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# Fall Detection Algorithm Using a Smart Wearable System for Remote Health Monitoring

**Abdelrahman Fawaz[*], Moaz Elsayed[*], Ahmed Sharshar[↑], Mohammed S. Sayed[*], Ahmed H. Abd El-Malek[*], Mohammed Abo-Zahhad[*]**
[*]Department of Electronics and Communications Engineering, Egypt-Japan University of Science and Technology
New Borg El-Arab City, Alexandria 21934, Egypt
[↑] Department of Computer Vision, MBZUAI, Abu Dhabi, UAE;(ahmed.sharshar@mbzuai.ac.ae)
E-mail: {abdelrhman.fawaz, moaaz.elsayed, mohammed.sayed, ahmed.abdelmalek, mohammed.zahhad}@ejust.edu.eg

***Abstract*** **-** Nowadays more people prefer to live independently, especially the elderly, leaving them prone to incidents that they might not be able to report. Falls, for instance, are responsible for over 3 million emergency hospitalizations for head injuries and hip fractures each year in the U.S. In addition, other cases often go unreported, leading to further complications including chronic disabilities and even fatality. Therefore, the detection of such incidents has become of urgent necessity. The purpose of this paper is to develop and propose a machine learning support vector classification (SVC) algorithm for fall detection using accelerometer, gyroscope, and magnetometer sensors embedded in a smart wearable system for remote health monitoring. The device is placed on the subject's wrist to collect data on various motion activities in real-time, such as walking, running, jogging, waving, and stair-climbing in addition to other static postures like standing, lying, and sitting. The constructed dataset comprises 30 subjects with over 1200 data frames. The model achieved an overall accuracy of 98.3% and a specificity of 98.2% in separating falls from other daily-life activities.

***Keywords*****:** Support vector machines, Internet of Things, wearable electronics, remote health monitoring, activity tracking

## 1. Introduction

The Internet of Things (IoT) has reshaped our lives by being part of a wide range of fields. It is considered the next technological revolution that is used to make internal connections between objects. In addition, it has been used in many applications such as smart cities, smart homes, waste management, industrial automation, and traffic congestion monitoring [1, 2]. In addition, the attention of medical research is now being directed towards the integration of IoT systems for health monitoring and diagnosis purposes, given its wide horizon of capabilities. That being said, among the most serious threats to overall public health and safety nowadays is falling, especially for the elderly.

According to the United Nations (UN), by 2050, the elderly population in 64 countries will have increased by more than 30%. According to the American Disease Control and Prevention Center reports, approximately 28% of people aged 65 and 32% of people aged 70 fall each year [3]. A fall is defined by the WHO as "an event which results in a person coming to rest inadvertently on the ground or floor or other lower level, either resulting in fatal or nonfatal consequences." For every death due to a fall among children in the People's Republic of China, there are four cases of permanent disability, thirteen cases requiring hospitalization for more than ten days, twenty-four cases requiring hospitalization for one to nine days, and 690 cases seeking medical attention or missing work/school.[4]

The causes of falls could be categorized into two main types: intrinsic and extrinsic. Intrinsic reasons relate to a person's characteristics, such as overall medical condition, age, nervous illnesses, mental impairment, and muscle strength. The extrinsic ones are the non-human factors, such as the surrounding environment, slick floors, dim lighting, sagging carpets, and unstable furniture. Extrinsic factors can be avoided with precautions, but intrinsic factors are unavoidable. Age, mortality, morbidity, disability, and frailty all contribute to an increase in the rate of falls. At healthcare facilities, it is extremely expensive to have 24/7 monitoring of one's health as it usually requires the presence of a personal nurse. Therefore, it is not practical in cases of the elderly and people with long-term medical impairments. Due to the shortage of nursing homes, more elderly people are required to stay at home and hence comes the need for easy-to-use health monitoring systems that require neither heavy equipment nor special technical experience. Implementation of such systems will directly contribute to reducing post-fall complications that are often the main result of serious medical cases.

The rest of the paper is organized as follows: Section 2 provides a review of previous advancements in relevant systems. Section 3 gives a piece of brief background information about fall detection. Section 4 presents the proposed system. Section 5 explains the procedures for data collection and pre-processing. Section 6 discusses the proposed system prototyping results. Section 7 concludes the paper.

## 2. Literature Review

During the past few years, several health monitoring systems have attempted to work on detecting and reporting different falls in real time. Some of these attempts resulted in relatively good accuracy. However, most of the proposed solutions are either limited to specific types of falls, too complex, or expensive. Different approaches have been implemented in order to recognize, interpret, and monitor various daily life activities and report falls. Among these approaches are wearable sensors and embedded micro-electro-mechanical systems (MEMS), that provide an inexpensive, small, and fairly accurate indication of different health signs such as movement, heart, and respiratory conditions. In order to detect a fall, movement tracking sensors are used to evaluate different patterns of the body's postures and movement during different activities. Linked to microcontrollers and/or mobile phones, movement trackers provide information about angular acceleration, body orientation, and the change in the magnetic field caused by movement in different directions. These data could then be processed using machine learning algorithms to give an accurate image of different types of activities. Moreover, the most important feature of wearable trackers is that, unlike other methods, neither environmental nor privacy concerns have significant effects on their performance.

In [5], the authors developed a smartphone-based online system for fall detection with alert notifications. The proposed system utilizes the accelerometer and gyroscope readings of sensors embedded in a smartphone to monitor participants' motion patterns. Using a regression model running on a linked cloud platform, the system succeeded in detecting 27 out of the 37 falls that occurred with sensitivity equal to 73.0% and resulted in one false alarm every 46 days for a span of 2070 days and 23 participating individuals. Another system developed in [6] uses a dedicated wearable motion-tracking device with accelerometer and gyroscope sensors to generate data about one's movement patterns. Using the publicly available UMA activity dataset from Universidad de Málaga collected from 19 subjects, data from wearable trackers placed in 5 different locations on the body was obtained. Following that, a recurrent neural network (RNN) based model is then developed to analyze a series of time intervals and detect falls from other daily life activities. The system produces results that are 92.31% accurate, which gives a relatively precise indication of fall events.

Another approach for detecting falls is ambient sensors. Instead of limiting their functionality to only monitoring the surrounding environment, some applications utilize external sensors already installed to track movement. The obvious advantage of ambient sensors is that they do not require the person to wear a dedicated device, providing an unobstructive solution with no possibility of a user forgetting to wear it. An example of this is the use of piezoelectric vibration detectors on the floor to detect falls based on the fact that everyday activities induce detectable vibrations on the floor in patterns that are distinct from those of falls. The impacts of falls on the floor could be differentiated from other types of vibrations. The study in [7] proposed an algorithm that uses floor vibrations to detect falls through the K-means algorithm and K nearest neighbor algorithm for classification with an accuracy of 91% in detecting human falls from other different postures. Other applications also use acoustic sensors and pressure sensors to detect vibrations. Although this method provides fair accuracy at a low cost, the type of floor presents highly affects the detection range of vibration sensors, thus resulting in unpleasant variations in results. Another ungovernable drawback of ambient vibration classification is the tremendous amount of noise produced due to background interference which lowers the accuracy, resulting in a lot of false-positive predictions.

The third approach to detecting falls utilizes computer vision and digital image processing techniques to recognize fall-like activities from surveillance footage. Specific movement patterns from the imagery of different types of activities are recorded and used to detect future fall activities. What makes camera-based techniques advantageous is that they do not interfere with the user's daily activities, meaning that a person does not need to worry about any special equipment. An example of this approach is human fall detection through the processing of RGB-D images of a Kinect sensor. The sensor includes an RGB camera, an IR projector, and an IR camera that produces a depth map in addition to normal RGB images. Therefore, the performance scores achieved were higher than traditional detection using only RGB image processing techniques. In addition, the distance between a person's centroid and the floor was measured from RGB images and utilized to obtain better detection accuracy. Table 1 illustrates the distinct features of fall detection approaches. It can be concluded that there is no absolute method that gives the best-desired performance, but rather a trade-off between multiple characteristics depending on each particular application.

Table 1: Characteristics of different fall detection approaches

| | **Wearable** | **Ambient** | **Camera** |
|---|---|---|---|
| **Price** | Cheap | Medium | Expensive |
| **Continuous monitoring** | Yes | No | No |
| **Monitor multiple subjects** | No | No | Yes |
| **Easy installation** | Yes | Yes | No |
| **Battery concerns** | Yes | No | No |
| **Obtrusive** | Yes | No | No |
| **Privacy issues** | No | No | Yes |
| **Environmental interference** | No | Yes | Yes |

## 3. Theory and Background Information

A very convenient feature for basic health monitoring is tracking one's movement, that is to detect everyday activities like walking, running, or exercise. The idea is to construct an activity recognition system based on the readings of various sensors that directly correspond to human activities. The output of the system signifies the correlation between different sensor outputs and how they form distinctive patterns that could then be determined mathematically, giving a precise indication of the current body movement. An extension to activity recognition is the ability of the system to detect and act in case of falling. Because falling can be of severe consequences, especially for the elderly, recent research has shed light on possible solutions to this serious issue. Thus, various activity-tracking devices are starting to develop shock detection features. However, none of the existing devices has offered a reliable solution.

An essential aim of our project is to develop an outstanding falling and shock detection algorithm followed by an emergency call in case of any heartbeat disturbances and/or no user response. This shall be of significant contribution to increasing the possibility of saving the lives of older people from various risks, such as concussion and loss of consciousness. In order to determine the movement patterns according to which a body moves while performing particular activities, we studied the operation of inertial measurement units (IMU). An IMU is an electronic device that uses a combination of accelerometers, gyroscopes, and magnetometers to monitor and detect a body's particular force, angular rate, and direction.

An accelerometer utilizes an electromechanical sensor to measure static or dynamic acceleration. The constant force acting on a body is known as static acceleration. To a significant extent, these pressures are predictable and uniform. For example, the gravitational acceleration is constant at 9.8m/s, and the gravitational force is about the same everywhere on the planet. A gyroscope has a spinning disc that is mounted on the base such that it can move freely in more than one direction so that the orientation is maintained irrespective of the movement in the base. Its operating mechanism is based on gravity and can be described as the product of angular momentum on a disc to create gyroscopic precession in the spinning wheel. A magnetometer is a device that is used to measure the magnetic field, specifically its strength and direction. Adding a 3-axis magnetometer along with a 3-axis gyroscope and a 3-axis accelerometer could significantly increase the detection algorithm's precision due to the measurable change in the magnetic field as the body moves in different directions.

## 4. The Proposed System

To deliver this fall detection application, among multiple other features, an IoT-based smart wearable system was designed for remote health monitoring purposes [8]. While the device contains multiple sensors, only relevant ones were selected for performing fall recognition.

### 4.1. Sensor Selection

Searching for convenient off-the-shelf motion sensors, the MPU9250 9-axis inertial measurement unit (IMU) was chosen due to its relatively low cost, small dimensions, and outstanding accuracy scores. In addition, it has other capabilities such as supporting I2C communication protocol which enables us to connect it directly to the Raspberry Pi Zero wireless controller. It also has its own analog-to-digital converter ADC mounted on-chip, reducing overall processing time. The selected IMU consists of 4 different sensors, namely a 3-axis accelerometer, 3-axis gyroscope, 3-axis magnetometer, and a temperature sensor. For fall detection applications, temperature measurement has been found not important in determining whether a time interval signifies a fall event or not.

### 4.2. Data Processing

While it may be preferable to have all of the readings sent straight to be processed and analyzed by medical professionals on a cloud, the expense of doing so is high in terms of power usage as a very high data transfer rate would be needed. Therefore, an onboard processing and control Raspberry Pi Zero wireless module is used to perform pre-processing and sensor interfacing. The module operates on a Linux-based operating system with built-in wireless and Bluetooth Low Energy modules, making it a perfect fit for our proposed applications.

### 4.3. Printed Circuit Board (PCB) Construction

A customized PCB was designed for our health monitoring system, which contains the MPU9250 module and other sensors. Figure 1 illustrates the two-layer PCB constructed. The manufactured device is shown in figure 2.

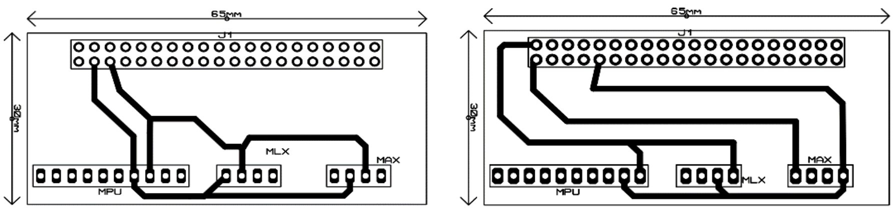


Fig. 1: Two-layer PCB layout.

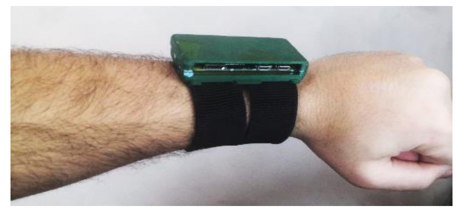

Fig. 2: Manufactured health monitoring device.

## 5. Data Collection and Pre-processing

A very crucial stage of building our system was the collection of data. Here, we try to monitor 3 motion parameters: Angular acceleration, 3-dimensional body orientation, and change in the magnetic field due to body movement.

The accelerometer sensor measures the angular acceleration of the body as the hand moves in different directions. It is then displayed in terms of the gravitational constant (g) or meters per second squared (m/s2). The gyroscope senses change in orientation and visualize it numerically in terms of angular velocity (degrees per second). The third sensor, the magnetometer, measures the strength of the magnetic field or magnetic dipole in 3-dimensional space as motion occurs. It then outputs this change in millitesla (mT).

### 5.1. Activities Collected

In order to sufficiently simulate real-life situations and provide the machine learning model with an adequate amount of data that represent various daily life activities, motion patterns of different activities were collected. Table 2 gives a comprehensive view of the activities that we focus on.

Table 2: Classification of activities

| Falls | Static | Other activities |
|---|---|---|
| Forward | Lying | Upstairs |
| Backward | Standing | Downstairs |
| Lateral: Right & Left | Sitting | Walking |
| Vertical | | Jogging |

### 5.2. Data Collection Program

After defining the parameters to be measured, we go on with writing the data collection program. A reliable I2C communication protocol was used to connect the master Pi controller with the sensors. Moreover, the program was written in Python to interface with the MPU9250 module, sense, and extract readings from dedicated registers. Readings are then stored in CSV format, preparing them to undergo the pre-processing stage. A timestamp is given to each row of data to indicate the specific instant of collection. Table 3 shows the format in which data is stored. The data were originally collected at a rate of 100Hz, meaning that each second consists of 100 rows of data.

Table 3: Format of the motion data array

| Timestamp | Accel | | | Gyro | | | Mag | | |
|---|---|---|---|---|---|---|---|---|---|
| DD/MM/YYYY | X | Y | Z | X | Y | Z | X | Y | Z |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |

In addition, we utilized the publicly available everyday activity dataset in [9] to broaden the scope of the recognized activities. We made sure that the selected dataset was constructed using the exact same sensors as ours, with no significant changes in the surrounding environmental conditions (i.e. Temperature, air pressure, etc.) beforehand.

### 5.3. Pre-processing

Before we move on with both the processing and model design stage, a series of pre-processing procedures are to be made to prepare the raw data for processing. Therefore, three main steps were taken.

1. *Equalize sampling rates:*

In order to process data from multiple sources, we had to equalize the different sampling rates. Hence, we performed a down-sampling of the 100Hz data collected from our device to 50Hz to match the data from the external activity dataset. This interpolation was done using MATLAB by averaging every 2 consecutive readings and combining them into one.

2. *Resize all dynamic files to the same length:*

As the proposed model requires the data fed to be of the same length, we had to resize all files to the same length. According to previous research, a fall takes usually between 0.45 to 0.85 seconds to occur, which comprises the time during which the posture and shape of the person changes [10]. Thus, we take equal time intervals of 1 second, or 50 rows of data, each. For data files consisting of more than 50 readings, we take a frame of 50 readings that contain the highest possible amount of signal power as shown in Figure 3. On the other hand, for ones with originally less than 50 readings, missing readings are compensated by padding the signal by mirroring the last few rows until the overall file size reaches 50 as shown in Figure 4.

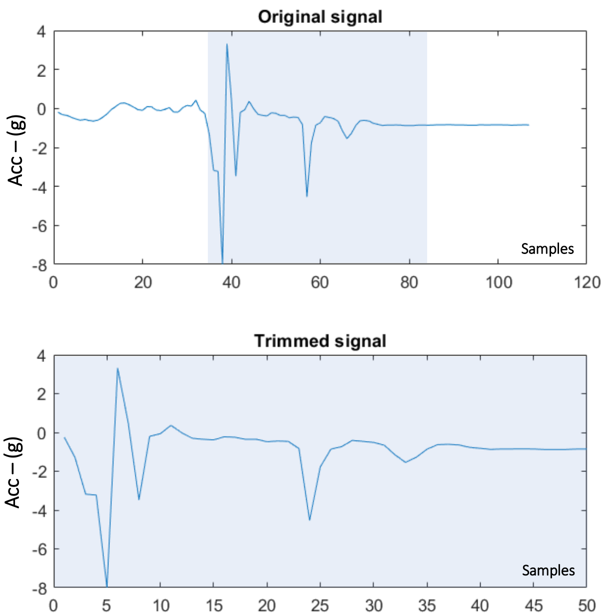

Fig. 3: Trimming accelerometer signal to the 50-readings frame with most signal power.

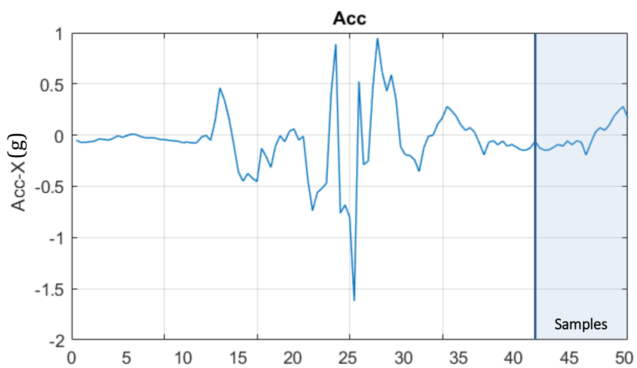

Fig. 4: Signal padding through mirroring.

3. *Trim static files to equal intervals:*

For each subject, a long duration of each static posture is taken. It is then trimmed to multiple 1-second (50 readings per frame) parts. Static postures include standing, sitting, and lying positions.

### 5.4. SVM Classifier

The next step was to build the actual classification algorithm that distinguishes between falls and other daily activities. For that purpose, the support vector machine modeling method was used. A support Vector Machine is a discriminative classifier that is formally designed by a separative hyperplane. It represents each instance as a point in space, mapping each point to a particular class by separating between various classes with a distance that is as large as possible. Furthermore, an SVM may do non-linear classification. SVM is particularly effective in the case of higher-dimensional spaces or where the number of samples is low relative to the number of dimensions [11]. A support vector machine aims to segregate the data as efficiently as possible. A specific margin is determined by calculating the distance between the nearest spots once segregation is completed. The method entails choosing a hyperplane with the greatest achievable margin between the support vectors in the data sets.

## 6. Results and Discussion

After constructing the model, we implemented it considering two different scenarios. The first one differentiates between all various activities including daily activities, static postures, and falls. The second one serves the generic aim of recognizing whether a fall event occurs in a specific time interval or not, that is to return a binary result of 'Fall' or 'No fall'. Here we consider all types of falls as 'Fall' while classifying all other activities as 'No fall'. We anticipate significantly higher overall accuracy scores in this model as it reduces the probability of misinterpreting a daily life activity for another. In this section, we present the outcomes and analyze the experimental results of the two scenarios of the fall detection algorithm based on the SVM classification approach. For each model, we measure multiple evaluation metrics such as:

- **Accuracy:** Indicates how efficiently a classifier is at predicting true labels correctly.
- **Precision:** Measures how many of the correctly predicted cases actually turned out to be positive.
- **Recall/Sensitivity:** Explains how many of the positive cases were successfully predicted as positive.
- **F1 Score:** Harmonic mean of precision and recall.

The methodology of calculating the mentioned metrics is explained in equations (1) through (4).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1) \qquad Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3) \qquad F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

$$TP: True\ Positive, \quad TN: True\ Negative$$
$$FP: False\ Positive, \quad FN: False\ Negative$$

### 6.1. First Scenario

Here, we feed the model with all collected data, labeling each different activity with its true label. In other words, the model could be called an activity recognition system that includes fall events as a separate activity. The next step is running the model 10 consecutive times and calculating the average scores. After running the model, we evaluate the results through statistical analysis. The confusion matrix shown in figure 5 represents the performance scores of our SVC. It can then be used to obtain the evaluation metrics, which can be tabulated in the classification report in table 4.

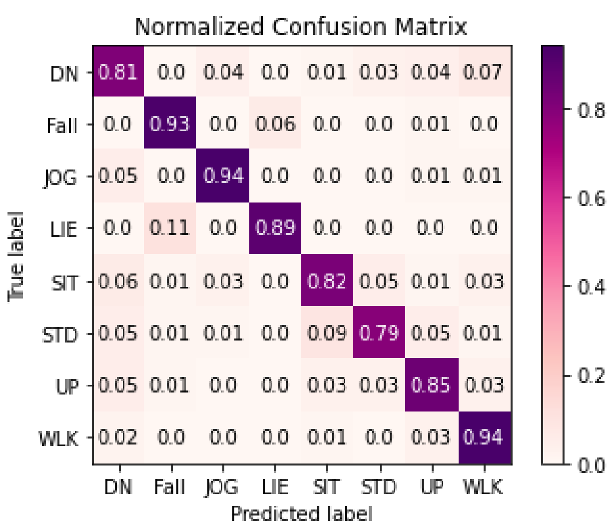


Fig. 5: Normalized confusion matrix of the first scenario SVM classifier.

Table 4: SVC classification report

| | Precision | Recall | F1 Score |
|---|---|---|---|
| **Fall** | 0.90 | 1.00 | 0.95 |
| **Downstairs** | 0.73 | 0.79 | 0.76 |
| **Upstairs** | 0.88 | 0.78 | 0.82 |
| **Walking** | 0.79 | 0.93 | 0.85 |
| **Jogging** | 0.88 | 0.91 | 0.89 |
| **Sitting** | 0.81 | 0.78 | 0.79 |
| **Standing** | 0.78 | 0.64 | 0.71 |
| **Lying** | 1.00 | 0.91 | 0.95 |

In addition, a comparison has been made with other previously mentioned systems in Table 5. The four systems are:

1. Our SVC model.
2. Random Forrest (RF) model using the same data.
3. Fall Detection and Activity Recognition Using Human Skeleton Features [12].
4. Using Floor Vibration to Detect Human Falls [7].

Table 5: Performance metrics of different systems

| Metric | Percentage (%) – 1st Scenario | | | |
|---|---|---|---|---|
| | System 1 | System 2 | System 3 | System 4 |
| **Accuracy** | 87.2 | 86.4 | 94.9 | 85.3 |
| **Precision** | 87.7 | 86.6 | 93.6 | 91.5 |
| **Recall** | 87.2 | 86.3 | 91.3 | 63.7 |
| **F1 Score** | 87.4 | 86.4 | 92.3 | 75.11 |

Although the third system might seem to produce better performance, this is only because the activities on which the focus was are all static activities (i.e. standing, sitting, lying, bending) that are more straightforward to classify. On the other hand, with applications similar to ours in terms of activities recognized, such as the second and fourth systems, our model produces significantly higher results. The reason for the low recall score in the fourth system is the increase of false negative predictions, meaning that the system frequently fails to correctly detect falls. This is considered of fatal consequence in this particular application because a fall that is not recognized can translate to an accident not reported or a person not saved.

### 6.2. Second Scenario

The system efficiency could be extended as we transform it into a binary classification model, meaning that the output of the model tells whether this event represents a fall or not without telling what the activity is in case of no fall. The confusion matrix in figure 6 illustrates the new performance scores, from which we can observe the improvement in classification efficiency. The improvement is also clearly evident if we examine table 6. A comparison is done between our system and others as follows:

1. Our binary SVC model.
2. Binary RF model using same data.
3. Fall detection algorithm based on accelerometer and gyroscope sensor data using Recurrent Neural Networks [6].
4. Smartphone-based system for fall detection [5].

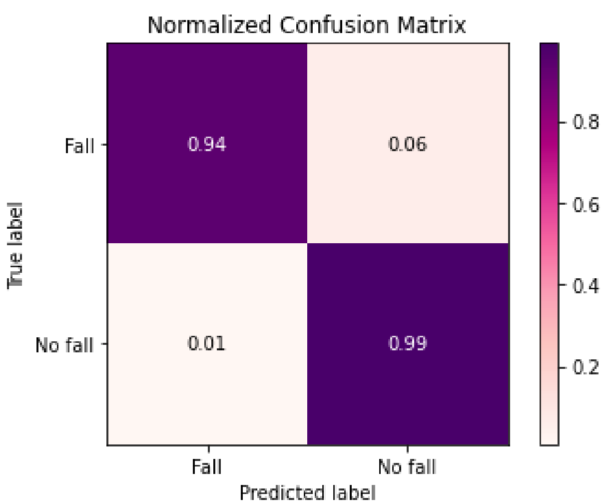


Fig. 6: Normalized confusion matrix of the second scenario (binary) SVM classifier.

Table 6: Performance metrics of different binary classification systems

| Metric | Percentage (%) – 2nd Scenario | | | |
|---|---|---|---|---|
| | System 1 | System 2 | System 3 | System 4 |
| **Accuracy** | 98.3 | 96.8 | 91.4 | 99 |
| **Precision** | 98.3 | 97.0 | 91.6 | 73.5 |
| **Recall** | 98.2 | 96.3 | 91.6 | 73 |
| **F1 Score** | 98.25 | 96.6 | 92 | 49.5 |

As could be deduced from Table 6, the efficiency of our system surpasses other alternatives in terms of performance metrics.

## 7. Conclusions and Future Directions

In conclusion, our study addresses the critical need for a reliable solution to detect falls, particularly among the elderly population. We have proposed an algorithm that leverages an IoT-based smart wearable wristband for remote monitoring, enabling the detection of fall events from everyday activities. Our SVM algorithm has demonstrated high accuracy, precision, recall, and f1 scores, as evidenced by the performance metrics. What sets our proposed system apart is its utilization of simple off-the-shelf sensors that are both cost-efficient and reliable. Despite the existence of previous trials achieving good efficiency scores, our system outperforms them with an impressive overall efficiency of 98% in detecting fall events within a specific time interval. Furthermore, its user-friendly implementation does not require specialized technical knowledge or additional hardware beyond a simple wristband, making it suitable for commercial applications.

Looking ahead, there are several avenues for future research and development. One direction involves expanding the capabilities of our model by incorporating additional everyday activities, thereby reducing the occurrence of false-positive predictions. Moreover, we plan to enhance the robustness of our algorithm by increasing the number of subjects included in the initial training process. These efforts will further refine the accuracy and reliability of our system, advancing its effectiveness in real-world fall detection scenarios. By continuously improving and refining our algorithm, we aim to contribute to the overall well-being and safety of individuals at risk of falls.

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