An IoT-Based Bed Fall Prediction System Using Force Sensitive Resistor

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***Abstract*—Patients with impaired mobility and neurological disorders such as Alzheimer's disease, Parkinson's disease, dementia etc. are vulnerable to bed falls, which can be damaging to their physical and psychological well-being. Existing systems are mostly fall detection based on wearable devices, which can be uncomfortable to wear or ambient devices such as cameras that invade privacy. A bed falls prediction system using force sensitive resistors (FSR) has been proposed in this paper. It is designed to eliminate privacy intrusion and discomfort issues. The system can identify the patient's different on-bed positions and determine the possibility of bed falls. In case of any risky position, the caretaker will be alerted to mobile applications via the Internet of Things (IoT), making patient monitoring more accessible and manageable. This integrated system yields an average of 92% accuracy for 5 different on-bed positions. The bed fall prediction system will facilitate caretakers/nurses to take care conveniently at homes, hospitals and assisted care facilities to ensure patients' health and safety.**

Keywords—Bed falls; Force sensitive resistors; Prediction system; Remote monitoring; Internet of Things

I. INTRODUCTION

Falling off a bed is a frequent and dangerous accident that can result in severe physical and emotional damage. Patients with both neurological and motor system disorders require special attention when they lie down on the bed. Conditions such as Parkinson's disease, dementia, impaired mobility, and even old age can make a person vulnerable to bed falls. Caretakers of the patients have to care for the well-being and safety of patients, especially in the absence of nursing personnel at night. The population above the age of 65 is expected to reach 1.4 billion by the year 2030, and 2.1 billion by 2050 [1, 2]. There is a significant gap in the ratio of nursing personnel to patients in assisted living facilities [3]. Especially at night shifts in the hospitals, when fewer nursing personnel are stationed, bed falls occur more often [4]. Thus, it is difficult to monitor and stay beside patients at all times.

Bed rails are the most common existing solution to this problem. In [2], statistics have shown 60-70% of hospital accidents and 80% of home accidents are bed falls. Even with bed rails, 50-90% of bed falls still occur [2]. The problem has been widely recognized and several existing fall detection and prediction systems have been developed.

A generic classification of similar systems has been discussed in [2] where Ibrahim et al. divided bed fall systems into three categories depending on their sensor placement: wearable systems, non-wearable systems, and fusion systems. Furthermore, the global categorization of analytical methods was discussed to process the data collected from the sensors. The methods are as follows: Rule-based method (RM), Threshold-based method (THM), and Machine Learning-based method (MLM). Choi et al. [5] proposed a design where an accelerometer had been attached to the patient's chest and a threshold-based analytical method was used to determine the prediction. The system was very fast and of low cost. However, the wearable design can be uncomfortable to wear and might even cause injury to patients.

In 2018, Umetani et al. [6] designed a fusion system to detect changes in sleeping conditions. The system consisted of rules-based analysis of environmental factors such as the temperature, acceleration, and humidity of the comforter. A camera was fixed on the wall to detect motion. The installation cost was too high and it also had high obstructiveness due to the complicated sensor systems. In 2018, Sri-Ngernyuang et al. [7] proposed a system that used an artificial neural network to recognize the on-bed movements of the patients and thus made predictions of bed

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falls. The non-wearable design had tactical sensors installed inside a mat. They categorized the patient's position into two sections: stable and unstable. When the patient would be close to the edge of the bed, it would be considered unstable, and vice versa. This was accessed using a thermal imaging camera. In another non-wearable device explained by Hong [8], the system integrates FSR-406 and FSR-408 sensors in a mattress to identify 3 primary postures, and detects the patients' positions to assess the fall risk. This system can also detect bedsores of the patients with impaired mobility.

Fall prediction systems are more desirable than detection systems in the medical industry [9]. Existing systems consisting of wearable devices can be sometimes uncomfortable. On the other hand, non-wearable devices such as cameras involve privacy issues and discomfort as the patients are aware of being recorded at all times.

Therefore, integrating a simple system that can detect multiple positions using a comfortable device that does not invade one's privacy is desired. Additionally, the work in our manuscript has been influenced by that presented in [8].

Our paper aims to make the following contributions: (1) improve patients' safety and well-being, (2) address the risk of bed falls among patients with impaired mobility, (3) real-time monitoring of the patients' positions, and (4) reduce the patients' dependency on the nurses for constant monitoring.

This article is divided into the following sections. Section II explains the experimental setup that we have implemented. Section III talks about Methodology. Results and Discussion of the system have been presented in Section IV and finally the paper is summarized and concluded in Section V.

II. EXPERIMENTAL SETUP

The design has been implemented with the help of FSR, which has the functionality to detect pressure when force is exerted on the sensor. These are resistive force sensors that change their resistance when a force or pressure is applied on it. The active area of the sensor comprises a sensing element, which is made up of a conductive element and coated with a conductive ink. When a force is applied on a FSR sensor, the conductive particles move closer, which increases the current flow and decreases the resistance. At idle state, the FSRs have a very high resistance, drawing less current. This makes the overall setup consume very less amount of power. The parameters of the sensor have been summarized in Table I.

The FSR has two pins, a supply pin and a data pin. The supply pin is connected to a 5V DC voltage source while the data pin transmits the analog output voltage reading based on the pressure exerted. The output voltage has been characterized in (1).

$$V_{OUT} = \frac{R \quad * V}{(R \quad + R_{fsr})} \tag{1}$$

TABLE I. PARAMETERS OF FORCE SENSITIVE RESISTORS [11]

Parameter	Specification
Actuation Force	~ 0.1N
Sensitivity Range	0.1N to 10N
Dimensions	43..69mm x 43.69mm
Active Area	38.10mm x 38.10mm
Thickness	0.51mm
Actuations Cycles	>1 million
Non-actuated Resistance	>10 MΩ
Resistance Range	10 MΩ to 1 kΩ

The working principle of the FSR sensors can be further explained with the help of the circuit schematic as shown in Fig. 1. The variable resistance of the FSR generates an output voltage, V_{OUT}, which is fed into the microcontroller. The output voltage, V_{OUT}, is directly proportional to the amount of pressure exerted. The analog voltage ranging from 0 to 5V is converted to discrete digital values, ranging from 0 to 1023 by the 10-bit ADC (analog-to-digital converter) of the microcontroller. The FSR has also been connected to the ground with a pull-down resistor of 10kΩ. A total of 62 FSRs have been used to make a pressure-sensing mattress to fit a standard hospital bed of dimensions 40" by 80" as shown in Fig. 2. For the processing unit and gateway, Arduino Mega 2560 and ESP-32 have been used respectively.

The 62 FSRs were multiplexed into the Arduino microcontroller. The data pins of all the FSR are connected to the microcontroller with the help of multiplexers. When a patient lies down on the mattress, the microcontroller receives pressure data from the sensors, processes and then sends it to the cloud using the ESP-32 module via IoT. The ESP-32 acts as a gateway for the exchange of data between the cloud and the device. The processed data is displayed on the dashboard in the Blynk platform [12] and can also be accessed later on for further diagnosis. The dashboard, shown in Fig. 6 is designed as such so that the nurses can view the patient's current position directly from their PCs or smartphones. Furthermore, the Blynk platform enables the feature of sending alerts, to the designated caregiver, in times of risky positions.

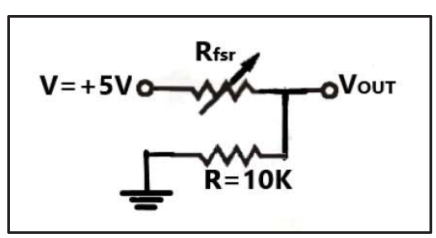

Fig. 1. Circuit Schematic of the FSR

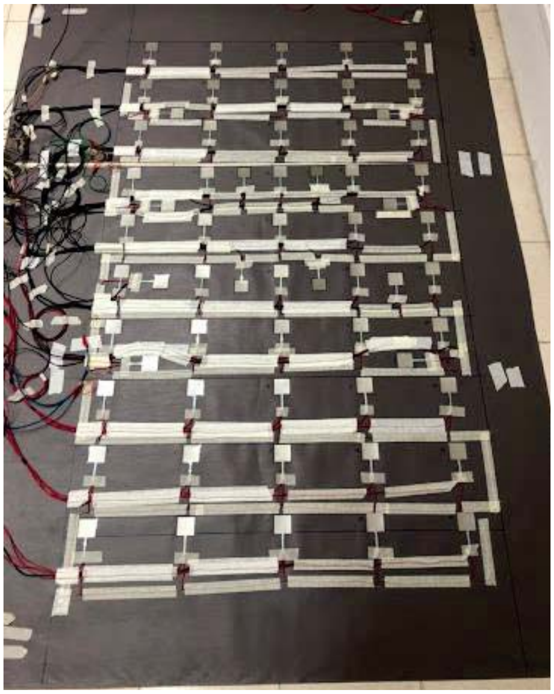

Fig. 2. Experimental setup showing the layer of 62 FSR sensors in grid layout

The layer of FSRs has been integrated within a mattress with proper insulating layers and a waterproof cover for the maintainability and safety of the patients. Additionally, a cushioned layer covers the sensors to ensure comfort. Due to the multiple layers above the sensors, the program calibrates the sensors to a certain threshold value so that the pressure by the human body can be detected accurately.

III. METHODOLOGY

A. System Overview

The primary objective of the proposed fall prediction system is to remotely detect the patient's on-bed positions and in return predict the risk of a bed fall, as well as to send an alert to the caregiver with the help of a non-wearable device. The entire system can be divided into four sections: pressure data collection, posture identification, prediction of risk of fall, and warning. It collects the pressure data with the help of a pressure-sensing mattress, which contains piezoresistive force sensors embedded inside the mattress. The processing unit then analyzes the pressure data to identify the correct posture based on the combination of sensors enabled in particular segments. Currently, the system can identify the three basic lying postures: supine, right lateral and left lateral and two risky positions: right risk and left risk. The right and left sides have been established based on the nurses' point-of-view. On-bed positions close to the edges of the bed are considered risky positions as the patient is prone to bed fall. If the patient is lying in any of the two risky positions, the caregiver or the medical staff gets a warning so that the patient can be attended immediately before he or she falls off the bed. This is done with the help of a gateway that sends the processed data to an IoT analytics platform such as Blynk to view the patient's posture. Fig. 3 shows the complete workflow and the sequence of the prediction system.

B. Sensor Layout/ Placement

The pressure sensing mattress consists of a layer of FSR sensors placed inside the mattress. Initially, 50 FSR sensors were arranged in a grid layout of 5 rows by 10 columns. After testing the system several times with several participants, it showed lower identification rate as shown in Table IV with variation of body structures, especially for lean subjects who would fall in between the columns of sensors resulting in fewer segment activations.

Also, it was difficult to differentiate between a normal lateral position and its corresponding risky position, for instance, the right lateral and right risky position. To make the system more universal for the inclusion of all types of body structures, 12 more FSR sensors have been added at positions that were not previously covered by the sensors. The upgraded system consists of 62 FSRs in total that are divided into 11 segments as illustrated in Fig. 4. This arrangement improved the identification rate as well as distinguishing the lateral and risky positions more accurately. The addition of these 12 new FSRs resulted in the formation of 4 new segments: 8, 9, 10, and 11.

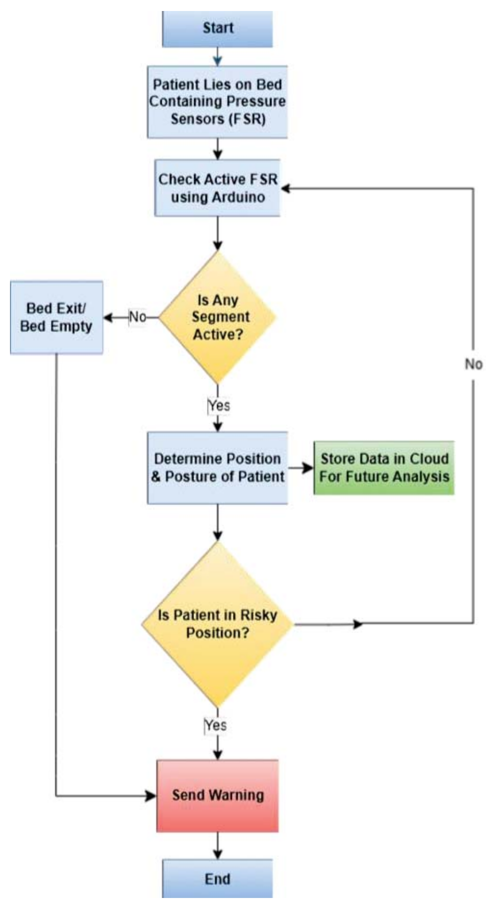

Fig. 3. Workflow of the System

C. Prediction Algorithm & Optimization

The posture prediction algorithm follows a rule-based approach that is, for each of the 5 positions, a certain combination of the segments must be active. During data collection, the occupied sensors gave analog readings ranging from 326 to 1023 for the pressure exerted. Therefore, when a particular number of sensors in a particular segment gives a reading above 300, the segment is then considered to be activated. To identify the pattern of the activated sensors for a specific posture, pressure data were collected from trial tests with several subjects. Based on the results, the average number of active sensors was calculated to identify the requirements for the activation of each segment.

The predetermined combination of the activated segments then detects the position of the patient lying on the bed. For instance, when a minimum of 3 sensors out of 8 in Segment 2 gives a value above 300 then the segment is considered to be active. Based on the position, the algorithm decides whether a risky position is detected and then finally predicts the possibility of a bed fall. Accordingly, an alert is sent to the caregiver or nurse via the Blynk dashboard.

The threshold value of the sensors was set to 300 owing to the fact that the sensors detect a small amount of pressure due to the weight of the pillows and bed sheets as well as the cushioned layer of the mattress. Before this case, the system was tested with reduced threshold value, e.g., 200 which resulted in lower identification rate compared to threshold value of 300 as shown in Table III. Hence, a higher threshold value was selected. The rule-based algorithm for the different positions has been summarized in Table II, which depicts the required segments to be activated and the conditions for their activation.

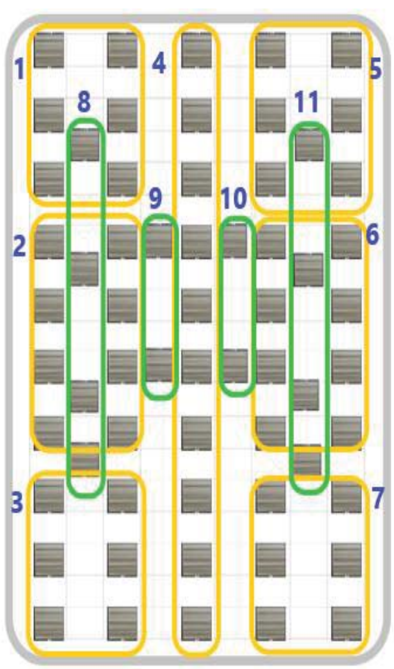

Fig. 4. FSR Sensor Layout

TABLE II. DECISION TABLE FOR THE RULE-BASED ALGORITHM

Position	Segments Activated	Minimum No of sensors for activation
Supine	seg 4 && seg 9 && seg 10	seg 4 =1 if active sensor >= 4
		seg 9 = 1 if active sensor >= 1
		seg 10 = 1 if active sensor >= 1
Left Lateral	seg 1 && seg 2 && seg 3 && seg 9	seg 1 = 1 if active sensor >= 2
		seg 2 = 1 if active sensor >= 3
		seg 3 = 1 if active sensor >= 2
		seg 9 = 1 if active sensor >= 0
Right Lateral	seg 10 && seg 6 && seg 5 && seg 7	seg10 = 1 if active sensor >= 1
		seg 6 = 1 if active sensor >= 2
		seg 5 = 1 if active sensor >= 2
		seg 7 = 1 if active sensor >= 2
Right Risk	seg 11 && seg 6 && (seg 5 || seg 7)	seg11 = 1 if active sensor >= 2
		seg 6 = 1 if active sensor >= 4
		seg 5 = 1 if active sensor >=3
		seg 7 = 1 if active sensor >= 2
Left Risk	seg 8 && seg 2 && (seg 1 || seg 3)	seg 8 = 1 if active sensor >= 3
		seg 2 = 1 if active sensor >= 3
		seg 1 = 1 if active sensor >= 2
		seg 3 = 1 if active sensor >= 2

D. Evaluation

The performance of the bed fall prediction system has been evaluated with the help of 15 healthy test subjects who fall within 22 to 24 years. For each of the 5 lying positions, the actual position and the predicted position has been recorded and analyzed using 3 different classification matrices: Precision, Recall and F_1 score.

The formulae used to calculate Precision, Recall and F_1 score has been characterized is (2), (3) and (4) respectively.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$F_1 \text{ score} = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

Here, TP is the true positive and TN is the true negative, FP is the false positive and FN is the false negative. These values have been calculated from the collected data and used to find the matrix scores. The closer the value is to 1, the better the score.

IV. Results and Discussion

The data collected from the test cases has been reviewed and analyzed to evaluate the performance of the system and its effectiveness in accurately predicting the risk of a bed fall.

Table III, lists the identification rate as affected by the different threshold values. The threshold value was first set to 200. With this threshold value, the prediction system was tested 35 times and gave an average identification rate of 85.71%, yielding successful identification for 30 tests. This threshold value of 200 gave false positives at times due to the weight of the pillow and few of the unoccupied sensors gave an initial reading above 200.

TABLE III. Identification Rate Based on the Threshold Values of the FSR

Threshold value	No of tests	Successful Identification	Identification rate (%)
200	35	30	85.71
300	35	33	94.29

For further improvement of the system, a higher threshold of 300 was used as an off-set value. This scenario could better identify positions with an identification rate of 94.29%. 35 tests were performed, out of which the system could properly detect the positions 33 times. Both scenarios involved all 5 positions as the control.

The test results are summarized in Table IV. It shows the number of tests carried out for each position and the corresponding number of successful identifications before and after the system had been optimized.

TABLE IV. Identification Success in Relation to Total Number of Tests Performed

Lying Posture	Total No of Tests	Successful Identification before Optimization	Successful Identification after Optimization
Supine	15	13	15
Left Lateral	15	9	13
Right Lateral	15	11	15
Left Risk	15	10	13
Right Risk	15	12	14

To evaluate the improvement in the device's performance, the results of the system before and after optimization were compared. In Fig. 5, it can be seen that after optimization, the identification rate has increased significantly for each of the positions.

For the optimized system with a threshold value of 300, both the supine and the right lateral position have an identification rate of 100% and that for the left lateral position is 86.67%. All the positions have an identification rate higher than 80%. Most importantly, the right risk position and the left risk position have an identification rate of 93.33% and 86.67% respectively. Thus, it can be said that the main objective of the fall prediction system has been successfully achieved as the identification rates of the risky positions are high, and it can predict bed falls with high accuracy.

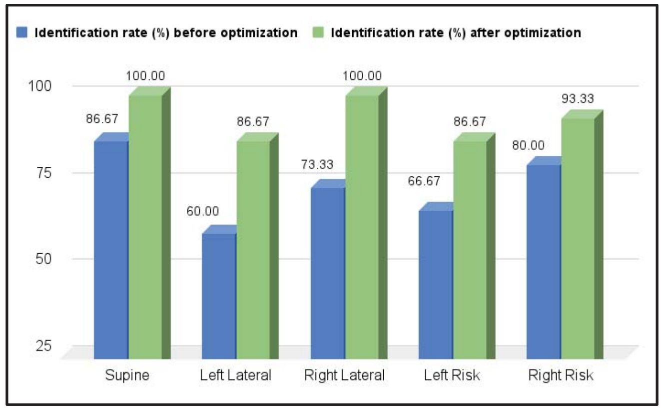

Fig. 5. Identification rate for each of the lying postures

To analyze further, Precision, Recall and F_1 score of the final system has been calculated for which, the supine, the left lateral, and the right lateral positions are considered as safe positions and the right risk and left risk position as risky positions. As shown in Table V, this system has both high Precision value and high Recall value which in turn yields a high F_1 score. This indicates that the system makes very few false alarms and the risk alerts are highly reliable.

TABLE V. Precision, Recall and F_1 Score of the Risky Positions

Precision	Recall	F_1-Score
0.964	0.900	0.931

The patient position status can be viewed by the caregivers on the IoT platform dashboard. For instance, the dashboard shows the corresponding position on the screen as illustrated in Fig. 6 when a patient is lying in the right risk position as shown in Fig. 7. In such cases, alerts are also sent from the IoT platform to warn the caregivers that the patient is required to be attended immediately.

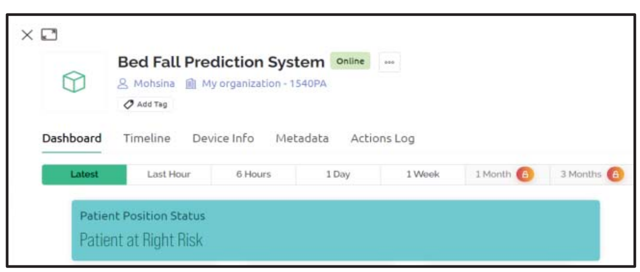

Fig. 6. Patient position status shown on the IoT platform dashboard

Fig. 7. Subject is lying at the Right Risky Position

Our bed fall prediction system yields a system accuracy of 94.7%, whereas similar bed falls prediction systems using tactile sensors give an accuracy of 89.1% [5].

V. CONCLUSION

The Bed Fall Prediction System proposed in this article incorporates the rule-based algorithm to detect different postures to predict the different on-bed postures and positions of the patients with impaired mobility and other neurological disorders. This system gives better accuracy than other bed falls prediction and detection systems. The algorithm predicts whenever the patients are at risk of falling off the bed and sends an alert to the assigned caregivers through the IoT platform to attend to the patient immediately. The system yields successful identification rates for the different positions, in particular the identification rates for the two Risky Positions: Left and Right Risky Positions. Since the system remotely checks for the on-bed positions, the patients can attain full privacy while the nurses are not obligated to physically monitor the patients at all times. Additionally, the system allows the nurses to attend other patients as well in times when there would be a shortage of medical staff.

Since, the data collected is for healthy participants, the actual on-bed patterns of the patients is likely to be different and may require modifications for better performance. However, it is to be noted that the system, in its current form, only predicts the risk of fall but does not prevent it.

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