc 95.87%
Alarifi and Alwadain [38]	-	Ac, Gy, and Mag (Xsens)	-	Head, Chest, Waist, Wrist, Ankle, Thigh	Heuristic AlexNet CNN	Acc 99.45%

*Sensors are abbreviated as follows: Ac (Accelerometer), Gy (Gyroscope), Mag (Magnetometer). ** Algorithm performances are abbreviated as follows: Acc (Accuracy), Sens (Sensitivity), Spec (Specificity).

data wirelessly. Later, we implement the MLP algorithm to distinguish fall and non-fall activities. With the addition of notification, the caregiver is able to give immediate attention to elderly individuals.

III. METHODS

The proposed fall detection system diagram is illustrated in Fig. 1, designed using a master-slave module configuration. Three modules serving as masters are placed on the waist, wrist, and thigh of the user. An improvement from our previous work [39] is done by adding two additional master modules with the same configuration as the original master. The three master modules serve as primary data acquisition and preprocessing units, where inertial data from the IMU are collected. The data preprocessing is then performed, consisting of a filter and an angular data fusion algorithm, before the data are transmitted to the slave module. Fall and non-fall activities are later classified using MLP, after which notifications are sent to the caregivers if a fall is detected.

A. Wearable Sensor Module

The master module consists of an IMU sensor, one microcontroller unit (MCU), and a power supply circuit block. The hardware design is developed using KiCad software. The overall system design is illustrated in Fig. 2. IMU MPU6050 was used, which integrates a tri-axial accelerometer and gyroscope. The tri-axial accelerometer provides an adjustable full-scale range of ±2g, ±4g, ±8g, and ±16g, while the gyroscope offers ±250°/s, ±500°/s, ±1000°/s, and ±2000°/s. The maximum sensitivity scale for both accelerometer and gyroscope sensors was set to ±16 G and ±2000°, respectively. This portable sensor can be attached comfortably to the user without disrupting their routine daily activities. The magnitude of total acceleration and total angular velocity can be calculated using (1) and (2).

$$A_{tot}[i] = \sqrt{a_x^2[i] + a_y^2[i] + a_z^2[i]} \quad (1)$$

$$\omega_{tot}[i] = \sqrt{\omega_x^2[i] + \omega_y^2[i] + \omega_z^2[i]} \quad (2)$$

Where

a_x, a_y, and a_z are the acceleration and
ω_x, ω_y, and ω_z are the angular velocity along the three axes

Next, the tilt angle can be calculated using accelerometer data in (3) and (4).

$$\rho_{acc}[i] = \tan^{-1}\left(\frac{a_x[i]}{\sqrt{a_y^2[i] + a_z^2[i]}}\right) \quad (3)$$

$$\Phi_{acc}[i] = \tan^{-1}\left(\frac{a_y[i]}{\sqrt{a_x^2[i] + a_z^2[i]}}\right) \quad (4)$$

where

ρ_{acc} and Φ_{acc} are the pitch and roll angles estimated using an accelerometer.

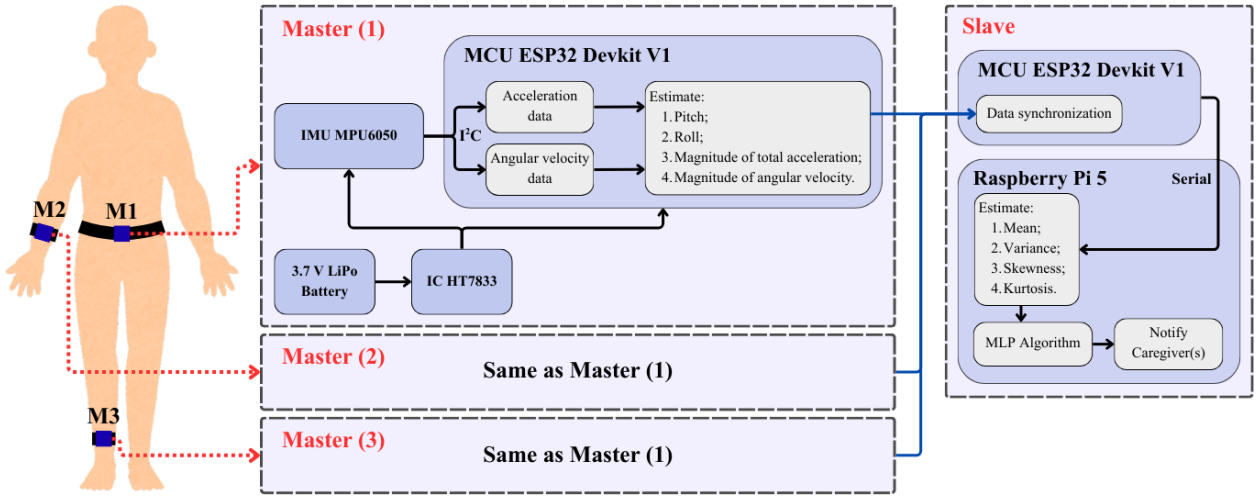


Fig. 1. Proposed fall detection system diagram

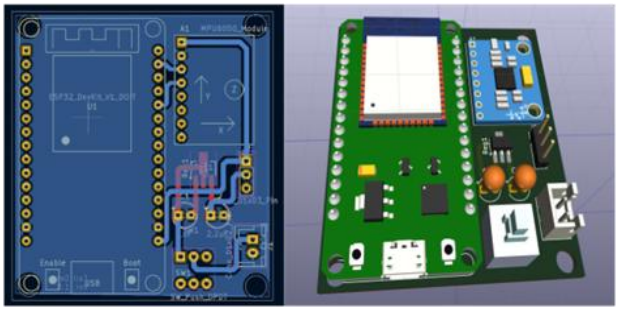


Fig. 2. Hardware design consisting of an IMU MPU6050, an ESP32 devkit V1 microcontroller, and a power supply circuit block

The tilt angle can also be calculated using gyroscope data in (5) and (6),

$$\rho_{gy}[i] = \rho_{gy}[i-1] + \omega_y[i]\Delta t \quad (5)$$

$$\Phi_{gy}[i] = \Phi_{gy}[i-1] + \omega_x[i]\Delta t \quad (6)$$

where

ρ_{gy} and Φ_{gy} are the pitch and roll angles estimated using the gyroscope.

ω_y and ω_x are the angular velocity values.

Δt is set to 10ms, obtained from a sample rate of 100 Hz.

Next, the Kalman filter is applied to estimate the tilt angle for pitch (ρ_{kalman}) and roll (Φ_{kalman}). This operation is done to overcome the bias drift that occurred in the gyroscope sensor data. Four data points, consisting of A_{tot}, ω_{tot}, ρ_{kalman}, and Φ_{kalman} values were sent via wireless data transmission from ESP32 to the slave module using the ESP-NOW protocol. ESP-NOW is chosen because of its long-range capability and low power.

For the MCU, the ESP32 Devkit V1 is chosen because of its Wi-Fi support and larger memory capacity compared to other MCUs like Arduino. Wi-Fi support allows the master module to communicate with the slave module wirelessly, reducing overall system complexity. The ESP32 features a dual-core Xtensa 32-bit LX6 microprocessor with clock speeds up to 240 MHz. The performance of data collection and preprocessing algorithms is supported by these specifications with real-time operation. Data exchange is performed, reading acceleration and angular velocity data using the I²C communication protocol at a 100 Hz sample rate. This sample, above 20 Hz, is sufficient to capture the rapid dynamics of fall events [40].

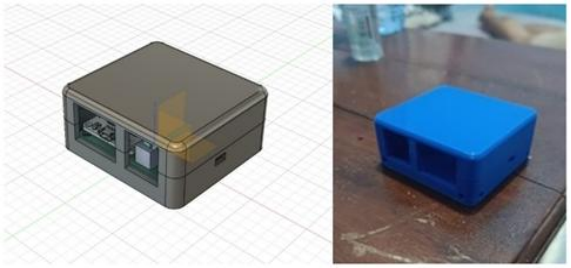


Fig. 3. Master module case design

Both the ESP32 and MPU6050 sensors operate at 3.3V,

TABLE II. FALL-RELATED FEATURES EXTRACTED FROM WEARABLE SENSORS

Features	Features Equation
Mean	$\mu = \frac{1}{N}\sum_{n=1}^{N} S_n$
Variance	$\sigma^2 = \frac{1}{N}\sum_{n=1}^{N} (S_n - \mu)^2$
Skew	$skew = \frac{1}{N\sigma^3}\sum_{n=1}^{N} (S_n - \mu)^3$
Kurtosis	$kurt = \frac{1}{N\sigma^4}\sum_{n=1}^{N} (S_n - \mu)^4$

which can be supplied using a single battery. A 3.7V 1S 900mAh Lithium Polymer (Li-Po) battery is used, connected to an HT7833 voltage regulator IC. This will convert the input voltage from the 3.7V - 4.2V battery to a stable output of 3.3V Direct Current (DC) voltage. This IC is chosen for its Low Drop Out (LDO) voltage characteristic of 360mV, meaning the minimum input voltage required is 3.66V. The voltage regulator maintains a stable 3.3V output even as the Li-Po battery voltage decreases during use, ensuring consistent overall system operation until the battery voltage drops below the minimum threshold.

To ensure both safety and user comfort for elderly users, a custom 3D-printed protective case is designed using Autodesk Inventor software. Three cases are designed for each of the three master modules, with the design illustrated in Fig. 3. PLA+ is selected as the material for its lightweight and robust characteristics. This material could withstand daily activities and fall impacts without compromising the sensitive electronic components inside the case. The case also includes mounting points for attachment of straps, which enable different sensor placement options for the user.

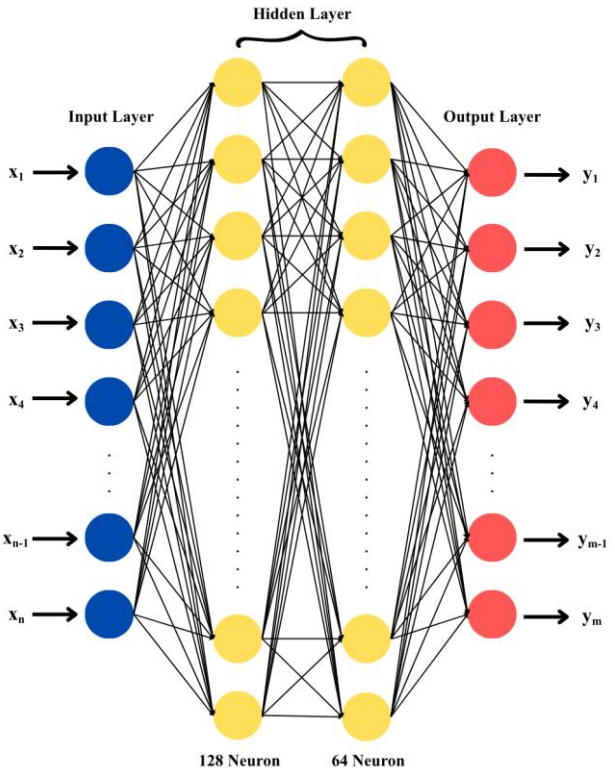


Fig. 4. MLP Network consisting of one input layer, two hidden layer, and one output layer

B. Fall Detection Algorithm

One slave module is used to synchronize the data coming from three master modules. It consists of a single ESP32 Devkit V1 with a USB cable attached to a Raspberry Pi 5, which serves as a power supplier and enables serial communication, sending data from the ESP32 to the Raspberry Pi 5. Next, the feature extraction process was performed. The raw data is divided into windows of 4 seconds duration each. A total of 800 data points is sampled from a 3-axis accelerometer and gyroscope in each trial. 12 features were extracted from each master module, that is, from MPU6050 accelerometer and gyroscope data. Statistical measures were calculated from the pitch and roll angles, which include mean, variance, skewness, and kurtosis for each, resulting in 8 features with equations shown in Table II [38]. Additionally, 4 features are derived from (1) and (2), including the minimum total acceleration ($\min(A_{tot})$), maximum total acceleration ($\max(A_{tot})$), minimum total angular velocity ($\min(\omega_{tot})$), and maximum total angular velocity ($\max(\omega_{tot})$). The fall-related patterns will be captured, providing information about body orientation changes and movement intensity while the fall occurred.

The Multilayer Perceptron (MLP) algorithm is implemented, characterized by interconnected layers of neurons with weights representing the strength of connections between layers. An input layer, two hidden layers, and an output layer are implemented. The input layer receives features extracted from three master modules, while the output layer classifies the result regarding fall detection. The proposed system MLP architecture is illustrated in Fig. 4. The network structure comprises an input layer with n = 36 neurons (12 features from each of the three master modules: waist, wrist, and thigh), a first hidden layer with 128 neurons, and a second hidden layer with 64 neurons. The Rectified Linear Unit (ReLU) activation function is used in each hidden layer to enable complex patterns in the sensor data to be learned by the network. The output layer is composed of m = 8 neurons (8 output classes) with a softmax activation function. If fall is detected from 8 different classes, a notification message will be sent to the caregiver.

IV. Results and Discussion

A. Experimental Setup

We tested our proposed system using data collected from 18 subjects, consisting of 13 males and 5 females. This study protocol and ethics were approved by the Committee of Ethical Approval, Faculty of Nursing Universitas Airlangga (No. 3354-KEPK). Due to the ethical considerations regarding the safety of elderly individuals, healthy volunteers were recruited for this study instead of an actual user. The mean and standard deviation of the subjects' age were 20.7 ± 0.41 years old. To address this limitation, the subjects were instructed to mimic elderly activity and fall patterns under controlled conditions. In each activity, the subjects are also required to wear three sensor modules, a protective helmet, an elbow decker, and a knee decker. Each subject is instructed to do 8 different activities, including: (1) stand still, (2) sit, (3) sit-to-stand, (4) walk, (5) sleep position, (6) forward fall, (7) sideways fall, (8) backward fall. Each activity is done for 20 seconds duration, with each of the events described as follows:

1) **Stand Still**
   The subject is conditioned to maintain an upright posture and remain stationary for the duration of the recording.
2) **Sit**
   The subject is positioned on a chair with back support and needs to maintain its seated position for the duration of the recording.
3) **Sit-to-stand**
   The subject began in a seated position on a standard chair and performed a transition to a standing position over approximately 3-5 seconds. After that, the subject needs to maintain its standing position until the end of the recording.
4) **Walk**
   The subject is conditioned to stand straight at a starting point and walk at a normal pace along a predetermined straight path for 10 meters. After that, the subject maintains a standing position until the end of the recording.
5) **Sleep Position**
   The subject lies down on a mattress and remains motionless until the end of the recording.
6) **Forward Fall**
   The subject began with a standing position in front of the mattress and performed a simulated forward fall by allowing their body to fall and impact safely. The subject lies in a prone position, then maintains their position until the end of the recording.
7) **Sideways Fall**
   The subject began with a standing position beside a mattress and performed a lateral fall to the left side.

TABLE III. EXPERIMENTAL TEST QUESTIONNAIRE RESULTS

Question	Agree	Disagree
Q1	18	0
Q2	16	2
Q3	15	3
Q4	15	3
Q5	13	5

The subject then maintains its position until the end of the recording.

8) **Backward Fall**
The subject began in a standing position with a mattress behind and performed a backward fall, landing in a supine position. The subject then maintains its position until the end of the recording.

B. Experimental Test Results

A questionnaire was given to all subjects to gather feedback regarding their experience with the proposed system after the trials. The questionnaire aimed to assess user comfort and safety concerns. Five questions were asked, including:

1) **Q1:** The subjects are in healthy condition and agreed to attend the experiment.
2) **Q2:** The subject experienced fear and anxiety when about to experiment.
3) **Q3:** The subject reported discomfort after wearing the device.
4) **Q4:** The subject experienced pain after the experiment.
5) **Q5:** The subject reported fatigue after completing the experiment.

The questionnaire result is shown in Table III. Two subjects expressed fear and anxiety when about to perform the intentional fall movements. This indicates the challenge of conducting fall detection experiments with subjects who previously may have had negative experiences with falls. The fear response also suggests that fear of falling can happen to anyone, especially elderly individuals, since about 30–50% of them experience this regardless of whether they previously experienced a fall or not [41]. Three subjects reported discomfort while wearing the fall detection system. Three subjects also experienced pain after the experiments. The physical dimensions of the master modules, the attachment using straps, and the unfamiliarity of wearing multiple sensors simultaneously are the primary causes of these. This result also indicates that the proposed system requires further refinement in the form of reducing module size and using alternative methods to attach the sensor to the body to improve user acceptance and safety.

C. Cost Analysis

A cost analysis of the proposed fall detection system is presented. The analysis focuses on the hardware components required for each master module, as shown in Table IV. The proposed fall detection system cost, consisting of one master module, has an estimated total hardware cost of $21.8 USD. Vargas et al. [42] construct a fall detection system with SBC that costs $150. Piñeiro et al. [43] use LIDAR sensor, which is more expensive in total. The overall cost for three master modules in our proposed system is $65.4, which is significantly cheaper. The proposed system can also operate with only one module and requires no monthly subscription fees. This offers a cost advantage over commercial fall detection devices, which typically charge $36.95 to $60 per month for subscription fees.

D. MLP Performances

The confusion matrix is shown in Fig. 5. K-Fold cross-validation is used in this experiment with K=5. Accuracy, precision, recall, and F-score were used as the performance metrics in this study. The accuracy, precision, recall, and F-score computed using (5), (6), (7), and (8),

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

TABLE IV. COST BREAKDOWN OF PROPOSED WEARABLE FALL DETECTION SYSTEM

Component	Model	Description	Quantity	Unit Cost (USD)*	Total Cost (USD)
IMU	MPU6050	Sensor to estimate parameters related to fall and non-fall activities	1	$2.1	$2.1
Microcontroller	ESP32 Devkit V1	Main microcontroller with Wi-Fi capabilities	1	$4.8	$4.8
Battery + Connector	3.7V 1S Li-Po	Li-Po battery, wiring, and connector	1	$6	$6
Voltage Regulator	HT7833	LDO voltage regulator to get stable 3.3 V	1	$0.8	$0.8
Custom PCB	Fabricated double layer-PCB	Custom fabricated double layer-PCB	1	$3.9	$3.9
3D-printed Case	PLA+ material	Custom printed 3D protective case	1	$4.2	$4.2
Total Estimated Cost	-	Total cost for three master modules	-	-	$21.8

*Prices retrieved on 15 October 2025 from official and online stores.

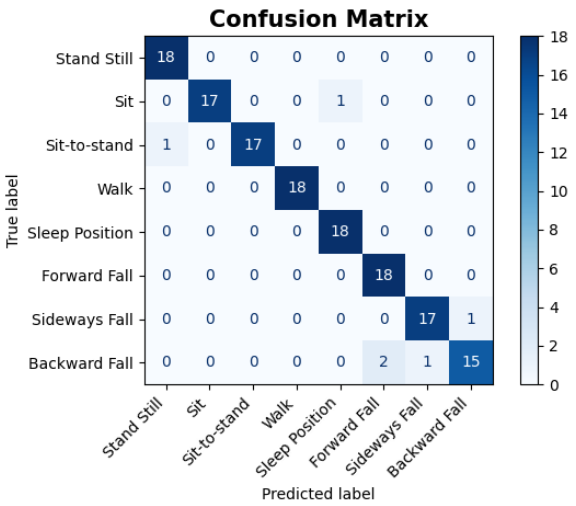


Fig. 5. Fall detection performances on 8 different classes



Fig. 6. Proposed fall detection system experimented on subject with (a) backward fall, (b) sideways fall

$$F-1\ score = \frac{2TP}{2TP + FP + FN} \quad (8)$$

where
TP is True Positive,
TN is True Negative,
FP is False Positive, and
FN is False Negative.

The proposed fall detection system showed a good performance across all activities, including non-fall (stand still, sit-to-stand, walk, and sleep position) and fall events (forward fall, sideways fall, and backward fall). Each class performance is shown in Table V. The system demonstrated 100% precision, recall, and F1-score for walking activity. For the sit-to-stand activities, both resulted in 94% recall and 97% F1-score. These activities have distinct motion patterns and are easily distinguishable by the MLP algorithm. One sit activity is misclassified as a sleep position, and one stand-to-sit activity is misclassified as a standing activity. These are likely due to similar acceleration patterns and body orientation in the three sensors.

Among fall activities, forward fall achieved 90% precision, 100% recall, and 95% F1-score. For the sideways fall, the algorithm achieved 94% precision, 94% recall, and 94% F1-score. One sideways fall event was misclassified as a backward fall, which is likely due to the direction classification being incorrect. For the backward fall, it demonstrated 94% precision, 83% recall, and 88% F1-score, with two samples misclassified as forward fall and one sample misclassified as sideways fall. These misclassifications for forward fall and sideways fall are mainly due to the MLP algorithm's struggles to distinguish fall direction and body rotation when the falls occur. Post-fall body position during the experiment is shown in Fig. 6.

TABLE V. EACH CLASS PERFORMANCE (%)

Class	Precision	Recall	F-1 score
Stand	95%	100%	97%
Sit	100%	94%	97%
STS	100%	94%	97%
Walk	100%	100%	100%
Sleep	95%	100%	97%
Forward Fall	90%	100%	95%
Sideways Fall	94%	94%	94%
Backward Fall	94%	83%	88%

TABLE VI. ACCURACY ON DIFFERENT SENSOR PLACEMENT

Sensor Placement	Accuracy (%)
Waist	90 ± 2.1%
Wrist	85.9 ± 3.1%
Thigh	85.4 ± 2.4%
Waist + Wrist	93 ± 3.4%
Waist + Wrist + Thigh	**95.3 ± 1.4%**

Different sensor placements are also analyzed to determine which performs better. Results are shown in Table VI. The use of all three sensor modules received the best accuracy of 95.3 ± 1.4%, which is a significant improvement over using only one module for each sensor or two modules. These are likely due to a lack of movement or position information, which the system is unable to distinguish between each activity perfectly.

Overall, the proposed fall detection system achieved an accuracy of 95.3 ± 1.4% across eight classes. The average inference time is 31 ms on Raspberry Pi 5. This performance is better than most of the machine learning-based fall detection systems proposed by the reviewed studies. The system also utilizes a 3.7V battery for each sensor module, which enables the device to run continuously for prolonged periods without requiring frequent recharging.

Bayar et al. [31] used a dataset containing accelerometer signal recordings of five normal activities and four fall events, for which they reported the accuracy of 88.29%. Siwadamrongpong et al. [23] reported an average accuracy of 94.72% for only 3-class classification. Lee et al. [21] applied various deep learning models, which reported the best accuracy of 97.6% using Conv-CNN, but our proposed system performs better than 1D-CNN, 2D-CNN, and LSTM. While the accuracy is still lower compared to state-of-the-art deep learning approaches, the proposed method offers less computational cost, making it more suitable for real-time applications in the context of a fall detection system.

V. CONCLUSION

In this paper, a low-cost wearable fall detection system is designed for elderly individuals. We conduct a cost analysis, which shows that the overall cost for three master modules in our proposed system is $65.4. This is cheaper

compared to most fall detection system research and commercial systems, with $36.95 to $60 per month. For the detection performance, the system showed a good result using the MLP algorithm using three sensor modules with the overall accuracy of 95.3 ± 1.4% across all activities, including non-fall (stand still, sit-to-stand, walk, and sleep position) and fall events (forward fall, sideways fall, and backward fall). While misclassification happens between classes, our system is still able to distinguish between non-fall vs. fall events with 100% accuracy. It is important to note that the result was obtained under a controlled environment. In real-world settings, the system may encounter more ambiguous scenarios, such as stumbling, which may result in a false positive. Future work should validate this condition to assess the system's performance under real-world conditions.

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