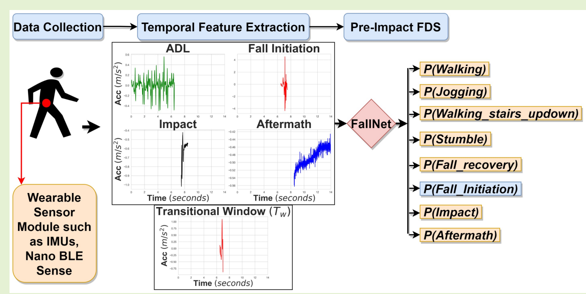
A novel Feature extraction method for Pre-Impact Fall detection system using Deep learning and wearable sensors

Rahul Jain, Vijay Bhaskar Semwal

***Abstract*— Fall detection and prevention are crucial in elderly healthcare and humanoid robotic research as they help mitigate the damaging after-effects of falls. In this work, we have presented a deep learning-based Pre-Impact fall detection system (FDS) that detects a fall within 0.5s of the fall initiation phase, thus providing a sufficient lead time of 0.5s which is far better than the state-of-the-art. To achieve this, we have developed an automatic feature extraction methodology that can extract temporal features from all types of human fall data collected using wearable sensors. A deep neural classifier based on the ensemble of convolutional neural network (CNN) and Long short-term memory network (LSTM) is trained on the extracted temporal features. The classifier has performed exceptionally well in detecting the Fall Initiation phase with a Sensitivity of 99.24% and an F1-score of 98.79% for different types of falls. A Sensitivity of 99.24% signifies that the model has sufficiently reduced the occurrence of false negatives, which is far more critical for an FDS. A concept of a transitional window is introduced to improve the reaction time of the FDS. We utilized two standard fall datasets, viz. SisFall and KFall for the experimentation. Dataset fusion is employed to increase the generalizability of the system. This work can be utilized to design and develop fall detection devices for the Internet of Healthcare applications (IoHT) and for imparting fall detection capabilities to humanoid robots and gait rehabilitation devices such as exoskeleton robots and smart prosthetic legs.**



***Index Terms*— CNN, Fall detection system (FDS), Fall Diagnosis, Humanoid Robots, Inertial measurement unit (IMU), Internet of Healthcare things (IoHT), LSTM, Push Recovery, Pre-Impact fall detection, Proprioception, Wearable sensors.**

I. Introduction

FALLS are the most common cause of injuries to the elderly and incur a significant cost burden to the healthcare system. Every year, hundreds of thousands of people, primarily the elderly, encounter some fall, which results in critical injuries causing severe disabilities and even fatalities. According to World Health Organization's (WHO) report [1], the elderly population are more prone to falls, with approximately 28-35% of people aged 65 and above falling each year, increasing to 32-42% for people aged 70 and above. Moreover, the elderly females are at higher risk of hip-related fractures during falls due to factors such as low bone mineral density (BMD) [2], and low Body mass index (BMI) [3]. Further, for persons with disabilities, diseases such as Parkinson's disease (PD) [3], post-operative conditions and injuries are again at relatively high fall risk due to impaired gait and weakened reflexes [4]. Hence, a robust fall detection and prevention system is imperative to counter this global health challenge.

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Falling is a result of a sudden imbalance in gait caused by a slip, trip, external push [5], or various gait abnormalities, resulting in a subject losing balance and falling on the ground. Falling is a postural instability problem in human gait research. Fall recovery is a behavioural-based learning mechanism involving neuromuscular interaction, dynamic stability, and proprioceptive sense. Human beings always have some bounded fall recovery capability [6] which varies with factors such as age, gender, terrain, fatigue, injury and posture. This capability decreases with age due to neuromuscular decline. Postural stability analysis can be utilized for an early diagnosis of elderly health to protect them from damages due to falls.

Broadly, the Fall data can be collected and analyzed in three ways: Vision-based methods, ambient sensor-based methods, and wearable sensor-based methods [7]. Vision-based methods use imaging devices such as video cameras placed at strategic locations to capture image sequences at discreet time intervals to detect the occurrence of falls. Ambient sensor-based methods use infrared cameras, floor sensors, microphone arrays, depth sensors and imaging devices deployed in the environment to capture gait data. The major limitation of these approaches is that they are relatively costly and restricted to laboratory environments, thus making them impractical for continuous gait monitoring in real-world situations. The third and the most popular method [8] is the wearable sensor-based approach. They collect the Kinematics and kinetics of human locomotion using wearable devices such as inertial measurement units (IMUs), magnetometers, electroencephalogram (EEG), and Electromyography (EMG). Wearable sensor-based methods are non-invasive and provide a practical solution for real-world usage, as they are independent of the environment, can be easily deployed on the subject without hindering their normal day-to-day activities, and are cost-effective [9]. IMUs placed near the subject's centre of mass (COM) produces a more accurate measurement of inertial signals [10], [11]; however, wrist-mounted devices are more comfortable for a subject to wear but are less accurate [12]. With rapid miniaturization of sensor modules and with the advent of the tinyML framework [13], both a comfortable and robust FDS solution can be provided. Moreover, a smartphone-based FDS will be an effective solution due to the widespread usage of smartphones.

An inertial fall data is an acceleration and angular velocity signal captured through the accelerometer and gyroscope of an IMU. An inertial fall data consists of four main phases, namely the activity of daily living (ADL), Fall initiation, Impact and Aftermath, as shown in the figure 1. ADL phase is characterized by periodic patterns in inertial signals corresponding to the activity the subject is performing. This periodicity is coherent with the periodicity in human gait [14]. A fall is a transition from the ADL to the falling phase, called the Fall initiation phase and is characterized by a sudden peak in the acceleration and angular velocity signals. This sudden peak is due to the gravity forces as the subject is under the free fall. The falling results in an impact on the ground, constituting the Impact phase and is characterized by a sudden drop in the acceleration and angular velocity signals. An almost flat line characterizes the aftermath phase in inertial signal and is representative of the subject is lying on the ground.

The two most common types of FDS are alarm-based FDS and preemptive FDS. Alarm-based FDS aims to gather assistance when a person has already encountered an impact on the ground [15]. Whereas, Preemptive FDS tries to predict the fall before impact, to prevent the fall from happening or to dampen the effects by employing some dampening measures such as the deployment of airbags [16]. Preemptive FDSs are also called as Pre-Impact FDSs. The reaction time metric characterizes a good Pre-Impact FDS. A short reaction time means that a fall is detected very early, and a sufficient lead time is available to initiate some preventive mechanism to dampen its impact. Further, in gait rehabilitation using exoskeleton robots and walk generation of humanoid robots, a shorter reaction time can help initiate some gait and posture correcting routines to negate the fall or its effect if the fall is inevitable.

This work presents a novel feature extraction methodology for Deep learning-based Pre-Impact FDS by addressing two critical challenges associated with fall data analysis. The primary challenge is how to interpret the fall inertial data to detect the Pre-Impact falls, and the second challenge is

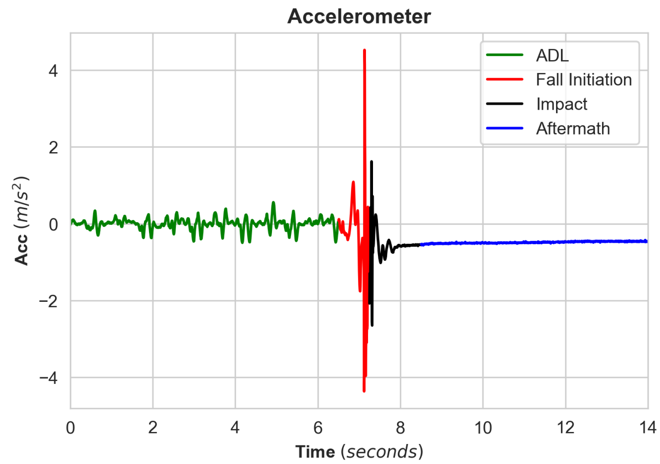


Fig. 1: Different Phases in a Fall activity.

how to minimize the reaction time of FDS to prevent the fall from happening? For proper interpretation of inertial fall data, temporal labels are required to identify the fall's beginning and end, which are missing in most publicly available fall datasets. To address these, firstly, we have developed a novel feature extraction methodology using statistical measures, which accurately segments the fall inertial data into its constituent temporal phases, namely the ADL, Fall Initiation, Impact and Aftermath. Our approach is fully automatic and does not require prior knowledge of the system (model-less). Secondly, we segmented the fall initiation phase into a transitional window (T_w) to explicitly train the deep neural classifier in the $ADL - to - Fall\_initiation$ transition features to minimize the reaction time of FDS. To build the FDS, we have trained a CNN-LSTM ensemble model on the extracted temporal features. We utilized Two benchmark fall datasets, viz. SisFall [11] and KFall [17] for the experimentation. We have fused the features extracted from two datasets to improve the generalizability of the FDS since the SisFall dataset has both adult and elderly data and is representative of the Colombian population. In contrast, the KFall dataset is representative of the Korean population and has only adult population data. Our proposed Pre-Impact FDS, named FallNet, is an 8-class classifier capable of distinguishing between different ADLs and various stages of falls. It has shown tremendous capability in detecting the Fall initiation phase with a $Sensitivity$ of 99.24% and an $F1score$ of 98.79% for all types of falls. With T_w, the estimated reaction time comes down to 0.5 seconds (s), giving a lead time of 0.5s, sufficient to inflate an airbag which takes about 0.133s [16] to inflate, thus outperforming the state-of-the-art. Moreover, we have validated our temporal feature segmentation results by comparing them with the temporal labels available in the KFall dataset and found our results consistent, thus providing a robust automatic alternative to the manual labelling approach demonstrated in the KFall dataset. With this work, we have provided a generalized framework to work with fall inertial datasets as it facilitates the development of autonomous adaptive systems which can adjust to each individual's gait pattern automatically, thus aiding in providing a personalized healthcare device.

The rest of the paper is organized as follows: The second section is the related work section which provides a brief literature review. The third section is the methodology section, where we have described the data preprocessing steps, proposed feature extraction methodology and the network architecture of the deep neural classifier. The third section is the results and discussion section, which provides the critical analysis of results and a comparative analysis with the state-of-the-art methodologies. The last section is the conclusion section, which also discusses the limitations and future implications of our work.

II. Related Work

Fall detection is an active research area, and many different approaches have been suggested in the literature, which can be broadly classified into threshold-based and Machine learning (ML) based methods. ***ML based FDS:*** Quadros et al. [18] have demonstrated a wrist-mounted FDS using both threshold-based and ML-based approaches. They collected the fall and non-fall data from 22 volunteers using a wrist-mounted IMU. The ML system achieved a $Sensitivity$ of 100% and specificity of 97.9%, whereas the threshold-based system achieved a $Sensitivity$ of 95.8% and specificity of 86.5%. Santoyo-Ramón et al. [19] have presented a study on the effect of a user's physical characteristics on the FDS. They identified that a certain divergence in height and weight of the subjects in both training and test set could hamper the $Sensitivity$ of the classifier by 20% and $Specificity$ by 5%. Yu et al. [20] have proposed a CNN-LSTM-based Pre-Impact FDS using wearable inertial sensors. They claimed to have obtained mean sensitivities of 93.15, 93.78, and 96% on non-fall, Pre-Impact fall and fall activities, respectively. Musci et al. [21] have proposed an Online FDS using recurrent neural network (RNN) architecture and a wearable microcontroller device equipped with inertial sensors. They have also described a tool for providing temporal annotations to raw inertial signals. Their FDS is a 3-class classifier viz. fall, alert and ADL (named BKG) with a fall detection accuracy of 96.06% and a $Sensitivity$ of 93.41%. They have exclusively performed training and testing on a single dataset, which contributes to the significant limitation of the study. Also, they have used a manual approach for temporal annotations against our automatic segmentation approach. Mrozek et al. [15] have presented the architecture of both cloud-based and edge-based FDS for large-scale monitoring of older adults. They used smartphone-based inertial sensors for data collection and Boosted decision trees as an ML classifier. They have claimed to have obtained 99.8% classification accuracy using this approach. ***Threshold based FDS:*** De Sousa et al. [22] presented a threshold-based Pre-Impact FDS using a MEMS accelerometer. They have utilized the concept of a balance boundary circle which is based on the subject's height and classified the activities outside of the balance boundary circle as a fall. They have obtained a lead time of $0.259s$, with a specificity of 97.7% and $Sensitivity$ of 94.04%. Wu et al. [23] have presented a threshold-based Pre-Impact FDS using wearable sensors. They employed fisher discriminant analysis to develop a 3-class classifier to distinguish between non-fall, backward, and forward fall scenarios. They achieved a $Sensitivity$ of 95.5% with a lead time of $0.376s$ for backward fall and $0.404s$ for forward fall. ***FDS for Biped Robots:*** Wu et al. [24] have presented a method for Biped robot fall prediction using a Support vector machine (SVM) as a classifier and BHR-6 robotic platform for experimentation. They have employed the concept of survival kernel by training a binary classifier to identify the possibility of fall and no fall. The major limitation of this work is that they have tested on a single robotic platform with very little training data, thus limiting the generalizability of the system.

III. Methodology

A. Data Collection and Preprocessing

We have utilized two standard fall datasets, viz. SisFall [11] and KFall [17] for this study. A brief description of these datasets is given in table I. SisFall dataset comprises ADL data of both adult and elderly populations, whereas fall activity data was collected only for the adult population except for the elderly subject *SE06*. In contrast, the KFall dataset comprises only adult population data for ADL and fall activity. We utilized ADL and fall data for only a selected set of activities, as mentioned in the table I, as these are the most common types of falls encountered in daily life. A feature extraction methodology is employed (explained in the following subsection) to extract the relevant features from the two datasets. Temporal features from both datasets were utilized for training the model to improve the generalizability of the classifier. Initially, two labelled datasets were prepared by extracting the temporal features individually from both SisFall and KFall datasets and assigning the class labels according to algorithm 1. The two datasets were then fused after performing the z-score standardization individually on the two datasets. Z-score standardization was again employed before the final data was fed into the network to normalize the features extracted from the two datasets. Cubic spline interpolation is performed on the KFall dataset to make its sampling rate equivalent to the SisFall dataset.

B. Feature Extraction methodology

Most publicly available fall datasets do not have the required temporal labels to mark the beginning and end of a fall activity, which is paramount for fall data analysis. Some datasets, such as KFall [17] have provided temporal labels, but they were estimated manually by synchronizing video recordings with the inertial fall data. Although it produces accurate labels, it is a very tedious and cumbersome process and inefficient for IoHT application, which requires long-term human gait monitoring. Musci et al. [21] have utilized a graphical annotation tool for assigning the temporal labels to fall activity data for the SisFall dataset, but again it was a manual approach and required a team of experts to perform the task. To overcome these limitations, we have developed a novel feature extraction methodology (described in algorithm 1) for automatically extracting temporal features from fall data using

TABLE I: Dataset Description.

Metric	**SisFall Dataset** [11]	**KFall Dataset** [17]
Subject Count	Adult: 23	Adult: 32
	Elderly: 15	Elderly: Nil
Age range of Subjects (Years)	Adult: 19-30	Adult: 24.9 ± 3.7
	Elderly: 60-75	Elderly: Nil
Data Collection Device	Inertial Measurement unit	Inertial Measurement unit
Device Placement	Waist	Lower Back
Sensors Utilized	3D accelerometer (2 units), 3D gyroscope (1 unit)	A single 3D accelerometer and gyroscope
Sampling Frequency	200 Hz	100 Hz
ADL Activities utilized (Activity ID, Activity Name)	D01: Walking slowly D02: Walking quickly D03: Jogging slowly D04: Jogging quickly D05: Walking upstairs and downstairs slowly D06: Walking upstairs and downstairs quickly D18: Stumble while walking	T10: Stumble while walking
Fall Activities utilized (Activity ID, Activity Name)	F01: Fall forward while walking caused by a slip F02: Fall backward while walking caused by a slip F03: Lateral fall while walking caused by a slip F04: Fall forward while walking caused by a trip F05: Fall forward while jogging caused by a trip F06: Vertical fall while walking caused by fainting	T28: Vertical(forward) fall while walking caused by fainting T30: Forward fall while walking caused by a trip T31: Forward fall while jogging caused by a trip T32: Forward fall while walking caused by a slip T33: Lateral fall while walking caused by a slip T34: Backward fall while walking caused by a slip

statistical measures. Our technique is fully automatic and does not require any prior knowledge of the system.

The algorithm begins by calculating standard deviation (std) on non-overlapping windows of size Ws along the Y-axis of the acceleration data. Y-axis points to the gravity direction [11] and hence is most sensitive to g-forces. Ws is kept at $1/4^{th}$ of the sampling frequency (sf), which is $0.5s$ in our case. We experimented with different window sizes and found that a window of $0.25(sf)$ is the aptest for accurate feature extraction. The instant of maximum std value implies the point of significant disturbance in the g-forces, thus signalling the fall initiation. This is based on the observation that during a fall activity, there is only one sudden spike and a subsequent drop in acceleration (refer to figure 2). The window with maximum std is now representative of the Fall initiation phase and is called the segmentation window (S_w). The starting frame of S_w will become the segmentation point (S_p).

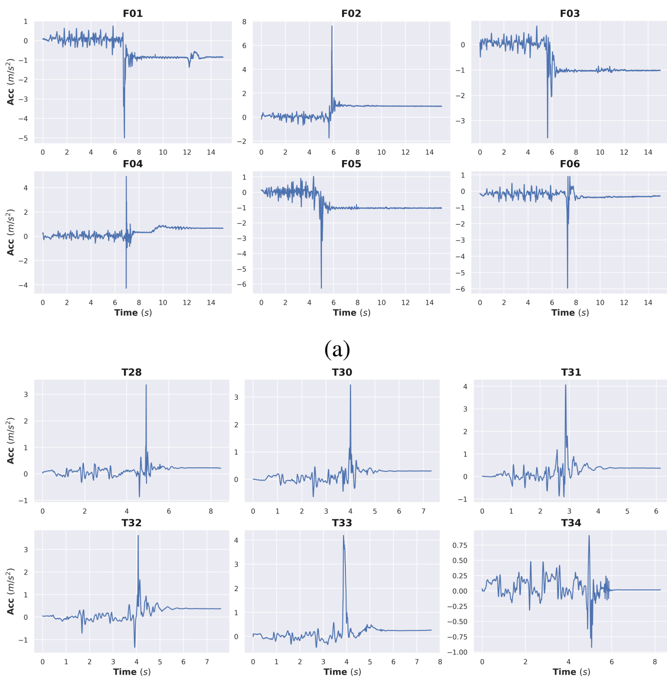
Our objective is to develop an FDS capable of distinguishing between different ADLs and various stages of falls. Hence, we prepared the input data by keeping them in one of the following eight classes: *("Walking", "Jogging", "Walking_stairs_updown", "Stumble_while_walking", "Fall_Recovery", "Fall_Initiation", "Impact", "Aftermath")*. As explained in algorithm 1, we took $4 * Ws$ worth of data along S_w, starting from (S_p), and labelled it as *"Fall_initiation"* phase. Further, $4 * Ws$ worth of data is extracted from the point after the S_w ends to the beginning of the Aftermath phase and is labelled as *"Impact"* phase. These two phases combinedly represent the complete fall activity. The S_w will not only consist of fall activity features but is also a representative of the transition from the ADL to the fall initiation phase ($ADL - to - Fall\_init$). This transition is the most crucial feature in detecting an early signal of a fall. To capitalize on this knowledge, we again extracted data starting from (S_p) to the midpoint of S_w to explicitly train a deep neural classifier on the transitional features to reduce the reaction time of FDS further. Again, this $0.5 * S_w$ window, called as the transitional window (Tw), is labelled as *"Fall_initiation"* phase. Further, $4 * Ws$ of data is extracted after the point when *Impact* phase ends to represent the *"Aftermath"* phase. This is illustrated in figure 3.

Twenty seconds' worth of ADL data is directly extracted from the SisFall dataset for the activities mentioned in table I. Activity IDs D01 and D02 are combined and assigned a common label *"Walking"*. Similarly, D03 and D04 are combined as *"Jogging"*, and D05 and D06 are combined as *"Walking_stairs_updown"*. Moreover, features of D18 and T10 are extracted using the algorithm 1 and are assigned with the labels *"Stumble_while_walking"* and *"Fall_Recovery"*. This feature enables the deep neural classifier to distinguish the Fall initiation phase with *Stumble_while_walking* and the *Fall_recovery* with the Impact on the ground. Stumble is a sudden imbalance in gait and is similar to fall initiation; however, it does not result in a fall, and the person recovers from it by achieving the original state of walking equilibrium called *Fall_Recovery*.

Algorithm 1: Feature Extraction methodology:

Input : $ACC\_Y \leftarrow Fall\_data$
Output : Segmentation of Fall Phases
Initialize: $Ws \leftarrow Sampling\_Frequency/4$;
$Size \leftarrow \textbf{length}(ACC\_Y)$;
$i \leftarrow 0$;

for $j \leftarrow 0$ **to** $Size$ **do**
  $Std\_dev[i] \leftarrow \textbf{std}(ACC\_Y[j : j + Ws])$;
  $j \leftarrow j + Ws$;
  $i \leftarrow i + 1$;
end
$S_p \leftarrow \textbf{index}(\textbf{max}(Std\_dev)) - 3$;
$ADl \leftarrow Fall\_data[0 : S_p * Ws]$;
$Fall\_Init \leftarrow Fall\_data[S_p * Ws : (S_p + 4) * Ws]$;
$Fall\_Init \leftarrow Fall\_data[S_p * Ws : (S_p + 2) * Ws]$;
$Impact \leftarrow Fall\_data[(S_p + 4) * Ws : (S_p + 8) * Ws]$;
$Aftermath \leftarrow Fall\_data[(S_p + 8) * Ws : end]$;



(a)

(b)

Fig. 2: The figure illustrates the behaviour of acceleration along X-axis during different fall activities as described in table I. (a) Represents fall activities of SisFall dataset, and (b) represents fall activities of kFall dataset.

C. Network Architecture and Performance measures

A deep neural classifier based on the ensemble of 1D CNN and LSTM, named FallNet, is used to develop our Pre-Impact FDS. CNNs were traditionally used for image data since they are excellent at capturing the spatial information present in images. In contrast, LSTMs are ideal for learning temporal dependencies and are commonly used for time-series predictions. Hence, the combination of CNN and LSTM is perfect for learning the Spatio-temporal features present in the inertial human gait data. A 3D input in the form of $(samples, timesteps, features)$ was given to the model. Each input sample contained one second's worth of data making the $timesteps$ 200 (as sf was 200). In each $timestep$, the tri-axial acceleration and angular velocity signals were given, making the $features$ set 6. The network architecture and list of hyperparameters are given in table II.

A CNN learns by applying n filters $(K_1, K_2, ..., K_n)$ of size k on the input data X, which is then passed on to a non-linearity such as $ReLU$ (equation 1). Each CNN layer is followed by a max-pooling layer that downsamples the convolution operation's output.

$$conv_{layer1} = ReLU(\sum_i K_i * X') \tag{1}$$

The working of LSTM is governed by a set of equations shown in algorithm 2. LSTM learns the temporal dependencies by using the concept of cell states $C^{(t)}$, which transfer the relevant information down the sequence chain. Hence a feature learned at the earlier time step will be remembered at a later time step. Gates in LSTM are used to overcome the vanishing gradient problem [25] present in traditional recurrent neural networks (RNNs). In algorithm 2, $\tilde{C}^{(t)}$, Γ_u, Γ_f, and Γ_o represents the candidate memory cell value, update gate, forget gate, and the output gate, respectively. $x^{(t)}$ represents the input vector at time step t, $h^{(t)}$ is the hidden state at time step t, and b is the bias value. The symbols W, U, and V represent the weight matrix for hidden-to-hidden, input-to-hidden, and hidden-to-output connections, respectively, whereas the symbols σ and $\circ$ represent the sigmoid function and the Hadamard product, respectively.

TABLE II: Network Architecture and list of Hyperparameters.

	Layer Type	Units	# Filters	Activation
LSTM	LSTM	256	-	$tanh$
	Dense 1	128	-	$ReLU$
	Dense 2	64	-	$ReLU$
	Dense 3	32	-	$ReLU$
	Dense 4	8	-	$Softmax$
CNN	1D CNN , MaxPooling (PS[1] = 2)	-	128 (FS[1] = 3)	$ReLU$
	Dense 1	1024	-	$ReLU$
	Dense 2	512	-	$ReLU$
	Dense 3	8	-	$Softmax$
Batch size	512			
Input Shape	200,6			
Epochs	200			
Learning rate	Default provided by Keras			
Optimizer	Adam			
Loss function	Categorical crossentropy			
Regularizer	Dropout (rate = 0.2), L1L2, Early stopping			

[1](PS: Pool Size, FS: Filter size)

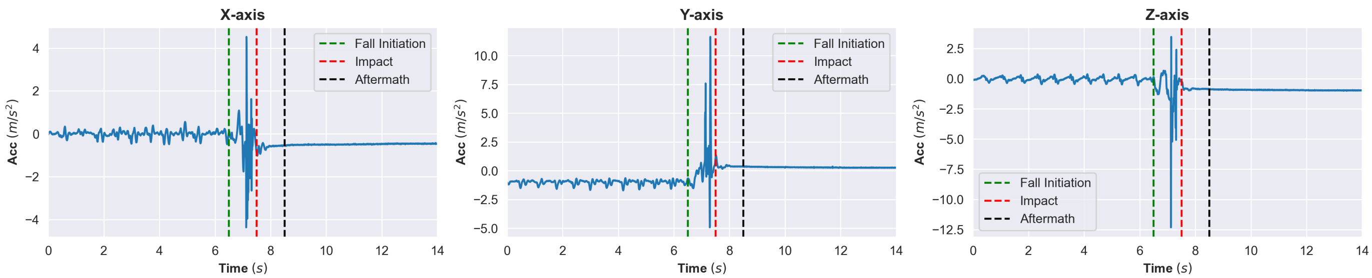
Our FDS is essentially a multi-class classifier, hence we evaluated its performance using the traditional metrics such as $Precision$ (eq 2), $Recall$ (eq 3), and $F1-score$ (eq 4). $Precision$ is the measure of the ability of the model to reduce false positives (FP), whereas the $Recall$ (also called $Sensitivity$) is the measure of the ability of the model to reduce false negatives (FN). $F1-score$ is the harmonic mean of $Precision$ and $Recall$ and is primarily used to compare the performance of two classifiers. After the time instant at which the fall is initiated (T_{Fall_init}), the lead time (T_{lead}) (eq 5) of an FDS is defined as the time interval remaining after the fall is detected (called as reaction time of an FDS (T_{react})) and before an impact on the ground (T_{impact}) [22].

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

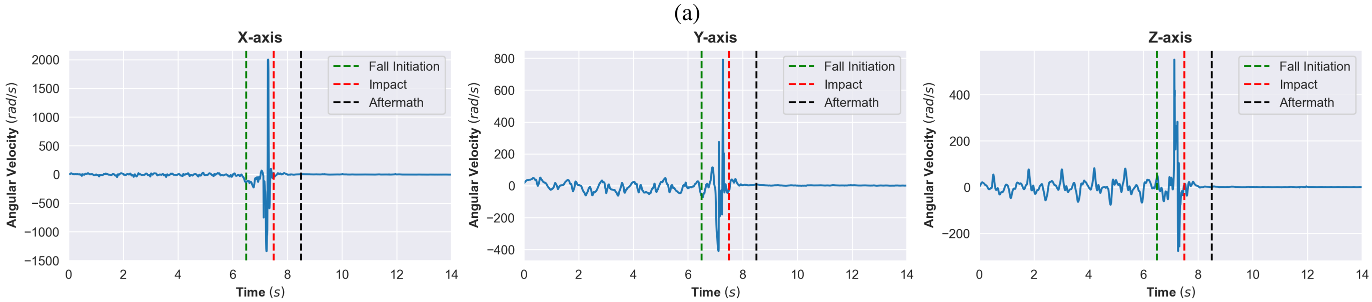
$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score = \frac{2}{Recall^{-1} + Precision^{-1}} \tag{4}$$

$$T_{lead} = \Delta T - T_{react}, \text{ where } \Delta T = T_{Fall\_init} - T_{impact} \tag{5}$$



(a)



(b)

Fig. 3: The figure illustrates the working of the proposed feature extraction methodology. Subplot (a) represents the temporal feature segmentation of raw acceleration signals in the X, Y and Z axes of the accelerometer, and (b) represents the temporal feature segmentation of raw angular velocity signals in the X, Y and Z axes of the gyroscope.

Algorithm 2: LSTM forward propagation.

for $t \leftarrow 0$ **to** n **do**

$\tilde{C}^{(t)} = tanh(Ux^{(t)} + Wh^{(t-1)} + b)$;

$\Gamma_u = \sigma(U_u x^{(t)} + W_u h^{(t-1)} + b_u)$;

$\Gamma_f = \sigma(U_f x^{(t)} + W_f h^{(t-1)} + b_f)$;

$\Gamma_o = \sigma(U_o x^{(t)} + W_o h^{(t-1)} + b_o)$;

$C^{(t)} = \Gamma_u \circ \tilde{C}^{(t)}) + \Gamma_f \circ C^{(t-1)}$;

$h^{(t)} = \Gamma_o \circ tanh(C^{(t)})$;

end

IV. Results and Discussion

All the experiments were performed on a local workstation using Python as a programming language. Standard Python modules such as TensorFlow, Keras, Pandas, and NumPy were utilized at the different stages of the experimentation. The workstation had a 64GB main memory, Intel Xeon CPU, and an Nvidia Quadro P1000 GPU with a 4GB memory.

To train FallNet, stratified K-Fold $(K = 5)$ cross-validation was utilized. Stratified sampling was used to handle the class imbalance in our data. The list of hyperparameters is given in table II. The model's generalizability is increased by feature fusion of SisFall and KFall datasets. To validate the efficacy of FallNet, 20% data was reserved in each fold for testing the model. The model has generalized exceptionally well on unseen data, as evident from the confusion matrix shown in the figure 4 and the classification report shown in table III. The model was trained on two different instances of *Fall_initiation* phase. The first instance is of ΔT duration (≈1s) and represents the point when the fall initiates to the point of impact on the ground. The other instance is $0.5\Delta T$ and is representative of the transition from $ADL - to - Fall\_init$ (T_w) to explicitly train the classifier on transitional features. The reason for this special input is to specifically train the classifier for the early detection of falls (Pre-Impact Fall). The T_w is of shape (100,6), which was interpolated to (200,6) using the cubic spline interpolation before inputting to the model. As evident from the results (table III and figure 4), the model has performed exceptionally well in detecting the *Fall_initiation* phase with a $Sensitivity$ of 0.9924, implying that the model has sufficiently learnt all the crucial fall features to minimize the occurrence of FN. $Sensitivity$ is critical for testing the efficacy of an FDS since a misinterpretation of true occurrences of falls could prove to be lethal in real-world situations. Moreover, FallNet has obtained an average $Precision$, $Sensitivity$ and $F1-score$ of 97.53%, 97.52% and 97.50%, respectively, for all the representative classes, and an accuracy of 97.52% is obtained. Further, since the T_w is of $0.5\Delta T$ duration, T_{react} becomes $0.5s$ as ΔT being $\approx 1s$, giving a sufficient T_{lead} of $0.5s$ (eq 5) to take a fall prevention measure, thus outperforming the state-of-the-art methodologies (refer to table V).

To validate our feature extraction methodology, we extracted temporal features from the KFall dataset using algorithm 1 and verified the start of the *Fall_initiation* and *Impact* frame with the temporal labels available in the KFall dataset [17]. Table IV shows the performance of our proposed feature extraction methodology compared to the ground truth values obtained from the KFall dataset. Pearson correlation coefficient $(r_{est,org})$ is utilized to establish the degree of similarity between the estimated (est) values of *Fall_initiation* and *Impact* frame with the ground truth (org) values. The same is depicted graphically using density plots in figure 5. Except for

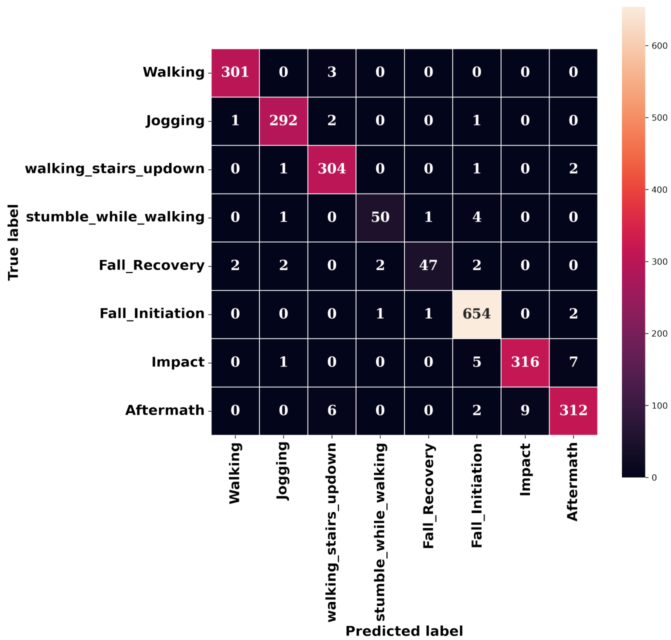


Fig. 4: Confusion Matrix depicting the predictions obtained on test data.

TABLE III: Performance of FallNet on test data.

Activity	Precision	Recall	F1-score	Support
Walking	0.9868	0.9803	0.9835	304
Jogging	0.9799	0.9899	0.9849	296
Walking_stairs_updown	0.9620	0.9870	0.9744	308
Stumble_while_walking	0.9455	0.9286	0.9369	56
Fall_Recovery	0.9792	0.8545	0.9126	55
Fall_Initiation	**0.9834**	**0.9924**	**0.9879**	**658**
Impact	0.9583	0.9787	0.9684	329
Aftermath	0.9778	0.9362	0.9565	329
Accuracy	0.9752	0.9752	0.9752	0.9752
macro avg	0.9716	0.9559	0.9631	2335
weighted avg	0.9753	0.9752	0.9750	2335

the activity T31, our methodology has performed exceptionally well in the feature segregation for all fall activities.

We have demonstrated a more generalized and detailed architecture of FDS, which is a closer representation of real-life fall situations. Our model is trained on both SisFall and KFall datasets and can distinguish between four ADLs and four phases of fall (8-class classifier). In contrast, Musci et al. [21] have presented a 3-class classifier with BKG, ALERT and FALL classes and used only the SisFall dataset for experimentation. Likewise, Yu et al. [20] and Wu et al. [23] have both presented a 3-class classifier with (Non-fall, Pre-impact fall, fall) and (Non-fall, backward fall, forward fall) classes, respectively. Moreover, De Sousa et al. [22] have presented an FDS which can only distinguish between fall and no fall scenarios. Hence, our proposed model carries more discriminative power and is better suited to real-life applications. A classifier trained on different ADLs and various phases of fall will learn the $ADL-to-fall\_init$ transitional features and can detect the early signal of fall initiating from any of the ADLs. Further, we have obtained a T_{lead} of $0.5s$ and $Sensitivity$ (eq3) of 99.24% in fall initiation phase, which is much better than the lead time of $0.259s$ and $Sensitivity$ of 94.04% reported by De Sousa et al. [22] and the lead time of $0.404s$ and $Sensitivity$ of 95.5% reported by Wu et al. [23]. A brief comparative analysis of our methodology with the state-of-the-art approaches is shown in table V.

A. Limitations

One of the key limitations of our work and most of the FDSs available in the literature is that the datasets utilised for experimentation are emulated fall datasets. Thus, it remains an open research question whether the emulated falls are a true representation of actual falls. A correlation needs to be established between the actual and emulated falls, which is only possible if actual fall data is available, which is challenging to acquire for apparent reasons. Also, since the subjects were young and healthy, will the FDSs remain equally efficient for the elderly population, which is the target population? These questions need further investigation, thus opening doors for future research directions.

Moreover, the proposed feature extraction methodology described in algorithm 1 is only tested on a selected set of activities as mentioned in table I. These are the most common fall scenarios encountered in daily life. However, the effectiveness of the algorithm 1 in other fall situations can only be evaluated through further experimentation. Also, since SisFall and KFall datasets are emulated datasets of young and healthy subjects, the adaptability of the proposed algorithm on real-world elderly fall data and pathological gait data cannot be convincingly established in this study. Further, the implementation issues of the proposed algorithm in resource-constrained environments such as micro-controllers and sensor networks are also not evaluated in this study.

V. Conclusion

In this work, we have presented a novel methodology for temporal feature extraction from inertial fall data for different fall scenarios and a deep neural classifier FallNet, a Pre-Impact FDS, capable of detecting the *Fall_initiation* phase with a $Sensitivity$ and $F1score$ of 99.24% and 98.79%, respectively, with an overall $Accuracy$ of 97.52%. A concept of transitional window (T_w) is introduced to improve the reaction time (T_{react}) of the FDS, resulting in an impressive lead time (T_{lead}) of $0.5s$, sufficient for fall prevention. T_{react} can be improved by tweaking the size of T_w. The feature extraction methodology is sufficiently validated with the laboratory-verified results, and the proposed system is thoroughly tested on two benchmark fall datasets. The initial results are promising and open doors for further experimentation in this direction. The key limitations of the proposed work are also discussed.

This work can be utilised for building IoHT-based fall detection and prevention devices for the elderly healthcare sector. The work can be extended by training the proposed FDS on pathological gait data for possible applications in gait rehabilitation. Gait rehabilitation devices such as exoskeleton robots and smart prosthetic legs can be equipped with fall detection capabilities which will further aid in the original

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TABLE IV: Comparative analysis of proposed temporal feature extraction approach with the ground truth values [17].

	Fall Initiation Frame					Impact Frame				
Activity ID *(refer to table I)*	μ_{est}	μ_{org}	σ_{est}	σ_{org}	$r_{est,org}$	μ_{est}	μ_{org}	σ_{est}	σ_{org}	$r_{est,org}$
T28	704.55	766.51	155.36	151.09	0.96	904.55	927.83	155.36	153.08	0.95
T30	532.68	612.07	116.36	112.3	0.95	732.68	760.52	116.36	116.96	0.94
T31	358.39	483.48	125.29	91.04	0.76	558.39	624.45	125.29	97.83	0.78
T32	526.73	597.37	123.21	124.95	0.98	726.73	736.97	123.21	133.9	0.96
T33	548.42	606.99	127.09	117.22	0.98	748.42	732.15	127.09	125.02	0.98
T34	721.1	782.6	143.11	137.02	0.97	921.1	909.26	143.11	140.26	0.98

(μ_{est}, σ_{est}: mean and standard deviation of estimated value (est), μ_{org}, σ_{org}: mean and standard deviation of the ground truth value (org), $r_{est,org}$: correlation between estimated and the ground truth value.)

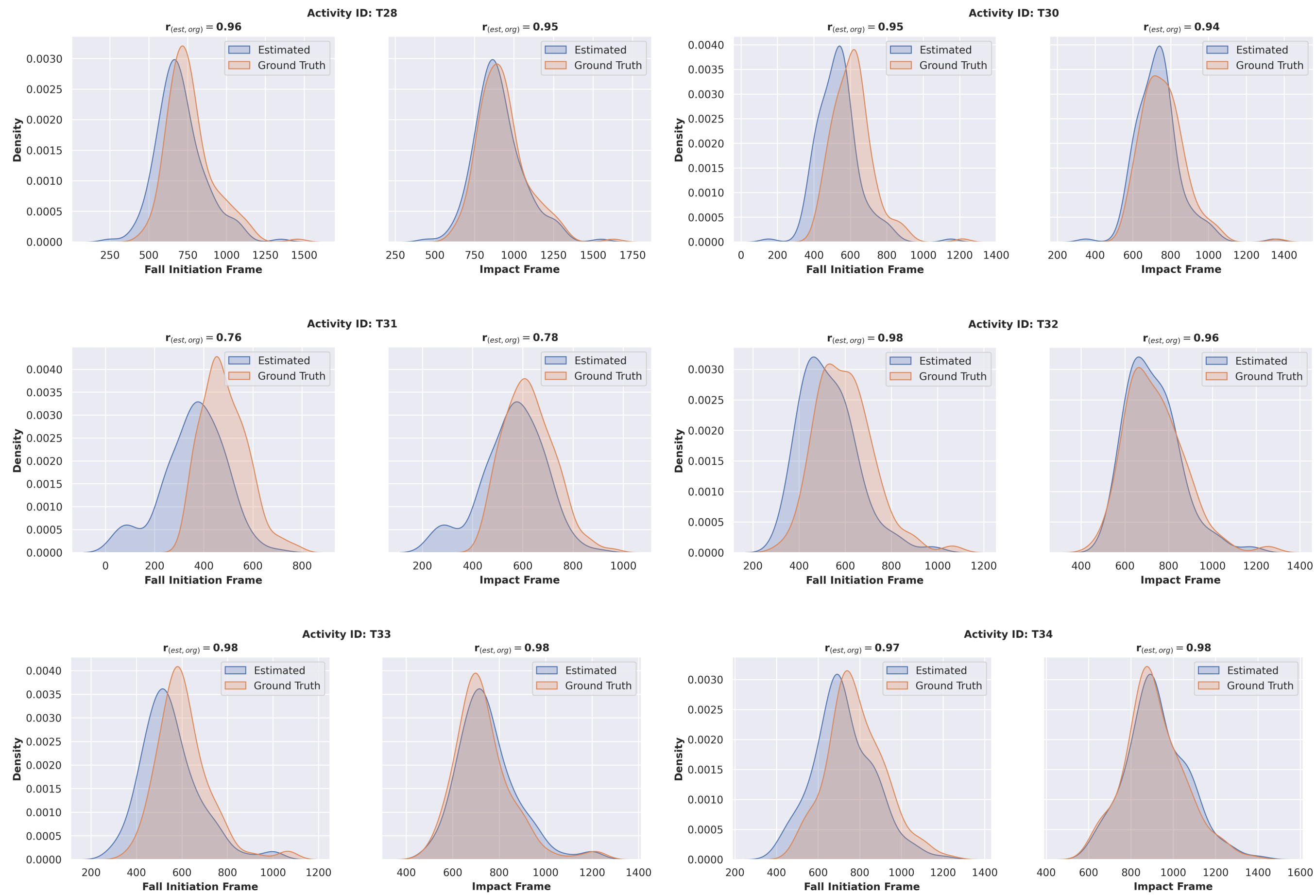

Fig. 5: Density plots representing the overlap between the estimated (est) and the ground truth (org) values for the $Fall\_initiation$ and $Impact$ frame. The degree of similarity between the est and the org [17] values is established using correlation coefficient ($r_{est,org}$). Activity IDs T28, T30, T31, T32, T33 and T34 represent different fall activities as described in Table I.

TABLE V: Performance comparison.

Reference	DPF[1]	T_{lead} (s)	Sensitivity	Accuracy
Musci et al. 2020 [21]	3 classes	Not Specified	PI: 93.41%	96.06%
De Sousa et al. 2021 [22]	2 classes	0.259	PI: 94.04%	95.86%
Yu et al. 2020 [20]	3 classes	Not Specified	PI: 93.78%	94.48%
Wu et al. 2019 [23]	3 classes	0.376 - 0.404	PI: 95.50%	95.80%
Proposed	**8 classes**	**0.5**	**PI: 99.24% M: 97.52%**	**97.52%**

[1](DPF: Discriminative power of FDS, PI: Sensitivity in detecting Pre-impact fall, M: Mean Sensitivity of the classifier)

gait restoration. Further, more fall activities can be included from diverse demographics to improve the generalizability of the FDS.

In future work, we aim to build a low-cost Pre-Impact FDS using a micro-controller such as Nano BLE sense and tinyML framework to develop a non-invasive FDS for IoHT applications to monitor the elderly population. Moreover, we aim to test the efficacy of FallNet on humanoid fall data, pathological gait data and real-world fall data. We also aim to collect our own heterogeneous multi-sensor fall dataset.

Compliance with ethical standards

All the ethical issues have been taken care of while writing the manuscript, and we have complied with all the standards to the best of our knowledge.

Conflicts of Interest

The author(s) proclaim no conflict of interest regarding this research paper with any person or organization. This manuscript is based on original research findings done by the authors themselves.

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