A Time based Sensor Data Analysis for Pre-Fall Prediction Using Machine and Deep Learning Approaches

Nazia Pathan
Queen Margaret University
Edinburgh, United Kingdom
npathan@qmu.ac.uk

Hongnian Yu
Edinburgh Napier University
Edinburgh, United Kingdom
H.Yu@napier.ac.uk

Michael Vassallo
Royal Bournemouth Hospital
Bournemouth, United Kingdom
michael.vassallo@uhd.nhs.uk

Pelagia Koufaki
Queen Margaret University
Edinburgh, United Kingdom
Pkoufaki@qmu.ac.uk

***Abstract*—Falls are a major cause of injury among older people, often leading to severe consequences, including death. To reduce this risk for both older and younger populations, Artificial Intelligence (AI) can play a critical role by predicting pre-fall states (conditions leading to a fall) and enabling timely intervention. Pre-fall prediction can be approached through various contexts, such as time-based, biological, and sensor data. This study focuses on predicting pre-falls through the time-based context by using the data from wearable sensors (accelerometer and gyroscope), while considering the time window feature of the dataset. The dataset used in this paper was collected using a MetaMotionR device and comprises two classes: "fall" and "no fall". A sliding time window approach of 5 seconds and 10 seconds was applied to prepare the dataset for pre-fall prediction. Notably, this type of dataset has not previously been utilised for pre-fall prediction. A variety of machine learning and Deep Learning algorithms were tested on this dataset. The machine learning models included Decision Tree (DT), Support Vector Machine (SVM), and Logistic Regression (LR), and Deep Learning models included Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN). Among machine learning algorithms, the DT demonstrated super performance, achieving accuracies of 95.99% and 95.75% for the 5-second and 10-second time windows, respectively. In the category of Deep Learning algorithms, Long Short Term Memory (LSTM) type of RNN models outperformed other approaches, with accuracies of 81.08% and 82.63% for the 5-sec and 10-sec windows, respectively.**

Keywords-Fall; Pre-Fall; Machine learning; Deep Learning.

I. INTRODUCTION

As the world's population ages more quickly, there is growing concern about the safety and health of the elderly. Unintentional falls are occurring frequently among older adults, which is associated to negative health outcomes. While falls can happen at any age, their impact is especially severe for the elderly, who often face longer recovery times and higher healthcare expenses; these factors can result in a reduced quality of life. The growing aging population underscores the urgency of addressing fall related risks. Therefore, fall prevention and early intervention are essential for maintaining well-being [1].

These challenges have made research on the detection and prevention of falls before they happen a priority, with recent developments in AI and wearable technology offering promising solutions [2][3]. By continuously tracking people's movements and predicting potential fall scenarios, AI systems can initiate timely interventions to prevent falls, ultimately saving lives and reducing injuries [4]. A key focus in this study is Pre-fall prediction, which can be approached from a sensor based perspective. In this approach, sensors collect data and timestamps to show early indicators of a possible fall. Each situation provides different perspectives on the elements that influence the risk of falling. This study adopts a sensor based approach, utilising gyroscope and accelerometer data to predict pre-fall instances. It highlights the importance of understanding the transitional period leading up to a fall, offering new insights into the factors that contribute to fall risk.

To facilitate this analysis, this study uses a publicly available dataset that includes sensor data collected during both fall and non-fall scenarios. To improve the understanding of Pre-fall (leading to fall) conditions, the dataset was segmented into fixed time windows of 5 and 10 seconds preceding each fall event. This segmentation captures the transitional phase before a fall and provides contextual data that enhance the predictive accuracy of the models. Both Machine Learning (ML) and Deep Learning (DL) algorithms were tested for their effectiveness in predicting pre-fall. The tested models included LR, DT Classifier, Support Vector Machine, Multi-Layer Perceptron, Gradient Boosting, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Long-Short-Term-Memory (LSTM).

Most existing studies focus on post fall detection and under-utilize temporal sensor data for pre-fall prediction. This study addresses these gaps by using gyroscope and accelerometer data within 5 and 10 second windows to enable early fall prediction and timely interventions.

The following are the main contributions of this study:

- Predicting pre-fall instances was achieved using wearable sensor data (gyroscope and accelerometer) segmented into 5 and 10-second time windows.
- A comparative analysis of ML and DL algorithms showed that DT performed the best among the machine learning models, while the LSTM model was the most effective Deep Learning model for pre-fall detection.

- The proposed framework for predicting fall risks in real time facilitates timely interventions, thereby reducing injuries caused by falls and providing overall safety through immediate fall risk assessment.

The remainder of this paper is organized as follows. Section II reviews related work and existing approaches. Section III presents the proposed methodology. Section IV reports experimental results, and Section V discusses the findings. Finally, Section VI concludes the paper and outlines future work.

II. Literature Review

With the aging population and associated risks, the need to address fall related challenges has become increasingly urgent. Researchers are now focusing on early detection systems and preventive measures to mitigate these risks [5][6][7]. The development of wearable sensor technologies, such as gyroscopes and accelerometers, has significantly transformed falls detection and prevention. These devices enable continuous, real-time motion tracking, making it possible to detect of unusual patterns associated with potential falls [8][9]. Due to their portability, non-invasive nature, and high data collection capacity, wearable sensors have proven to be extremely useful for developing ML and DL models [8][10]. While fall detection research has historically concentrated on post-fall identification, more recent studies emphasise pre-fall prediction to allow for prompt intervention. Pre-fall prediction identifies transitional movements indicating an elevated risk by analysing motion patterns during brief time windows before a fall [11][12].

Strong performance in classifying fall related data has been shown by machine learning techniques, such as Logistic Regression (LR), Decision Tree (DT), Support Vector Machine (SVM), and Gradient Boosting [5]. However, time series sensor data analysis is a perfect fit for Deep Learning models, especially LSTM networks, which have demonstrated exceptional performance in capturing temporal dependencies in sequential data [13][14].

When developing and accessing fall detection systems, datasets play an essential role. One example of such datasets are SisFall[15], which is gathered using an accelerometer and gyroscope. It contains classes for Activities of Daily Living (ADL) and falls, gathered from both younger and some older individuals. These activities were selected based on a literature survey [15]. UpFall includes the dataset of 17 individuals who performed 11 daily living activities, as well as falls [16]. The UMAFall dataset highlights the difference between the various approaches of machine learning to fall detection [17]. KFall is a comprehensive dataset for fall inertial sensors (acceleration, gyroscope and Euler angles) which are synchronised with video based fall labels [18]. These datasets were gathered from numerous sensors, both wearable and non-wearable, during everyday activities and simulated falls. Under controlled circumstances (Lab-based environment), these datasets allow researchers to train and validate ML and DL models. Recent advancements in fall prediction and detection are increasingly using wearable and vision based technologies. For instance, the system presented in the study [19] uses both wearable and vision-based sensors, giving a sensitivity of 96% using Hidden Markov Models (HMM) and a decision tree. Many other studies are focusing on real time applications, [20] employs the ConvLSTM network and techniques for real time fall detection and prediction, achieving a high accuracy rate of 98.3%. Similarly, KNN, GRU(Gated Recurrent Unit), and SVM algorithms, along with the wearable sensors, are used to predict falls with an accuracy of 93.5% [21]. Heterogeneous Hidden Markov Model (HHMM) is used for the effective recognition and prediction of falls by utilising the 3D Vision based body data with an accuracy of 81.5% [22]. Additionally, the Kinect System, along with Zero Moment Point (ZMP) and SVMs approaches, was used to reach an accuracy of 91.7% [23]. Deep Learning methods are commonly used in fall detection and prediction research, such as the use of CNNs with Class Activation Maps (CAM), which can detect the impact of a fall before it happens by utilising the wearable sensors. This approach has achieved an accuracy of 95.33% [24]. The PreFallKD system, which integrates CNNs and Vision Transformers with knowledge Distillation, demonstrates strong performance with a 92.66% F-1 score in real time fall prediction using wearable sensor data [25]. However, most existing fall detection systems focus on post fall identification, which limits the potential for prompt interventions. Additionally, temporal data for pre-fall prediction remains underutilised. This study addresses these gaps by leveraging accelerometer and gyroscope data within 5 and 10 second time windows to predict pre-fall conditions. We assess conventional machine learning models (e.g. SVM, DT, and more sophisticated DL architectures (RNN and CNN)), offering a framework for early intervention and fall risk mitigation.Table I shows the comparison of fall detection and prediction approches.

To the best of our knowledge, our study is among the first studies to use this specific MetaMonitor dataset with sliding time windows of 5 s and 10 s for pre-fall prediction, combining both ML and DL models to emphasize the role of temporal context in improving pre-fall prediction.

III. Methodology

The subsequent Figure 1 illustrates the methodological process in this study. The methodology includes various components, such as dataset sampling (data generation), dataset cleaning, preprocessing, modelling and evaluation.

A. Dataset

This study utilised a publicly accessible dataset [26] collected using the MetaMotionR sensor. Data was gathered using two wearable sensors (accelerometer and gyroscope) positioned at the user's waist. The dataset comprises recordings from 17 participants (4 females, 13 males) with an average age of 30 ± 8.02 years, height 174.18 ± 7.85 cm, and weight 74.35 ± 9.71 kg performing various Activities of Daily Living (ADLs) and simulated fall (lab based) events in controlled conditions. The ADLs included jumping, running and stopping, sitting on a chair, and pulling the sensor. The fall scenarios included

TABLE I. COMPARISON OF FALL DETECTION AND PREDICTION METHODS

No.	Refrence	Prediction	Detection	Real Time	Wearable	Vision	AI/ML	Accuracy / Perf.
1	[19]	Yes	Yes	No	Yes	Yes	HMM, DT	Sens: 96%
2	[20]	Yes	Yes	Yes	Yes	No	Conv, LSTM, Smoothing	Acc: 98.3%
3	[21]	Yes	Yes	Yes	Yes	No	KNN, GRU, SVM	Acc: 93.5%
4	[22]	Yes	Yes	Yes	No	Yes	HHMM	Acc: 81.5%
5	[23]	Yes	Yes	Yes	No	Yes	SVM, Mod. ZMP	Acc: 91.7%
6	[24]	Yes	Yes	Yes	Yes	No	CNN + CAM	Acc: 95.33%
7	[25]	Yes	Yes	Yes	Yes	No	CNN + ViT KD	F1: 92.66%

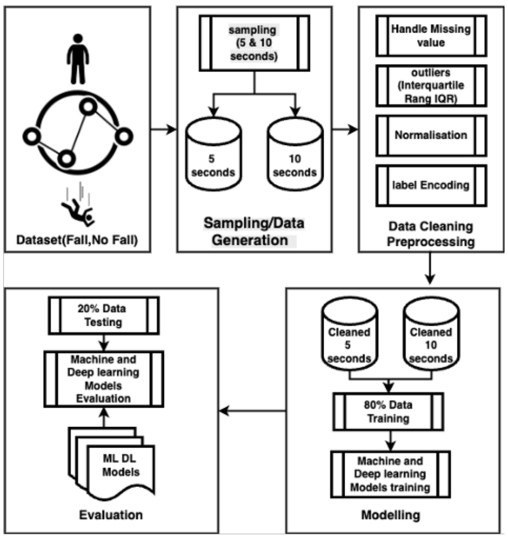

Figure 1. Methodology.

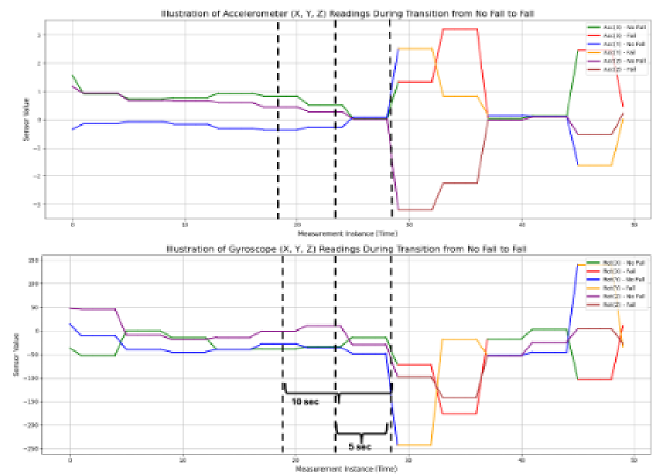

Figure 2. Illustration of all Instances (Fall, no fall) sub figure (a) shows the sensor values of accelerometer and sub figure (b) shows the sensor values of gyroscope.

forward falls, right-side falls, left-side falls, and backwards falls. MetaMotionR sensor records acceleration, rotation, and orientation. Falls were performed on a mat for safety, with a 1-second data window captured when acceleration exceeded 2.5 G. This dataset was chosen due to the nature of the sensor and time stamping for evaluating the performance of various ML and DL algorithms. In this study, we only considered two classes: fall and no fall. Figure 2 shows the values of features (x,y,z) from both the accelerometer and the gyroscope for instances of fall and no fall. It can be observed that both fall and no fall follow distinct patterns; the value of the accelerometer (Acc(X)) is lower in the fall instance and higher in the no fall instance. In case of Acc(Y), the values are higher for the fall event but lower when there is no fall. Acc(Z) shows lower values during fall and higher values for no fall. For the gyroscope readings, fall events are associated with higher Rot(X)and Rot(Y) values while Rot(Z) values are lower. These observed patterns highlight the potential of sensor based features in distinguishing between fall and non-fall events.

B. Sampling/ Data Generation

Data sampling was conducted to create the pre-fall dataset, capturing the time window preceding each fall event. The dataset comprises timestamps (e.g., 5 seconds, 10 seconds), sensor readings, and a binary fall indicator (e.g., 1 representing a fall). The timestamp denotes a fixed time window (e.g., 5 seconds) before each fall, facilitating the identification of conditions that lead to a fall event. Data was chronologically sorted by timestamp to generate the dataset, with fall events marked as 1 and Pre-Fall events as 0. This relationship can be expressed mathematically as follows:

$$prefall = t_{fall} - T_w \leq t_{event} \leq t_{fall} \tag{1}$$

Where t_fall is the timestamp of the fall event, T_w is the time window before fall, which is taken for prefill, which in this case is 5 and 10 seconds, and t_{event} is the timestamp of any row in the dataset. Figure 3 further illustrates the sensor (both accelerometer and gyroscope) reading from a typical no-fall to a fall transition. The pre-fall period is virtually highlighted for both 5 and 10-second windows preceding the fall, showing the temporal dynamics captured in the dataset.

C. Data Preprocessing /Cleaning

The data cleaning process contains several techniques. Firstly, the dataset was checked for missing values [27]. If any missing values are found, they were replaced by the mean of their respective columns. After addressing missing values, the next step was identifying and removing outliers. Outliers were removed using the interquartile range method to prevent them from destroying model training and accuracy [28]. Once the dataset is refined, normalisation is applied in standard scaling to ensure that all data points fall within a consistent range. While ML models often require normalization, feature selection, or handcrafted feature extraction, DL models can automatically

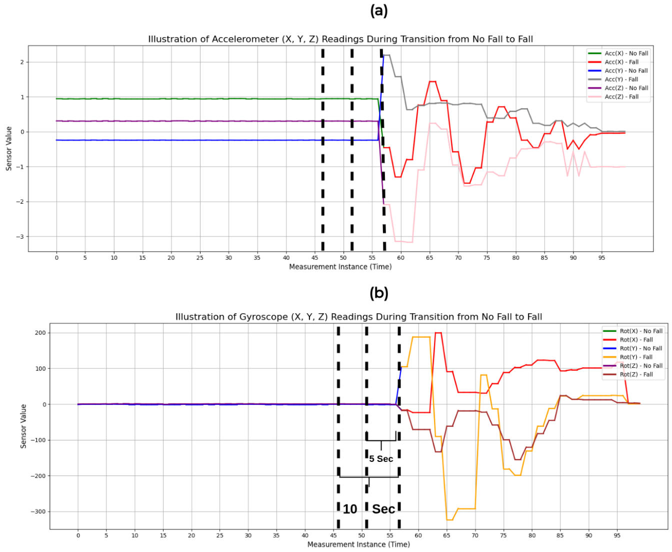

Figure 3. Illustration of sensor readings from Fall to no Fall sub figure (a) shows the sensor values of accelerometer and sub figure (b) shows the sensor values of gyroscope.

learn hierarchical features from raw sensor data, simplifying the overall workflow and potentially capturing more complex temporal patterns.

D. Data Modeling

After completing the preprocessing and data cleaning stages, 80% of the data was utilised to train ML and DL algorithms. For the ML, the data was trained using LR, DT, SVM, Multilayer perceptron (MLP), perceptron, and gradient boosting. The DL algorithms employed include LSTM, CNN, RNN, and DNN. Once the models were trained, the remaining 20% of the data was used to test the ML and DL algorithms. The model's performance was evaluated using Accuracy (the ratio of the number of correctly classified instances to the total number of instances predicted), Precision (the ratio of correctly predicted positive instances to all positively predicted instances) and Recall (the proportion of predicted positive instances to all actual positive instances) factors. These parameters provide comprehensive evaluation of model's performance to predict pre-fall.

IV. Results

The experiments for this study were conducted using Google Colab and Python, utilising 32 GB of RAM and 128 GB of storage. The DL models were trained over 20 epochs after which no significant performance gains were observed, and early stopping was applied to prevent overfitting. The results obtained from experiments using 5-second and 10-second window data by applying ML and DL algorithms, as proposed in the framework. The performance of ML and DL algorithms with the parameters Accuracy(Acc), Precision(Pre) and Recall(Rec) is summarised in Table II. Among all ML models, the DT classifier model has performed efficiently with an accuracy of 95.99% and 95.75% on 5-second and 10-second windows, respectively. For DL models, LSTM has performed efficiently with an accuracy of 81.08% and 82.63% on 5-second and 10-second windows, respectively. Figure 4 illustrates the precision-recall curve and ROC (Receiver operating characteristic) curve for the DT under 5 and 10-second windows. The curves demonstrate a high area under both metrics, indicating strong model accuracy. The 10-second window shows a slightly steeper curve, reflecting marginally improved performance.

TABLE II. ACCURACY, PRECISION AND RECALL FOR 5 AND 10-SECOND TIME WINDOW

5 Second Window			
Algorithms	**Acc**	**Pre**	**Rec**
Logistic Regression	78.75%	59.21%	46.86%
Decision Tree Classifier	95.99%	92.26%	91.58%
Support Vector Machine	82.02%	60.26%	81.41%
MLP Classifier	82.24%	62.02%	73.81%
Perceptron	69.72%	43.88%	77.93%
Gradient Boosting Classifier	84.58%	63.16%	91.18%
RNN	80.60%	56.84%	88.17%
CNN	78.53%	55.00%	70.26%
DNN	75.97%	54.86%	13.48%
LSTM	81.08%	57.42%	89.52%
10 Second Window			
Algorithms	**ACC**	**PRE**	**Rec**
Logistic Regression	78.98%	62.11%	53.78%
Decision Tree Classifier	95.75%	92.27%	91.72%
Support Vector Machine	83.49%	64.03%	86.57%
MLP Classifier	82.13%	65.51%	69.35%
Perceptron	73.18%	49.75%	81.00%
Gradient Boosting Classifier	85.08%	65.13%	94.55%
RNN	82.08%	60.79%	90.05%
CNN	78.74%	61.74%	50.74%
DNN	78.13%	57.89%	62.22%
LSTM	82.63%	61.69%	89.84%

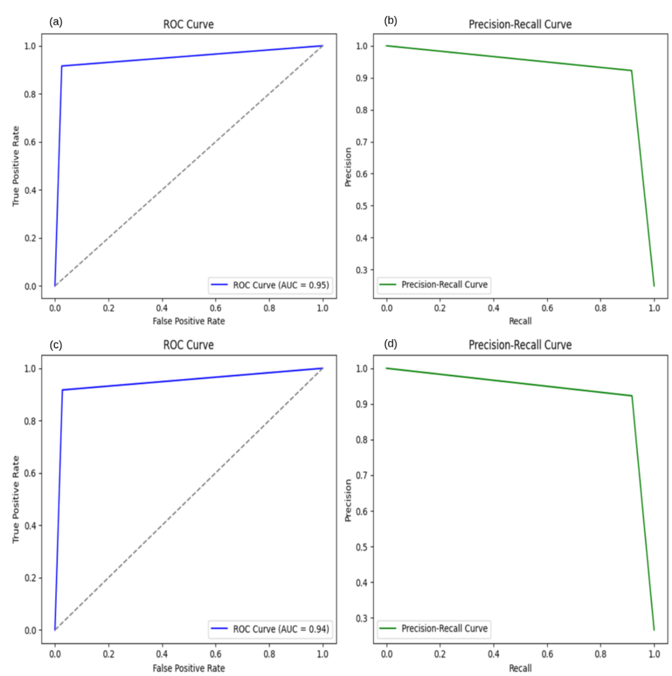

Figure 4. ROC Curve and Precision Recall Curve. (a) and (b) represent ROC curve and Precision recall curve for decision tree for 5 second window and (c) and (d) show ROC curve and Precision recall curve for decision tree for 10 second window.

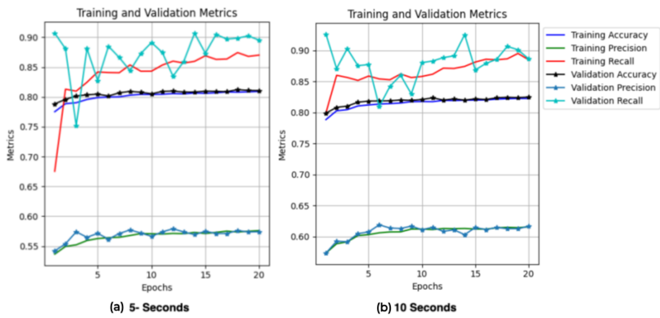

Figure 5. (a) Training, Validation and Testing Accuracy, precision and recall over 20 epochs for LSTM on 5 second window (b) Training, Validation and Testing Accuracy, precision and recall over 20 epochs for LSTM on 5 second window.

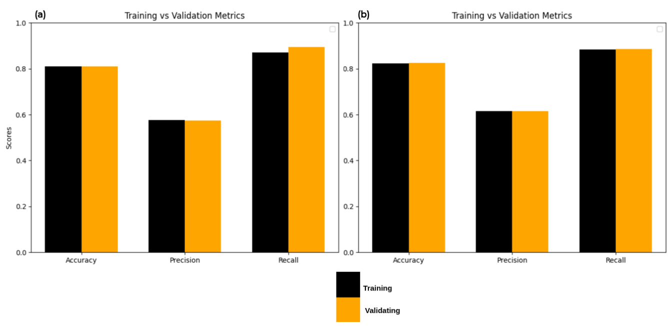

Figure 6. (a) Training and testing validation accuracy, precision and recall on 5 second window (b) Training and testing validation accuracy, precision and recall on 10 second window.

Figure 5 illustrates line graphs for training and validation accuracy, precision and recall over 20 epochs for the LSTM model. The graph highlights a steady improvement in these metrics as training progresses. A slight gap between training and validation metrics indicates that the model fits well and is generalised effectively.

Figure 6 compares training and validation precision and recall for the LSTM model across 5 and 10 second windows. The minimal difference between training and validation metrics suggests the model's robustness and adaptability to the use case.

V. Discussion

This study investigated pre-fall prediction using time stamped data collected from wearable sensors. The dataset included readings from the accelerometer and the gyroscope. The dataset consists of two classes, fall and no fall. To predict Pre-fall events, the dataset was transformed to 5 and 10-second time windows preceding fall occurrence. Both ML models, including Logistic Regression, Decision Tree Classifier, Support Vector Machine, MLP Classifier, Perceptron, Gradient Boosting Classifier and DL models, such as RNN, CNN, DNN, LSTM, were evaluated to identify their effectiveness for pre-fall prediction. The results of model tests indicate the that the DT Classifier is the best performing ML model, achieving an accuracy of 95% across both time windows. This means that the predictions made by the model for the pre-fall events were correct 95% of the time. The DT model was able to perform so well because of its ability to handle datasets with temporal features. In this study sensor readings were taken as temporal feature, which enhance the predative strength of DT model. Among DL models, LSTM performed well, achieving the accuracies of 81.08% and 82.63% for 5 and 10 second windows, respectively. Based on the comparative analysis, the results suggest that although LSTM is good with temporal features, traditional ML models, such as Decision Trees, are more suitable for this dataset due to their structure and features. The robustness of the proposed solution can be seen by the fact that models were tested across multiple time windows (5s and 10s) and using diverse ML and DL models. The consistent performance of DT in ML models and LSTM in DL models across both 5 s and 10 s windows demonstrates the framework's ability to generalize well under varying temporal conditions, which is crucial for reliable real world deployment. Since all of the experiments are performed on single dataset uniform sensor type i.e. accelerometer and gyroscope there exist the chance of data bias which only be studied and covered by including more dataset as discussed in future work.

VI. Conclusion and Future work

In this study, a time-stamped dataset was used to predict pre-fall using machine learning and Deep Learning. The threshold windows set for pre-fall prediction were 5 seconds and 10 seconds. Based on these time frames, ML and DL algorithms are applied to this dataset. The results indicated that the best performing model is a decision tree with an accuracy of 95% for both 5 and 10-second windows. For DL, LSTM has been demonstrated to be the most suitable model. The nature of data favored traditional machine learning models such as decision trees. The main contribution of this study includes, to perform pre-fall prediction on time-stamped datasets and provide the evaluation scores for these techniques. Additionally, this study evaluated and compared the performance of ML and DL models for pre-fall prediction and established the baseline performance for future research. In the future, more advanced ML and DL approaches will be explored on real-time datasets to further enhance the accuracy and generalisation of pre-fall prediction systems.

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