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# Contactless Fall Detection using RFID Wall and AI

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**Abstract**—Fall detection (FD) in elderly people is crucial to prevent serious injuries that could result in prolonged dependence and could even lead to death in severe cases. The world health organization reports that 50% of elderly people fall every year. Therefore, early FD is essential to prevent elderly people from getting hospitalised or dying in accidents. FD systems can be broadly classified as wearable or non-wearable sensor-based systems, where security and privacy concerns make wearable sensor-based FD systems unacceptable. This paper proposes a contactless fall detection system that leverages a passive UHF RFID tag array to measure the received signal strength indicator (RSSI). The contactless method observes RSSI fluctuations in response to estimate fall activity using data-driven predictive. Specifically, we exploit deep learning (DL)-based classifiers to efficiently predict different activities when trained on features extracted from raw data. Our proposed contactless system is capable of detecting indoor falling activity with an accuracy of 95%, which demonstrates the efficacy of the proposed approach.

## I. INTRODUCTION

Early fall detection (FD) of elderly patients has emerged as an important research area that could prevent serious injuries and hospitalization. As per statistics, there are 37.3 million falls happening every year that cause 0.68 million fatalities worldwide [1]. Also, it has been argued that falls cause the second most unintentional deaths after road accidents. In the UK, 62% of elderly people have acquired injuries due to falls over a five-year period, where 28% people suffered serious injuries, 21% lost confidence, and 10% lost their independence [2]. On average, falls have caused 4 billion pounds in medical costs and 4 million bed days for the UK National Health Service [3]. These factors lead to a specific focus on developing FD systems to enhance elderly care. FD systems are reported to reduce mortality rates by 80% and improve hospitalisation by 26% by providing a prompt indication of fall incidents that lead to immediate medical assistance [4].

In the literature, the use of radio frequency identification (RFID) tags or wearable sensors for FD has been demonstrated. However, these approaches have two major drawbacks, i.e., continuous use of wearable devices increases discomfort and their proper maintenance is another challenge. Therefore, it becomes challenging to monitor elderly adults having intellectual injuries using sensor-based activity recognition. Alternately, contactless fall detection systems has gained significant attention, eliminating the need for wearing devices. They can detect an individual's activities within an indoor environment using signal fluctuation from RFID. This paper presents a contactless (device free), inexpensive, and maintenance-free FD system, which is based on a passive UHF RFID tags array. Figure 1 shows the experimental setup in an indoor environment for FD using our proposed device free method.



Figure 1: Experimental setup for data collection in a mock room to detect falling activity using Tag Array.

## II. RELATED WORK

In the literature, passive RFID tags have been used to monitor elderly patients. The signal from a passive RFID tag includes additional sensing information, such as identification, and RSSI, which measures how strongly the antenna received the signal from the tags. In [5], the authors deployed a passive RFID tag that was embroidered into the clothing and a small RFID reader on the body. As the body moves, the RSSI values of the tag fluctuate and this information can be used to identify activity. However, an elderly person might feel uncomfortable and risk injury if they wear such weighty devices. In a similar study [6], the authors mounted an array of RFID tags to the wall and installed the reader and antennas on a shelf in front of the reader. This approach measures the change in RSSI value while an elderly person walks through a region. However, RSSI measurements become less accurate in detecting activity when multiple elderly people are in the room. Toda et al. [7] deployed RFID tags attached to the room shoes that could detect specific activities and used machine learning algorithms to identify falling activity. However, their system is unable to immediately detect falls. Similarly, the TagFall approach is presented in [8], which uses abrupt changes in RSSI values to distinguish between falls and everyday activities. An interesting observation is that all aforementioned approaches employed a variety of tags to measure RFID variations. On the contrary, the key objective of our proposed system is to exploit an array of RFID tags in a completely contactless way to enable RFID systems to detect falling activity.

## III. METHODOLOGY

### A. Experimental Setup

All experiments were conducted in a  $5 \times 5m^2$  room at the James Watts south building at the University of Glasgow,

United Kingdom. Furthermore, we deployed a  $1.5 \times 1.5$  m<sup>2</sup> tag array on one wall of the room, as shown in Fig. 1. The wall has 15 tags that are arrayed in three rows and five columns. The horizontal distance between the circularly polarised antenna and the wall's centre is fixed at 3.5m, and the subject is positioned 0.5m away from the wall. The antenna is placed 0.74m above the ground, and passive UHF Gen-2 RFID devices are used to detect falling activity without any modifications to the hardware or firmware. The Impinj R700 passive UHF RFID tag array with RFID reader has an RF power of 30dBm and a wavelength of 0.32m. All RFID tags have been pre-screened to produce generally consistent performance with an average  $\pm 4$ dBm RSSI difference.

A human subject was instructed to naturally fall in between the antenna and the installed tag array for data collection. Specifically, we have collected 20 samples for the standing, falling, and empty activities. Figure 2 highlights that activity at the same location is indicated by the RSSI fluctuation dropping due to tags being blocked. It is noted that the RSSI strength is seen to vary between  $-55$ dBm (max) and  $-69$ dBm (min). When the reading of the tags is below the threshold levels (i.e.,  $-69$ dBm), it indicates the falling detection (Fig. 2). Whereas, the model training was performed on a Dell PC (DELL-FR1QYD3) with an Intel Core i7 CPU, 16 GB RAM, and NVIDIA RTX 2070 GPU.

### B. Data Collection, Preprocessing and Analysis

The pre-processing stage required additional steps to prepare the raw data for DL algorithms. The raw data of each tag and activity are stored in CSV files and then parsed using the popular python data analysis toolkit *Scikit*. The CSV file contains linear data that just needs to be label-encoded for further processing. For comparative analysis, we evaluate three models (i.e., LSTM, CNN, and RNN) using the collected dataset containing RSSI values of tags. The LSTM model has a single flatten and dropout layer. The CNN model uses a 1D convolution layer since the data was linear. In addition, there are two identical 1D convolutional layers and two max pooling layers and the dense layer is used between the output and last convolutional layer. In the third model, we employed an RNN layer having 100 units and one dense layer. We used the ADAM optimiser with a weight decay of  $1e^{-6}$ , a learning rate of 0.01, and maximum of 10 epochs. The models were trained and evaluated using a split of 80% for training and 20% for testing, respectively.

## IV. RESULTS AND DISCUSSIONS

The results of the proposed device-free system are presented in Fig. 3, which demonstrates that the LSTM model provided a maximum 95.3% accuracy while outperforming CNN and RNN, which had an average accuracy of 89% and 88%, respectively. The models detect standing and falling activity more accurately at 3.5 metres. The most reasonable reason is that the distance between the transmitter and the subject blockage has an effect on the RSSI measurement.

## V. CONCLUSIONS

This study presented the use of RFID technology to provide a low-cost, device-free, and privacy-preserving fall detection

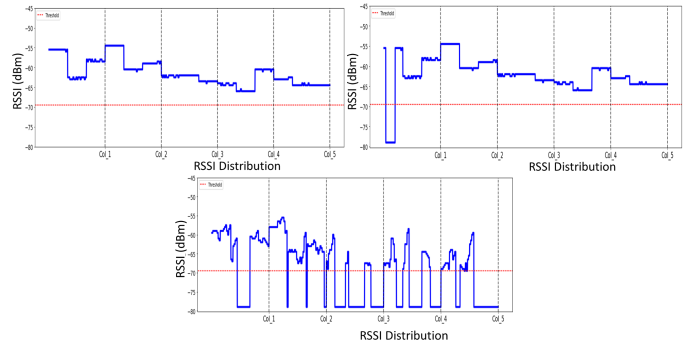


Figure 2: Data samples containing RSSI for different activities: empty (top left), standing (top right), and falling (bottom).

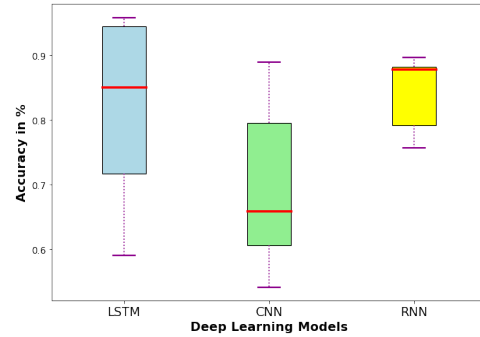


Figure 3: Comparison of three DL models for fall detection.

method. We demonstrate how a tag array can detect indoor falling activity without tagging targets. We evaluated three different deep learning models, where an LSTM network provided a superior performance of 95%, as compared to CNN and RNN. In the future, we plan to incorporate more activities and a dynamic experimental setup for evaluation.

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