Accelerometer-based Human Fall Detection Using Fuzzy Entropy

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***Abstract*—Falls are considered as one of the greatest risks and a fundamental problem in health-care for older adults living alone at home. The number of older adults living alone in their own homes is increasing worldwide due to the high expense of health care services. Therefore, it is important to develop an accurate system with the ability to detect human falls during daily activities. The focus of this study is to distinguish and detect human falls in Activities of Daily Living (ADL) based on data acquired from an accelerometer device. In this paper, a novel method based on Fuzzy Entropy measure is investigated to detect and distinguish human fall from other activities with a high degree of accuracy. The proposed method is tested and evaluated based on a publicly available URFD dataset. The experimental results show that Fuzzy Entropy achieved a sensitivity and specificity of 100% and 97.8%, respectively. Comparisons with other methods have also provided further support to the proposed method.**

***Index Terms*—Human fall detection, activities of daily living, fuzzy entropy measure, human activity recognition, tri-axial accelerometer.**

I. Introduction

The population of older adults over 65 in developed countries has drastically increased in the last few years. The majority of older adults prefer to stay in their own homes rather than move to care homes because of privacy concerns and high healthcare costs [1]. The research has shown that the number of older adults living alone in their home environment has increased, due partly to the high expense of health care services [2], [3]. Studies have identified that 30% of the older adults over 65 have at least one fall each year [4], and that 47% of older adults who have fallen cannot then get back up without assistance from others [5].

To support older adults with their independent living, assistive technologies such as automated fall detectors are utilised to assist and support them to live safely in their own homes [6]. Several research studies have been carried out on detecting human falls during daily activities, using different types of sensor. These studies can be classified into three main categories, namely; ambient sensor-based [7], vision-based methods [8], [9] and wearable sensor-based [10]. Ambient sensors such as pressure sensors are installed in the bed or on the floor. They are utilised to capture vibrations and the sound in detecting the presence of the person [11]. Even though these devices are inexpensive and do not disturb the person, they detect false alarms because of ambient noise, which leads to a low detection rate [12]. Alternatively, several studies have been carried out based on computer vision for human fall detection utilising single [8], multiple [13], and omni-directional [14] cameras. Recently, depth sensors such as Microsoft Kinect [9], [15] have been utilised for human fall detection. The Kinect sensor is a motion-sensing depth and colour images, which integrates an RGB camera and a depth sensor to capture moving objects in 3D [15]. On the other hand, several works have utilised wearable sensors, such as a wrist-worn accelerometer or gyroscopes to detect human falls during Activities of Daily Living (ADLs) [10], [16], [17]. These types of sensors are widely utilised to capture human body movements to detect a fall. Thus, analysis of the movement of the human body through an accelerometer or gyroscope allows for detection when there is a fall [18].

In many applications, the entropy measure is used to help model and represent the degree of uncertainty. However, to measure the subjective value of information under the condition of uncertainty, fuzzy entropy measure is considered as a useful measure to distinguish a fall from other activities. Therefore, detecting human falls in ADLs using accelerometer sensors is the challenge addressed in this paper. Distinguishing and detecting falls for older adults is essential for healthcare management. It is important to develop an accurate system with the ability to detect older adults' falls in their daily activities. This research aims to investigate whether Fuzzy Entropy measure can be utilised to detect human falls during daily activities.

The remainder of this paper is organised as follows: A short review of related studies on human fall detection methods are presented in Section II. Section III presents a short description of the proposed method for human fall detection based on Fuzzy Entropy. Section IV gives information about the dataset used, explains the experimental results and represent comparisons with state-of-the-art methods. Finally, pertinent conclusions are drawn in Section V.

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II. Related Work

Detecting human falls in a home environment is still a significant challenge for researchers. In recent years, research has been carried out on detecting human falls utilising statistical techniques, including the Hidden Markov Model (HMM) [19] and the Hierarchical Hidden Markov Model (HHMM) [20]. In [19], the authors proposed a model, namely three X-Factor Hidden Markov Models (XHMMs), for human fall detection using a wearable device. The idea of their study was to detect unseen falls by modelling transitions between normal daily activities to train an HMM and adding a new state to model unseen falls. Their experiments were based on two human activity recognition datasets collected using an accelerometer and gyroscope. The experimental results obtained from this study show that two of the XHMM models can detect human falls with an accuracy of 96.6%.

The researchers in [20] proposed a video analysis based on an HHMM method for fall detection during daily activities. They used HHMM with two layers; in the first layer, two states are utilised, one related to an upright standing pose and the other to a lying one. The object of their research was to study the relationship between angle sequences in the 3D world and their projection onto the image plane. The results obtained from their research indicate that the overall system can correctly detect 98% of human falls in a home environment.

As an alternative to statistical methods, computational intelligence techniques, such as the Support Vector Machine (SVM) [5], [9], [15], [21], Recurrent Neural Network (RNN) [16], Deep Neural Network (DNN) [22] and Convolutional Neural Network (CNN) [8], [10], [23], [24] are widely used to detect human falls in ADLs. An SVM was utilised in [9] to distinguish a falling pose from normal daily activities using machine vision techniques on RGB-D images. Their experiments were evaluated based on the publicly available URFD dataset [15]. The dataset contains 30 videos capturing different cases of falling and 40 videos demonstrating ADLs. The experimental results obtained from this study show that the proposed approach outperformed similar studies where images or accelerometers were utilised, achieving a sensitivity and specificity of 100% and 97.5%, respectively. There are some limitations, however, including the point that the proposed model failed to detect falling on a bed or sofa, as well as the inherent limitations of the Kinect camera.

A relatively new research study, [21], has proposed novel camera-based real-time automated human fall detection in a home environment using SVM. The idea of their research was to detect the moving person in the home and utilise features of the bounding ellipse, then apply SVM to classify the activities into fall and non-fall events. The authors evaluated their model based on the publicly available URFD dataset, and the proposed method achieved detection rates at 98.15% sensitivity and 97.1% specificity.

Recently, several research studies have been conducted to detect human falls in daily activities employing deep learning techniques. A study reported in [25] used a CNN based on dynamic motion and shape variations to detect older adults' falls during daily activities. They utilised a new vision system based on novel two-stream CNNs for older adult fall detection. Firstly, the human image is extracted based on person recognition and background subtraction. Then, History of Binary Motion Image (HBMI) is integrated into the first stream, distinguishing human shape variations. Experiments were conducted based on two publicly available datasets, which are the Multiple Cameras Fall (MCF) dataset [26] and the URFD dataset. It is also reported that the proposed system achieved a sensitivity and specificity of 100% and 92.5%, respectively. However, the authors also suggest that some further work is required to improve the proposed method by utilising depth cameras and using region-based CNNs (R-CNN) to improve the shape-based stream by extracting features from different body shapes.

In [16], a fall detection method is proposed based on an RNN method, which can process and encode the inherent information contained in sequential data. The authors used a dataset gathered from an accelerometer placed near the pelvis area of the user, and depth cameras. The results obtained from their research indicate that the proposed method achieved better results compared to the previous methods mentioned in their literature review, with an accuracy of 98.57%.

Accelerometer-based human fall detection utilising CNNs is proposed in [10]. The authors evaluated their approach using three open datasets and compared the results to other methods. The experimental results for this approach showed that around 99.86% of human falls can be detected. The authors also suggest that some further work is required to evaluate other deep learning techniques for human fall detection, improve the proposed method to detect multi-class events and distinguish various activities.

Based on the literature review conducted, the proposed method in this paper, based on Fuzzy Entropy measurement analysis of data gathered from an accelerometer device, has not yet been applied for human fall detection. The details of why this can be considered an important alternative method are presented in the next section.

III. Methodology

In this section, an overview of the proposed method for detecting human falls while conducting the activities of daily living in a home environment is presented. As part of this methodology, a brief explanation of the Fuzzy Entropy measure is also provided below.

A. System Overview

This paper proposes a method for detecting human falls in the home environment, solely based on the information gathered from a wearable motion-sensing device. Since the resident's normal daily activity pattern is completely different when an abnormal event has occurred, the data recorded from accelerometer devices during daily activities is used to show abnormal (e.g. fall) patterns. The research hypothesis is that the level of changes in a resident's ADL patterns in a home environment is an indicator of normal or abnormal activities [27]. Therefore, the entropy measure could be used as an indicator of the level of randomness in the accelerometer data. This method can be utilised for detecting abnormalities when the sample data is mostly normal. The proposed method is based on the hypothesis that the value of entropy is high when there is a fall event. Therefore, the proposed method aims to detect a large value of the entropy. It is supposed that human falls have greater acceleration than other ADLs. Nevertheless, considering high acceleration only can lead to many false alarms during fall-like activities such as sitting down speedily [28]. Therefore, a suitable measure must be utilised to distinguish falls from other activities accurately. After an extensive investigation, it was identified that Fuzzy Entropy is the most suitable technique in distinguishing between actual falls and other daily activities.

A flow chart of the proposed fall detection framework is shown in Fig. 1, and comprises three main stages.

- In the first stage, the accelerometer data representing ADLs is gathered and pre-processed.
- In the second stage, Fuzzy Entropy is applied to the gathered data in order to detect abnormalities in daily activities. The standard deviation is then computed.
- In the third stage, the standard deviation is utilised with the Fuzzy Entropy measure to detect whether or not a fall event has occurred.

B. Fuzzy Entropy

Fuzzy Entropy (FuzzyEn) was proposed by Chen et al. [29], and is defined as a method to calculate the ambiguity and uncertainty in time series data. The following is a description of the procedure for the FuzzyEn-based algorithm as presented in our previous work [27]. FuzzyEn excepts self-matches and beholds only the first $(N-m)$ vectors of length m to confirm that A_i^m and A_i^{m+1} are determined for all $(1 \leq i \leq N-m)$.

For the time series with N samples $A = [a(i) : 1 \leq i \leq N]$, the vector sequences A_i^m can be defined as:

$$A_i^m = \Big\{a(i), ..., a(i+m-1) - a_0(i)\Big\}, i = 1, ..., (N-m+1) \quad (1)$$

where $a_0(i)$ is the average value of A_i^m over the set of m values defined as:

$$a_0(i) = \frac{\sum_{j=0}^{m-1} a(i+j)}{m} \quad (2)$$

The distance between vectors A_i^m and A_j^m is given by d_{ij}^m and calculated as:

$$d_{ij}^m = Max_{k=0,...,m-1}\left|\Big(a(i+k) - a_0(i)\Big) - \Big(a(j+k) - a_0(j)\Big)\right| \quad (3)$$

According to the fuzzy membership function $\mu\Big(d_{ij}^m, r\Big)$, the similarity degree D_{ij}^m between the vector A_i^m and the next vector A_j^m is defined as:

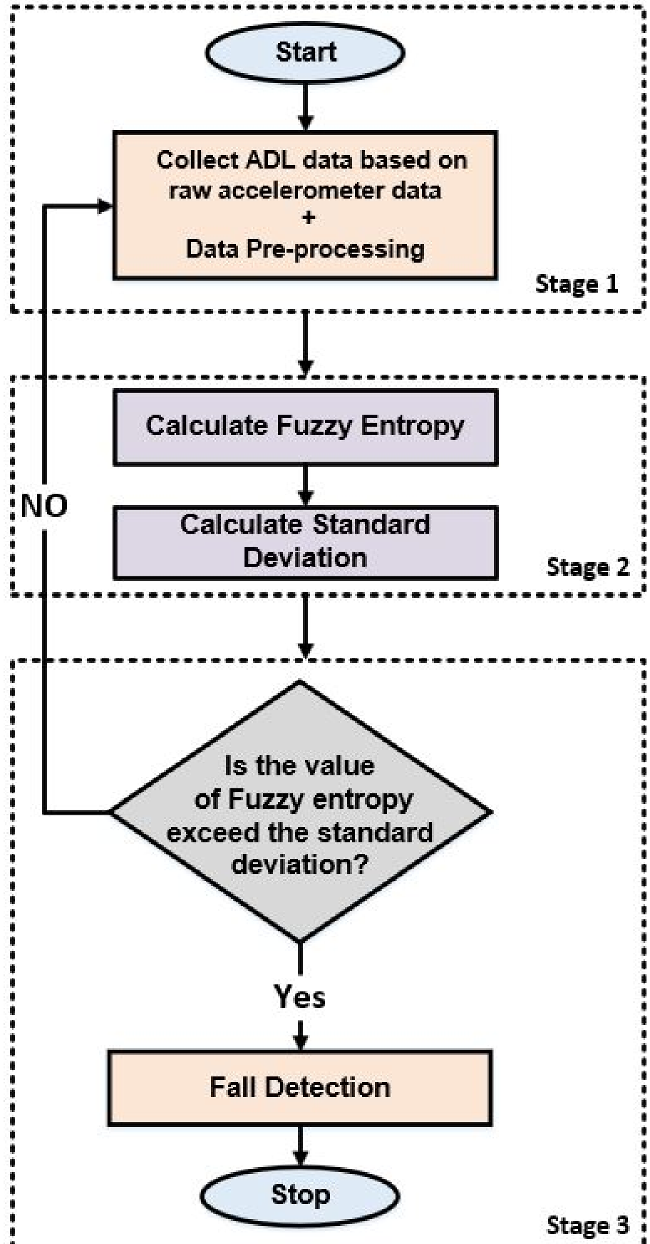

Fig. 1. Flow chart for the proposed method for human fall detection.

$$D_{ij}^m = \mu\Big(d_{ij}^m, r\Big) \quad (4)$$

where the fuzzy membership function $\mu\Big(d_{ij}^m, r\Big)$ is an exponential function defined as:

$$\mu\Big(d_{ij}^m, r\Big) = exp(-(d_{ij}^m)^n / r) \quad (5)$$

where n and r are the gradient and width of the exponential function, respectively.

For each vector $A_i^m; i = 1, ..., N-m+1$, averaging all the similarity degree of its next vectors $A_j^m; j = 1, ..., N-m+1, andj \neq i$ is defined as:

$$\phi_i^m(r) = \frac{\sum_{j=1, j\neq i}^{N-m} D_{ij}^m}{N-m-1} \tag{6}$$

Then, the $\phi^m(r)$ is defined as:

$$\phi^m(r) = \frac{\sum_{i=1}^{N-m} \phi_i^m(r)}{N-m} \tag{7}$$

And for A_i^{m+1}, averaging all the similarity degree of its next vectors is defined as:

$$\phi^{m+1}(r) = \frac{\sum_{i=1}^{N-m} \phi_i^{m+1}(r)}{N-m} \tag{8}$$

The FuzzyEn(m,r) is then calculated as:

$$FuzzyEn(m,r) = \lim_{N\to\infty} \left[\ln \phi^m(r) - \ln \phi^{m+1}(r) \right] \tag{9}$$

Finally, the Fuzzy Entropy can be defined for the finite time series of length N as:

$$FuzzyEn(m,r,N) = \ln \phi^m(r) - \ln \phi^{m+1}(r) \tag{10}$$

IV. Results

In this section, detection of human falls during ADLs in a home environment where the data includes falls is represented. The FuzzyEn presented earlier is applied to data gathered from a wearable motion-sensing device.

A. Dataset

The proposed method has been evaluated based on University of Rzeszow Fall Detection (URFD) dataset [15]. It is a dataset publicly shared through the Interdisciplinary Centre for Computational Modelling, at the University of Rzeszow. This dataset was gathered using one accelerometer sensor placed near the pelvis area of the human body, and two Kinect cameras. In total, the dataset contains 30 fall sequences and 40 activities of daily living sequences, such as lying on the floor, bending down, sitting down on a chair, picking an object up from the floor, and lying on the sofa/bed. In addition to this, the falls sequences contain two types of falls performed by five people, which are falling from sitting on a chair and from a standing position. Fig. 2 shows examples of acceleration change curves during daily activities such as lying down on the floor, picking up an object and fall events, using the URFD dataset. In our research, only accelerometer data is used, corresponding to 30 sequences containing human falls and 40 activities of daily living sequences.

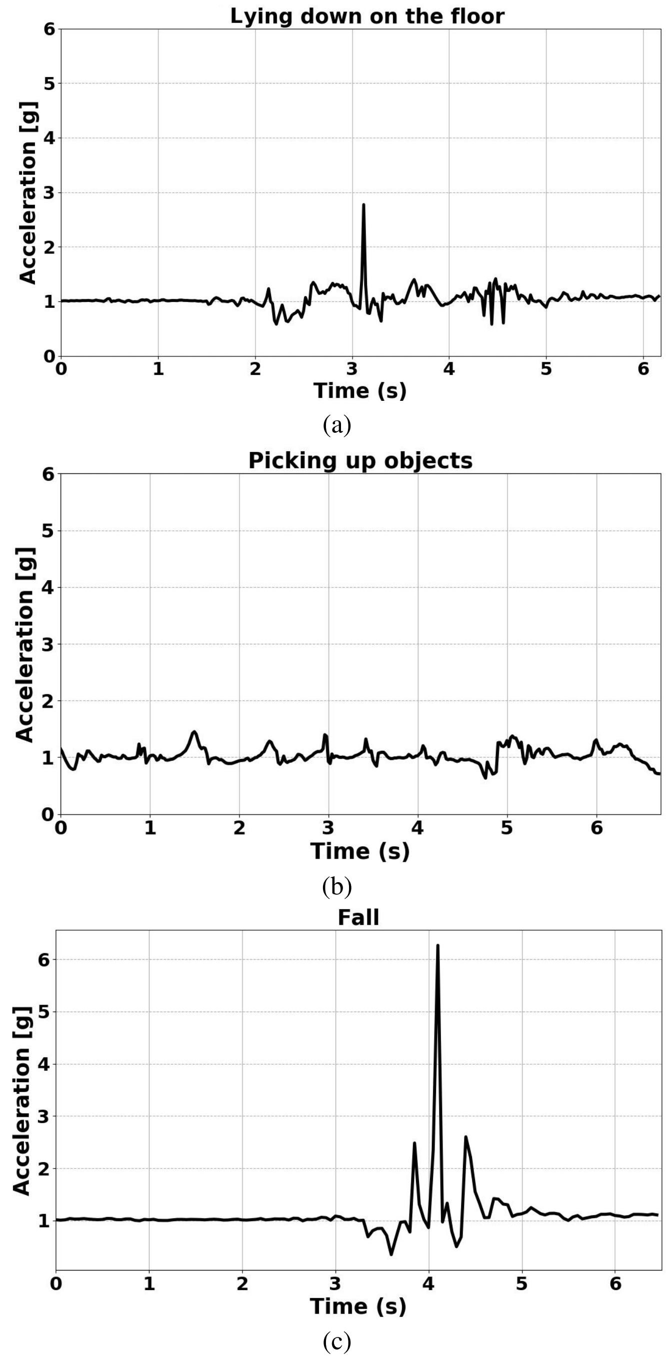

Fig. 2. Examples of acceleration over time for URFD datasets [15] representing; a) lying down on the floor, b) picking up an object and c) fall.

The accelerometer gathers data in three dimensions (the x-axis, y-axis, and z-axis) at time t, which are used to compute the magnitude of acceleration M as follows:

$$M(t) = \sqrt{A_x^2(t) + A_y^2(t) + A_y^2(t)} \tag{11}$$

where $A_x(t)$, $A_y(t)$, and $A_z(t)$ represent acceleration in the x, y, and z axes respectively at time t.

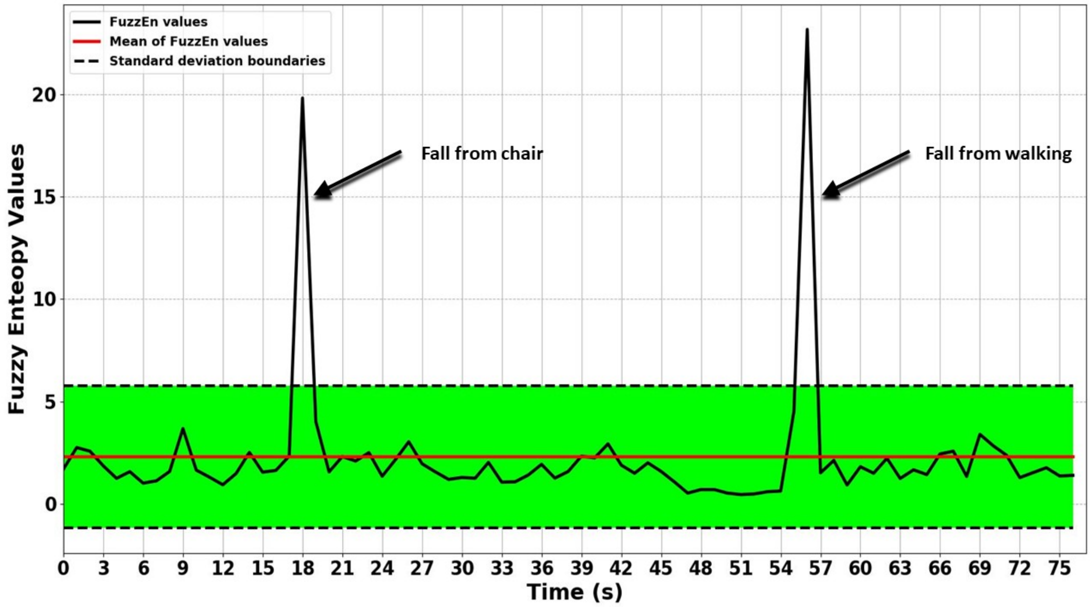

Fig. 3. Samples detecting one fall from a chair and one fall from walking using FuzzyEn based on the URFD dataset.

B. Experiments

This research aims to determine whether FuzzyEn is a useful measure for detecting human falls during ADL in a home environment and whether it might allow the detection of changes in activities of daily living levels. In order to make the dataset appropriate for FuzzyEn computation, the magnitude of acceleration M is used as an input vector to the FuzzyEn measure. The magnitude is converted to a set of data points equally spaced in time, and dependent on the calculation period of the FuzzyEn measure. The FuzzyEn is computed every second, at 60 samples per second. Therefore, the vector sequence A_N, which consists of a 60 sample set equally spaced in time, is used as the input for FuzzyEn. FuzzyEn is dependent on two parameters, which are required for FuzzyEn computation; embedded dimension m and tolerance r. Therefore, the algorithm for FuzzyEn is affected by the choice of these parameter values. The best results are obtained when the values of the parameters m and r utilised in expression (10) are 3 and 0.2 respectively.It appears that when m and r values are increased, the performance of the algorithm is decreased. After the FuzzyEn is calculated, a novel feature, namely the standard deviation of the mean of FuzzyEn values, is calculated as:

$$SD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^2} \tag{12}$$

where x_i is the i'th value in the dataset, $\overline{x}$ is the average of the x-values in the dataset, and N is the number of frames.

The standard deviation is applied to confirm whether or not there is a fall. The proposed method is based on the hypothesis that when the value of the FuzzyEn measures exceeds the upper standard deviation boundaries, then the event is detected as a fall. Fig 3 shows the results obtained by applying the FuzzyEn method to the URFD dataset. It can be noted that the fall events were successfully detected because the value of FuzzyEn is higher than the upper standard deviation boundaries.

C. Performance Evaluation

To evaluate the performance of the proposed method, the dataset contains 30 falls and 40 activities of daily living which are each manually labelled as a fall or non-fall event. As can be observed from Table I, there are 30 events indicating falls and 40 events indicating other normal activities of daily living. The FuzzyEn method successfully detected all the 30 fall events. However, for the other normal activities included in the dataset, the proposed method detected 39 activities out of 40 activities and failed to classify only one activity.

The evaluation of performance is computed automatically using a confusion matrix. There are four possible results for testing a sequence as a fall event in the home environment, which are presented as follows:

- True Positive (TP): an accelerometer data contains a fall, and it is correctly detected as a fall event.
- False Positive (FP): an accelerometer data does not contain a fall but is incorrectly detected as a fall.

TABLE I
DETECTION ACCURACY OF FUZZYEN FOR URFD DATASET.

Events	Total	Detected	Not detected
Falls	30	30	0
Other activities	40	39	1

- True Negative (TN): an accelerometer data does not contain falls and is correctly detected as non-fall.
- False Negative (FN): an accelerometer data contains a fall but is incorrectly detected as not a fall.

The classification performance of FuzzyEn measure is evaluated using:

Sensitivity= TP/(TP+FN);
Specificity= TN/(TN+FP);
Accuracy= (TP+TN)/(TP+TN+FP+FN);
False positive rate= FP/(FP+TN);
False negative rate= FN/(FN+TP);
Positive predictive value or precision= TP/(TP+FP);
Negative predictive value= TN/(TN+FN)

The results presented in Table II show the classification performance of the proposed fall detection algorithm on the URFD dataset. The proposed method achieves 97.8% specificity, which means that one of the normal daily activities has not been detected. However, the proposed method achieves 100% sensitivity, and this means that all falls are detected as a fall event. The accuracy of human fall detection is 98.6%. The proposed method for human fall detection shows high detection rates of 100%, which means that the false negative rate of fall detection is 0%. Based on the results achieved, FuzzyEn is a powerful measure to detect abnormality (here, falls) in behaviour when the sample data mostly represents normal activities. This also confirms that the FuzzyEn measure could be used to detect human falls.

D. Comparison of the Proposed Method with Existing Methods

Considering the literature review conducted for this research, the most commonly used methods for detecting human falls are SVM, RNN, and DNN. Therefore, to evaluate the proposed method carried out in this research, the results obtained by applying the FuzzyEn entropy measure are compared to other methods using the same URFD dataset. The comparisons were made in terms of sensitivity and specificity, as shown in Table III.

Considering the results achieved, the FuzzyEn entropy measure is considerably better for human fall detection compared to other approaches. The FuzzyEn produces 100% sensitivity and 97.8% specificity. This also confirms that the FuzzyEn measure could be used to detect human falls during ADLs in a home environment.

TABLE II
THE CLASSIFICATION PERFORMANCE OF FUZZYEN USING THE URFD DATASET.

Description	Obtained Result
Sensitivity	100%
Specificity	97.8%
False positive rate	0.025%
False negative rate	0%
Positive predictive value	97.2%
Negative predictive vale	100%
Accuracy	98.6%

TABLE III
COMPARISON OF THE PROPOSED METHOD WITH OTHER METHODS BASED ON URFD DATASET.

Methods	Sensitivity (%)	Specificity (%)
Extended CORE9 [30]	93.3	95
SVM [15]	100	96.6
DNN [22]	75	92.1
RNN [16]	100	96.67
FuzzyEn (Proposed method)	**100**	**97.8**

V. CONCLUSION

The experimental work presented in this paper investigates how FuzzyEn measure can be used to detect human falls in a home environment. A novel feature, namely the standard deviation of the mean of FuzzyEn values is used to confirm whether or not there is a fall. Therefore, when the value of the FuzzyEn measure exceeds the upper standard deviation boundaries, then the event is detected as a fall. It is shown that FuzzyEn obtained a high detection rate, of 100%, and a low false positive rate, of 0.025%. The proposed method can detect a human fall from a non-fall with 98.6% accuracy. The conclusion for this investigation is that the Fuzzy Entropy measure is a promising technique to detect human falls during activities of daily living in a home environment.

Further work will be conducted to compare different entropy measurements in order to evaluate the performance of all entropy measures in detecting human falls. Moreover, a different public dataset representing human falls will be applied to the proposed method.

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