



# Wearable Fall Detection Based on Motion Signals Using Hybrid Deep Residual Neural Network

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**Abstract.** There have been several approaches for wearable fall detection devices during the last twenty years. The majority of technologies relied on machine learning. Although the given findings appear that the issue is practically addressed, critical problems remain about feature extraction and selection. In this research, the constraint of machine learning on feature extraction is addressed by including a hybrid convolutional operation in our proposed deep residual network, called the DeepFall model. The proposed network automatically generates high-level motion signal characteristics that can be utilized to track falls and everyday activities. FallAllD dataset, a publicly available standard dataset for fall detection that gathered motion signals of falls and other events, was utilized to analyze the proposed network. We performed investigations using a 5-fold cross-validation technique to determine overall accuracy and F-measure. The experimental outcomes show that the proposed DeepFall performs better accuracy (95.19%) and F-measure (92.79%) than the state-of-the-art baseline deep learning networks.

**Keywords:** Fall detection · Wearable sensors · Deep learning · Deep residual network

## 1 Introduction

The importance of fall detection systems (FDSs) for the elderly derives from the concept that serious fall-related problems could well be avoided with prompt and adequate medical care. The FDSs might be classified as either ambient or

wearable. The first category is limited to residential use, but the latter benefits following the elderly inside and outside. This article discusses wearable fall detection technologies, and the sensors frequently utilized in this equipment are discussed in the next section.

Micro-Electro-Mechanical Systems (MEMS) permitted the production of a range of sensors, including accelerometers and gyroscopes, in compact and light-weight packaging as wearable technology advanced. These MEMS-based sensors are commonly employed in wearable devices presently. Accelerometers are the most often utilized sensors for fall detection and human activity identification due to their low energy consumption and techniques used to collect important body movement data.

Several FDSs have been designed in the past twenty years. Some of these strategies are threshold-based [12], however the most are machine learning-based [15], to mention just some. In threshold-based approaches, thresholds are determined based on the available data. Correspondingly, with machine learning-based approaches, the training phase depends on the available information.

Based on the interpretation of the findings acquired by wearable inertial sensors, machine learning (ML) techniques have demonstrated remarkable efficacy in differentiating between falls and typical motions or Activities of Daily Living (ADLs). Random forest, Support vector machine, Multi-layer perceptron, and k-nearest neighbors are four well-known and commonly employed ML techniques in FDSs [5]. Nevertheless, the effectiveness of these ML approaches was constrained by manual feature extraction.

Deep learning (DL) has been utilized extensively in the majority of areas throughout the globe [10,11,17]. In recent years, fall recognition has benefited more from the application of DL techniques [1,7] than threshold-based procedures [2]. Designs of DL comprise layers, and each layer extracts the characteristics of the provided data or transforms the data. Typically, the last layers of models consisted of synthetic neurons. The data could be recorded as a vision-based image, raw data from an accelerometer and gyroscope. Several DL approaches are employed to identify autumnal occurrences [8]. Some systems are constructed using a single DL algorithm, while others combine many methods to get a greater detection rate [6]. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are the most prevalent DL models for fall detection [9,20].

In this study, we proposed a convolutional and residual block-based deep neural network named DeepFall model. Using the TensorFlow platform, the recommended model has been trained to identify falls and ADLs. The suggested model was assessed and compared on a public benchmark dataset against various baseline DL models (FallAIIID dataset).

The article continues with the following outline: New relevant research is included in Sect. 2. The details of the proposed model are outlined in Sect. 3. The outcomes of our investigations can be seen in Sect. 4. The study finishes with a discussion of necessary future studies in Sect. 5.

## 2 Related Works

### 2.1 Fall Detection System

Current fall detection technologies may be loosely categorized into vision-based, ambient, and wearable sensors.

Vision-based sensors gather motion information by monitoring systems and extracting a person's body photograph orientation or human skeleton annotations from collected video or image data [21] to detect a fall. Typically, the ambient sensor measures fall by gathering infrared [19], radar [13], and other signals from the scene sensor. Although it does not pose any privacy concerns, it comes at a slightly higher price. It is susceptible to noise and has a somewhat restricted detection range. Multiple low-cost sensors are used by wearable technology to monitor falls [18]. Its detecting abilities depend on the sensor being worn in real-time. However, the elderly may be unable to do so in some situations, such as having a bath. Furthermore, some older individuals may experience pain from their apparel.

Due to the inexpensive cost of sensors in recent times, wearable sensors have gained increasing popularity. To acquire the three-axis acceleration at various points and the three-axis rotation angular velocity in a gyroscope, the most popular locations for wearable sensors are the calf, spine, head, pelvis, and feet [4].

### 2.2 Automatic Fall Detection by Using DL

Approaches for ML are primarily separated into classical pattern recognition and classification and recognition based on DL. Conventional recognition techniques depend on manually extracted features for identification. Consequently, researchers recommend stricter parameters for fall detection. Initially, it is required to identify the physical components involved in the falling procedure. Second, it is necessary to evaluate how these traits are separated from ADLs such as sitting and leaping; otherwise, the feature selection method will be significantly slowed down. Classification and identification based on DL are being used in fall detection systems that can automatically extract feature data. Due to this benefit, DL approaches have gained increasing popularity among the scientific community. They have been utilized in various fields where they have performed a part equal to that of human specialists. In principle, the stages required in DL approaches using sensor data from wearable devices are to pre-process the received signals, extract features from signal segments, and train a model using these features as input [16]. Thus, current studies in wearable sensor data fall risk assessment concentrate primarily on technical aspects that optimize performance. Various DL methods utilize the retrieved information as input to forecast the occurrence of falls. Klenk et al. [3] built a fall detection system based on long short-term memory (LSTM), which used a long-time sequence as input and extracted temporal features efficiently.

### 3 Fall Detection Approach

The sensor-based fall detection approach used in this investigation includes four main operational phases, as shown in Fig. 1: data acquisition, data pre-processing, data generation, and evaluation.

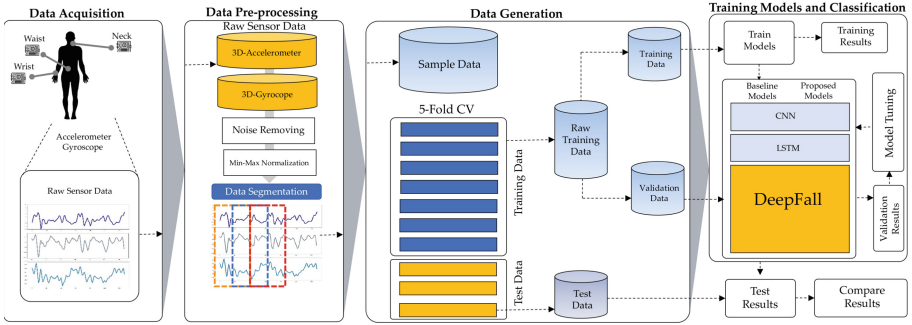


Fig. 1. Sensor-based fall detection approach

#### 3.1 FallAllD Dataset

The FallAllD dataset [14] is a free public standard dataset for fall identification. Motion signal data was collected from 15 healthful people (age 21–53, height 158–187 cm, and weight 48–85 kg) using three types of equipment: an accelerometer, gyroscope, magnetometer, and barometer. The individuals wore the wearable devices on three distinct body locations (neck, wrist, and waist). In this dataset, 44 categories of ADL and 35 categories of falls were conducted.

Each information recorder has an inertial measurement unit, LSM9DS1, built for tracking movement. This module includes 1) a 3D accelerometer (a sampling rate 238 Hz and a broad dynamic scope of 8 g), 2) a 3D gyroscope (a sampling rate 238 Hz and a geometric proportion of 2000 DPS), and 3) a 3D magnetometer (a frequency response 80 Hz). In addition, a separate data recorder is integrated with an MS5607 barometric sensor with 10 Hz sampling rate.

#### 3.2 Pre-processing of Data

Original sensor data of the accelerometer and gyroscope were processed by making the following adjustments. First, the median filter and a third-order low-pass Butterworth filter with a 20-Hz cutoff frequency were employed to reduce noise. Then, the Min-Max method was utilized to normalize the data. Segmentation of the pre-processed sensor data was conducted using fixed-width 1-second of sliding windows with a 50% overlapping, as shown in Fig. 2.

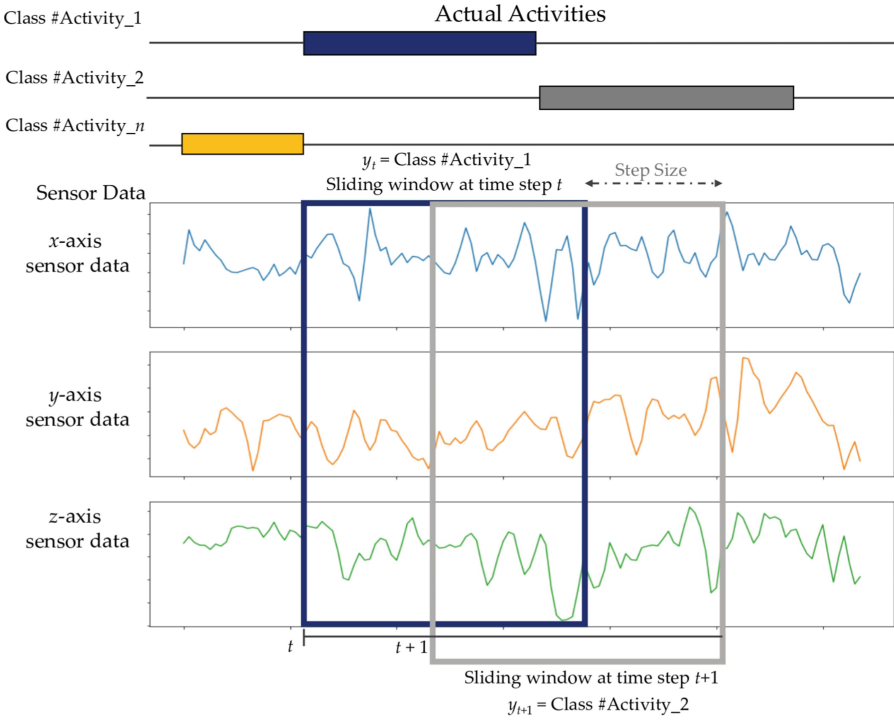


Fig. 2. Fixed-length sliding window

### 3.3 Hybrid Deep Residual Neural Network

DeepFall model, a hybrid deep residual neural network introduced in this paper, consists of two primary details. The first part is a convolutional block automatically extracting low-level characteristics from unprocessed movement inputs. The second method hierarchically recovers combination characteristics from a mixture of Spatio-temporal and channel-specific data using the residual block. This residual block contained Conv1D, BN, and ReLU layers, including a direct connection to LSTM, as seen in Fig. 3.

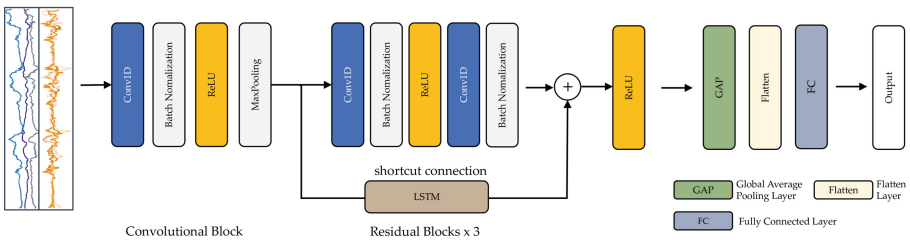


Fig. 3. The proposed DeepFall structure

### 3.4 Interpretation Measurements

The effectiveness of the proposed DL model is evaluated using four standard evaluation metrics obtained during the 10-fold cross-validation process: accuracy, precision, recall, and F-measure. These four metrics can be calculated using the following formulas:

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

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F - measure = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

The four most often used KPIs for fall detection are listed above. The classification is considered true positive (TP) for the group under study, whereas, for all other groups, it is considered true negative (TN). When sensor data from one group is incorrectly assigned to another, this is called a false positive (FP). On the other hand, a false positive (FP) designation could occur if data from an activity sensor that belongs to a different group was wrongly labeled as belonging to that group.

## 4 Experimental Results

In the Google Colab-Pro+ system, every experiment in this research is conducted. We experiment to assess the recognition interpretation of the offered network and compare the model to benchmark DL algorithms in this study (CNN and LSTM). To assess the efficiency of the algorithm, we divided these laboratory experiments into three scenarios:

- Scenario I: using movement signal data from neck-mounted wearable sensors,
- Scenario II: using movement signal data from wrist-mounted wearable sensors,
- Scenario III: using movement signal data from waist-mounted wearable sensors.

During experiments, movement signal data were acquired employing a 5-fold cross-validation methodology. Several tests were done to assess the identification effectiveness of various standard DL models (CNN and LSTM) and the suggested network. The precision and loss quantify the experimental findings, and F-measure is indicated in Table 1.

The proposed network obtained the maximum accuracy and F-measure in every scenario, according to the data. Incorporating an accuracy of 95.19% and an F-measure of 92.79%, the recommended network with movement signals from the waist position shows the most satisfactory performance.

**Table 1.** Identification effectiveness of baseline models compared with the proposed DriveNeXt model

Model	Identification effectiveness		
	Accuracy	Loss	F1-score
Scenario I: Neck			
CNN	74.21% ( $\pm 0.006\%$ )	0.57 ( $\pm 0.000$ )	42.60% ( $\pm 0.002\%$ )
LSTM	81.72% ( $\pm 0.363\%$ )	0.40 ( $\pm 0.002$ )	72.18% ( $\pm 0.934\%$ )
Hybrid deep residual network	92.13% ( $\pm 0.938\%$ )	0.28 ( $\pm 0.028$ )	89.61% ( $\pm 1.381\%$ )
Scenario II: Wrist			
CNN	83.02% ( $\pm 0.004\%$ )	0.46 ( $\pm 0.001$ )	45.36% ( $\pm 0.001\%$ )
LSTM	87.62% ( $\pm 0.291\%$ )	0.29 ( $\pm 0.005$ )	72.70% ( $\pm 1.383\%$ )
Hybrid deep residual network	93.82% ( $\pm 0.467\%$ )	0.26 ( $\pm 0.021$ )	88.81% ( $\pm 0.678\%$ )
Scenario III: Waist			
CNN	79.50% ( $\pm 1.280\%$ )	0.50 ( $\pm 0.032$ )	56.91% ( $\pm 15.846\%$ )
LSTM	86.37% ( $\pm 0.153\%$ )	0.32 ( $\pm 0.006$ )	76.80% ( $\pm 0.718\%$ )
Hybrid deep residual network	95.19% ( $\pm 0.353\%$ )	0.24 ( $\pm 0.033$ )	92.79% ( $\pm 0.561\%$ )

## 5 Conclusion and Future Studies

Applying wearable sensors, we developed a hybrid DL model to address the fall detection challenge in this work effectively. The proposed DL method utilizes some of the benefits of residual blocks. In this study, we investigated the proposed DeepFall network using the FallAllD standard dataset for wearable sensors. Experimental findings revealed that the proposed network surpasses other models with the best accuracy (95.19%) and F-measure (92.79%).

Future research could also include evaluating the proposed DL model using a larger sample size of people with various fall circumstances. The efficacy might be significantly increased with the development of increasingly complex and compact DL networks and specific data representations based on time-frequency analysis.

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