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Towards an Accelerometer-Based Elderly Fall Detection System Using Cross-Disciplinary Time Series Features

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ABSTRACT Fall causes trauma or critical injury among the geriatric population which is a second leading accidental cause of post-injury mortality around the world. It is crucial to keep elderly people under supervision by ensuring proper privacy and comfort. Thus the elderly fall detection and prediction using wearable/ non-wearable sensors become an active field of research. In this work, a novel pipeline for fall detection based on wearable accelerometer data has been proposed. Three publicly available datasets have been used to validate our proposed method, and more than 7700 cross-disciplinary time-series features were investigated for each of the datasets. After following a series of feature reduction techniques such as mutual information, removing highly correlated features using the Pearson correlation coefficient, Boruta algorithm, we have obtained the dominant features for each dataset. Different classical machine learning (ML) algorithms were utilized to detect falls based on the obtained features. For individual datasets, the simple ML classifiers achieved very good accuracy. We trained our pipeline with two of the three datasets and tested with the remaining one dataset until all three datasets were used as the test set to show the generalization capability of our proposed pipeline. A set of 39 high-performing features is selected, and the classifiers were trained with them. For all the cases, the proposed pipeline showed excellent efficiency in detecting falls. This architecture performed better than most of the existing works in all the used publicly available datasets, proving the supremacy of the proposed data analysis pipeline.

INDEX TERMS Machine learning, feature selection, activities of daily living, feature extraction, signal magnitude vector.

I. INTRODUCTION

The hospital emergency department is frequently filled with elderly fall cases, which is the second most frequent reason for accidental deaths around the world [1], [2]. It may be a sign of poor physical condition and declining body functions [3], [4]. According to the Kellogg International Working Group, a fall is an unexpected event of coming down to the ground or a lower level due to a blow, loss of consciousness, or health-related issues [5]. The incident that happens when the center of gravity of the body is momentarily rejected is called a fall [6]. It is an involuntary change of posture of a person that eventually consequences to drop on the floor [7].

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With age, people become physically less active to respond to immediate changes during regular activities [8], [9]. Among the elderly, fall cases cause not only injury but also death. Every year almost 37.3 million fall incidents happen worldwide, which receives medical treatment from the hospitals. In addition, 646,000 disastrous falls take place which results in death, and individuals aged over 65 experience most of them [10]. Thirty percent of older adults experience falls at least once in a year, and this trend is rising up to 42 percent for individuals aged over 70 [11]. About 22.6% of the older fall patients were reported to experience at least a single recent fall event in a half-year [12]. If older people are not identified and secured when they fall, it may lead to significant injuries and even can cause death [13]. However, trying to predict a fall event and prevent it from happening would be a hard to solve problem. The research of fall detection systems thus becomes a substantial interest in preventing complications from falls in older people. Various fall detection methods have been explored and discovered over the past two decades. Different algorithms were studied alongside the utilization of various types of sensors (such as wearable, environmental, vision) for the purpose of fall detection and prevention.

Among the recent researches, wearable sensor-based fall detection has become popular [14]–[22]. Nho *et al.* [14] in proposed an adaptive fall detection approach, where a fusion of heart rate sensor and an accelerometer was used. Authors used a 13-dimensional feature subset that was reduced through a filter and wrapper feature selection method. A cluster analysis based Gaussian mixture model (GMM) was proposed to detect fall. Saleh *et al.* [15] described a fall detection approach, where a low-cost accelerometer was used to collect data. Mean and standard deviation of accelerometer data was used as a feature set that required low computational effort, where fall was classified using a support vector machine (SVM) classifier. A real-time fall detection method using an accelerometer was introduced by Sucerquia *et al.* [16]. The signal from the accelerometer was passed through filters (a Butterworth and a Kalman filter) to extract features at a low computational cost. Finally, a threshold value was imposed on the features to detect fall events. Xi *et al.* [17] introduced an activity and fall detection approach, where surface electromyography (sEMG) sensor was used. This sensor was attached to the subjects, and fifteen feature extraction and five classification approaches were considered. Montanini *et al.* [18], employed an accelerometer and force sensors embedded on a smart shoe, and these sensors gather motion and foot orientation data to analyzed abnormal orientation of the subjects to detect falls. A wrist-worn device-based fall detection method was introduced by Quadros *et al.* [19]. The device contained a gyroscope, accelerometer, and magnetometer to capture data, which was used to extract different kinds of features. Different Machine Learning (ML) algorithms and threshold-based classifiers were finally attached to the proposed architecture to determine falls/activities of daily living (ADL).

Genovese *et al.* [20] introduced fall prevention and detection method through a waist-worn device. A wearable inertial measurement unit (WIMU) was attached at the subject's waist, where a data logger was maintained to not only to detect falls but also reduce its risk. Hussain *et al.* [21] showed an ML and wearable sensor-based approach to detect the pattern of falls and activities related to fall. The authors used a publicly available dataset, a sliding window approach, and different ML classifiers in the proposed architecture. Kerdjidj *et al.* [22] showed a method where low power consumption was assured in a wearable device through orthogonal matching pursuit and compression sensing matching pursuit to detect fall and classify activity. Different ML methods (such as K-Nearest Neighbor (KNN), SVM, Decision Tree (DT), Ensemble Classifier) were used in this study for classification tasks. Novelty detectors were introduced in fall detection by Medrano *et al.* [23], where fall detection was considered as anomaly detection. They trained different novelty detectors in real-world ADLs, which ensures adaptation in a new user's case. Finally, the classification was performed based on the best combination of features.

These fall detection systems were mainly developed using shallow ML, deep ML or rule-based algorithms. In all the cases, feature extraction is an important step to obtain the best features for fall detection. In the previous studies, researchers identified many features to detect falls, but no features were state-of-the-art for fall detection. This research gap is addressed in this article to identify meaningful features for any fall detection dataset using an accelerometer sensor. We propose a fall detection data analysis pipeline to extract cross-disciplinary time-series features for identifying potential falls and reducing overfitting. This article has computed a large variety of features for our incorporated publicly available fall detection datasets from cross-disciplinary time series domains using a highly comparative time-series analysis (HCTSA) package [24]. The main reason behind calculating cross-disciplinary time-series features was to find a new feature set from different time series domains, which can play a significant role in fall detection on top of existing features already used in previously studies. Moreover, this makes the feature extraction process less domain-specific as we do not have to calculate pre-determined hand-engineered features. Several feature selection steps have been adopted to find out the most relevant features for any dataset. Different ML classifiers (SVM, Logistic Regression (LR), DT, Random Forest (RF), KNN, Naïve Bayes (NB)) are used to detect fall events. We have compared the proposed pipeline with existing methods. The main contributions of this paper are given below:

1) A set of features have been proposed for fall detection, which is not previously used.
2) A fall detection data analysis pipeline is used, which automatically extracts a large set of features and selects the dominant features for any fall detection dataset.

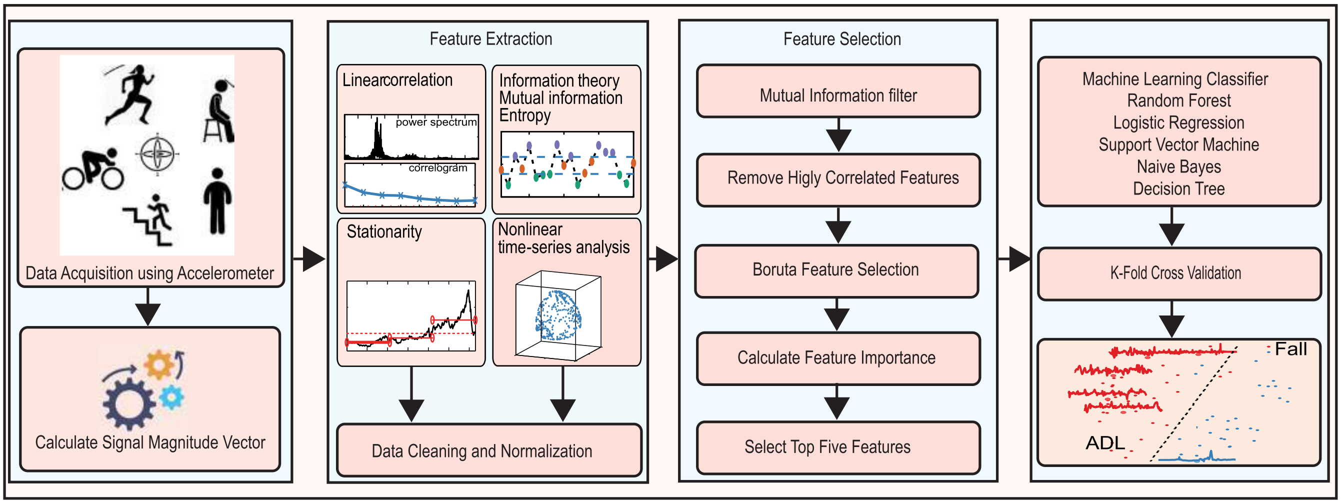

FIGURE 1. **Proposed fall detection data analysis pipeline where the Accelerometer sensor collects movement data from the subject. The SMV for each sample is then computed. Feature extraction is then performed based on cross-disciplinary time series methods and then performed several feature selection steps. Different ML classifiers are used for fall detection.**

3) We have analyzed our proposed method using three popular publicly available datasets.

The rest of the paper is organized as follows. The proposed method and utilized datasets are discussed in section II. The experiments and the results are discussed in section III. Discussions and conclusions of this study are described in section IV and section V, respectively.

II. METHODOLOGY

In this study, fall detection is considered as a time-series problem to explore the cross-disciplinary time-series features. We have used a single accelerometer sensor for fall detection and collect raw acceleration data containing a multivariate time-series signal. We have converted raw acceleration data into a univariate time series signal by calculating the signal magnitude vector (SMV) (see details in subsection II-C). Then our goal is to extract cross-disciplinary time-series features for these univariate SMVs. We have extracted more than 7700 cross-disciplinary time-series features for each dataset using the HCTSA package. As there are huge number of features for each time-series event, we need to find the most significant features for the fall detection task and eliminate the remaining features.

We have proposed a data analysis pipeline (Fig.1), which can reduce the massive number of features into a few dominant features set and reduce overfitting. At first, we applied a mutual information feature selection algorithm (discussed in subsection II-F1) to select the top 500 dominant features to identify falls and ADLs. The Pearson correlation coefficient (see subsection II-F2) between each feature was calculated to remove highly correlated features. We grouped all the correlated features and took one feature from each group using feature importance. As a result, redundant and highly correlated features were discarded, and the feature matrix's size decreased significantly. In this way, the number of features becomes almost half. Then we have applied the Boruta feature selection algorithm (see detail in subsection II-F3) to the uncorrelated features. Afterward, we have calculated the feature importance of each feature obtained from the Boruta algorithm and selected the top five dominant features based on feature importance. Finally, these top five dominant features were used to train different ML classifiers for fall detection. To evaluate the performance of our method, we have used K-fold cross-validation. The detailed description of each step is discussed in the following subsections.

A. DATASETS

Many fall detection datasets have been developed throughout the last few years. These datasets were mainly developed based on different sensor categories such as wearable, vision, ambient and multimodal. We have searched existing literature to find the wearbale sensor-based publicly available datasets. A summary of wearable sensor-based different fall detection datasets has been shown in Table 1. These datasets utilize accelerometer, magnetometer, gyroscope, EEG sensors etc. to collect falls and ADL events. In this work, we have proposed an accelerometer sensor-based fall detection data analysis pipeline to detect falls, so that we need to incorporate some accelerometer based dataset. We also want to analyze our pipeline on different sampling rate to see the robustness of our method towards different sampling rate. As a result, we need to select different accelerometer based datasets having different sampling rate. We have used three popular publicly available fall datasets (UR Fall, MOBIFALL, UP Fall) to evaluate our data analysis pipeline where sampling rate of these datasets are highly varies. A summary of each dataset is described in the following subsections.

1) UR FALL DATASET

The University of Rzeszow developed the "UR Fall" [26] dataset, which is now publicly available. This dataset contains

TABLE 1. Name, Sensor, Sensor Placement, Type of Fall and ADL, and Sample Number of Different Wearable Sensor Based Publicly Available Fall Datasets.

Reference	Dataset	Sensor	Sensor placement	Sampling rate	No. of Fall / ADL type	No. of Fall / ADL sample
[25]	MOBIFALL	Acc, Gyr	trouser pocket	100 Hz	4 vs 9	288/342
[26]	UR Fall	Acc	Pelvis	256 Hz	3 vs 5	30/40
[27]	UP Fall	Acc, Gyr, IR, EEG	neck, wrist, waist, ankle, and pocket	18.4 Hz	5 vs 6	255 / 306
[28]	SisFall	Acc, Gyr	Waist	200 Hz	15 vs 19	1798/2707
[29]	tFall	Acc	Pocket	50 Hz	Normal vs 8	1026/9883
[30]	UniMiB SHAR	Acc	trouser pocket	50 Hz	8 vs 9	4192/7579
[31]	UMAFall	Acc, Gyr, Mag	ankle, wrist, waist and chest	200 Hz	3 vs 8	209/332
[32]	Cogent Labs	Acc, Gyr	Chest, Thigh	100 Hz	6 vs 8	448/1520
[33]	DLR	Acc	Belt	100 Hz	NS vs 6	53 /1077

Legend: Acc–Accelerometer; Gyr–Gyroscope; Mag–Magnetometer; NS–Not Specified; NA–Not Available; IR–Infrared

70 events, 30 of which are fall events, and the rest 40 events are daily activities. Different daily activities and fall events were recorded using two Microsoft Kinect cameras and one waist-mounted accelerometer sensor simultaneously. The dataset contains RGB images, depth images, and corresponding acceleration sequences. The acceleration sequences are converted into a total sum vector and saved against a timestamp in milliseconds. This article only considered the waist mounted accelerometer data for the analysis.

2) MOBIFALL DATASET

The MOBIFALL [25] dataset was developed based on smartphone inertial sensor (accelerometer and gyroscope) data as the number of smartphone users has increased. A Samsung Galaxy S3 device was used to capture four different types of falls and nine different daily activities. Eleven volunteers have been recruited to perform each type of fall and ADL in the experimental environment. Among them, five participants were female, and the rest of the participants were male. The age range of the recruited participants was 22-36 years old. A five-centimeter-thick mattress was used to perform fall activity freely. The Samsung device was placed at the trouser pockets of each participant during data collection. Three trials were conducted for each activity and fall event by each recruited participant. The sampling rate was 100 Hz. We only used the accelerometer data in this research work.

3) UP FALL DATASET

UP fall [27] is a publicly available dataset that was first published in 2019. Seventeen young volunteers were recruited to perform different ADLs and fall events. The age range of recruited volunteers was 18 to 24 years. The average height and weight of recruited volunteers were 1.66 meters and 66.8 kg, respectively. This dataset consists of six different daily activities and five various fall types. Different wearable sensors, environmental sensors, and vision sensors were used to capture these 11 activities in an experimental setup. Wearable sensors such as accelerometer, gyroscope, electroencephalograph (EEG) were utilized. Accelerometer and gyroscope were placed at five different parts of the body (neck, wrist, waist, ankle, and pocket). The EEG sensor was placed at the forehead of the recruited subjects. Five infrared sensors and two Microsoft cameras were also used. We only considered the waist mounted accerleormeter data from this dataset.

B. RAW ACCELERATION SIGNAL

In this article, we have considered a wearable accelerometer sensor for fall detection. The accelerometer sensor measures human movement due to fall events and other daily activities. The accelerometer sensor gives its outcome in a three-dimensional vector. Many previous research works incorporated a wearable accelerometer sensor to distinguish between fall and non-fall events. It is observed that the accelerometer gives a higher peak in fall samples in contrast to the ADL events. Three publicly available datasets incorporate accelerometer data of various sampling rates and acceleration ranges. A robust method has been created that can detect falls without the need of a further preprocessing step.

C. SIGNAL MAGNITUDE VECTOR

Sometimes, raw acceleration signals cannot identify fall events that are close to normal daily activities (see Fig.2). We need to extract significant features from the raw acceleration signal. In this research work, we have calculated the SMV from the measured acceleration signal. The mathematical expression of the SMV is given in the Eq. (1).

$$SMV = \sqrt{(A_x)^2 + (A_y)^2 + (A_z)^2} \tag{1}$$

Here, $A_x = x$ axis acceleration, $A_y = y$ axis acceleration, $A_z = z$ axis acceleration. Fig. 3 depicts the SMV of different fall and ADL events in the UR fall dataset. The triaxial accelerometer signal (x,y,z) is interpreted as a univariate

TABLE 2. Existing Fall Detection Literature Features on Accelerometer Sensor Equiped Systems.

Features	
median	correlation coefficients
mean frequency	differential of acceleration
kurtosis	harmonic ratios
maximal amplitude	maximum absolute value
autocorrelation	mean absolute deviation
mean	Pearson correleation
median frequency	principal frequency
first quartile	range
minimal amplitude	root mean square
entropy	signal magnitude area
number of zero-crossing	skewness
third quartile	spectral centroid
SMV	standard deviation
energy	variance

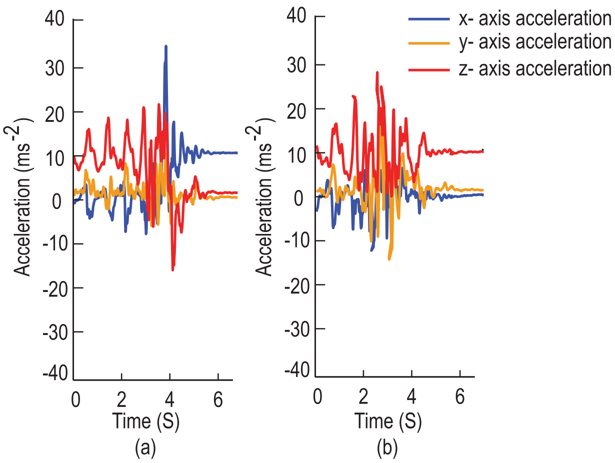

FIGURE 2. Raw tri-axial acceleration signal (a)Fall (b)Fall similar ADL

SMV signal to make the framework orientation independent. As this work considered more than 7700 features for each signal, the tri-axial accelerometer signal will be complex and time consuming.

D. FEATURE EXTRACTION

In this article, we have considered the fall detection task as a time-series analysis problem. There are different types of concepts and methods in the time series literature, such as static distribution, correlation, information theory, stationarity, basis functions, model fitting, and so on. In this work, apart from the literature features (see Table 2) used in previous fall detection approaches, we have analyzed and compared different time-series features from diverse scientific domains, and various types of methodological families.

We are using the HCTSA Matlab package which can calculate more than 7700 time-series features from a diverse range of scientific fields. We have provided each event of a publicly available dataset as an input to the HCTSA package. The analysis was made length independent thus, fixed signal window was not considered for feature calculation. The HCTSA extracts more than 7700 features for each time-series event and produces a feature matrix. Every row in the feature matrix represents an event, and columns denotes the extracted features to that event. We have fed each time-series event as an input to the HCTSA package to extract features from whole event. Motivation of the proposed method is to analyze features from the cross-disciplinary time-series domain and find useful features to detect fall events. As a result, the analysis of fall detection will be less domain-specific. There are many other packages for time-series features, but the HCTSA package provides high interpretability. We can also examine any features from the HCTSA package manually.

E. DATA CLEANING AND NORMALIZATION

As HCTSA had computed 7700 features automatically for each sample of the dataset, there is a possibility of having special valued features in the feature matrix. When the special valued output contains not a number (NaN), error, or infinity value, a lower performance is likely to occur in the classification result. Fig. 4(a) illustrates the quality of the extracted feature matrix for the UR fall dataset containing NaN, infinity, error and good value.

We have eliminated all the features that contained special values. The number of feature reduces to almost 4500 after performing this step. Moreover, we have also performed normalization to the feature matrix because it might provide unexpected results due to the feature scale variation. We have applied z-score normalization [34] to confine all the feature values on the same scale. Fig. 4(b) delineates the cleaned and normalized feature matrix of the UR fall dataset. We reordered rows and columns to put similar ones together. Therefore, time-series analysis methods that yielded similar output across the data would be organized and would be closed to each other. We can define similarity as having similar outputs across these features in Fig. 4(c). All the fall events have been represented by red colour while blue colour represents ADL. We observed that a few fall events are similar to the ADL. From the Fig.4(c),we can clearly see that, which features contributed more to separate the dataset.

If we visualize this high dimensional feature matrix in a low dimensional space, it provides better visualization. Here

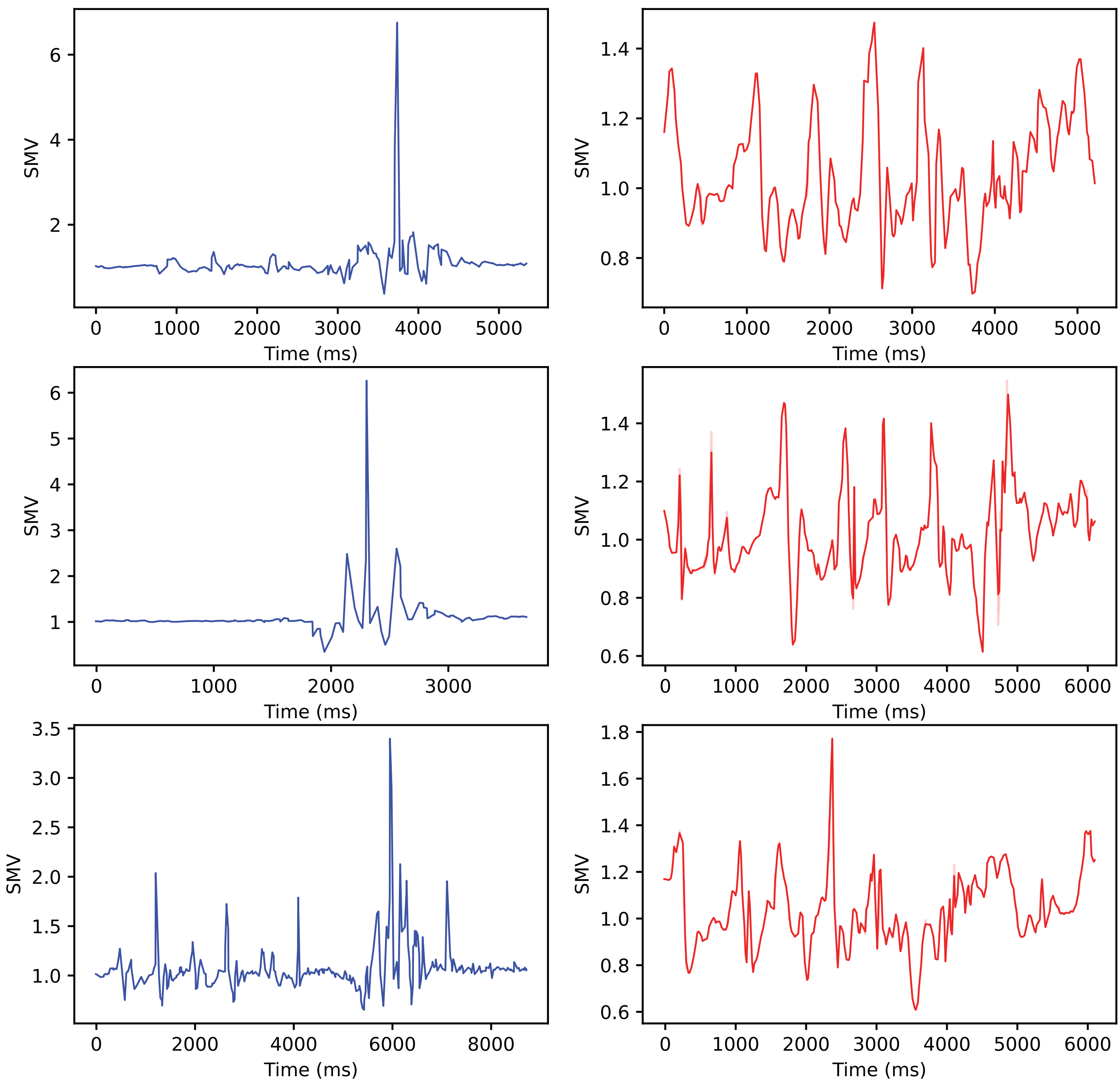

FIGURE 3. SMV of different fall and ADL events where blue line represents falls and red line represents ADLs.

we have used principal component analysis to visualize the distribution of fall and ADL samples in Fig. 4(d). Two principle component clearly distinguishes the fall and ADL samples easily. It can be said that we can find dominant features for fall detection through a potential feature selection pipeline.

F. FEATURE SELECTION

Feature selection is a vital step in the case of a large number of features. As the number of features increases, the dimensionality of the feature matrix will also elevate. Due to the curse of dimensionality, there is a high chance of overfitting. In our fall detection architecture, we implemented some feature selection algorithm to select the most important features and minimize dimensionality.

1) MUTUAL INFORMATION FEATURE SELECTION

Mutual information [35] is a widely discussed topic in information theory and communication domains. It measures the information between two or more random variables and quantifies information for one random variable through learning from another random variable. In other words, mutual information estimates the declination of the uncertainty of

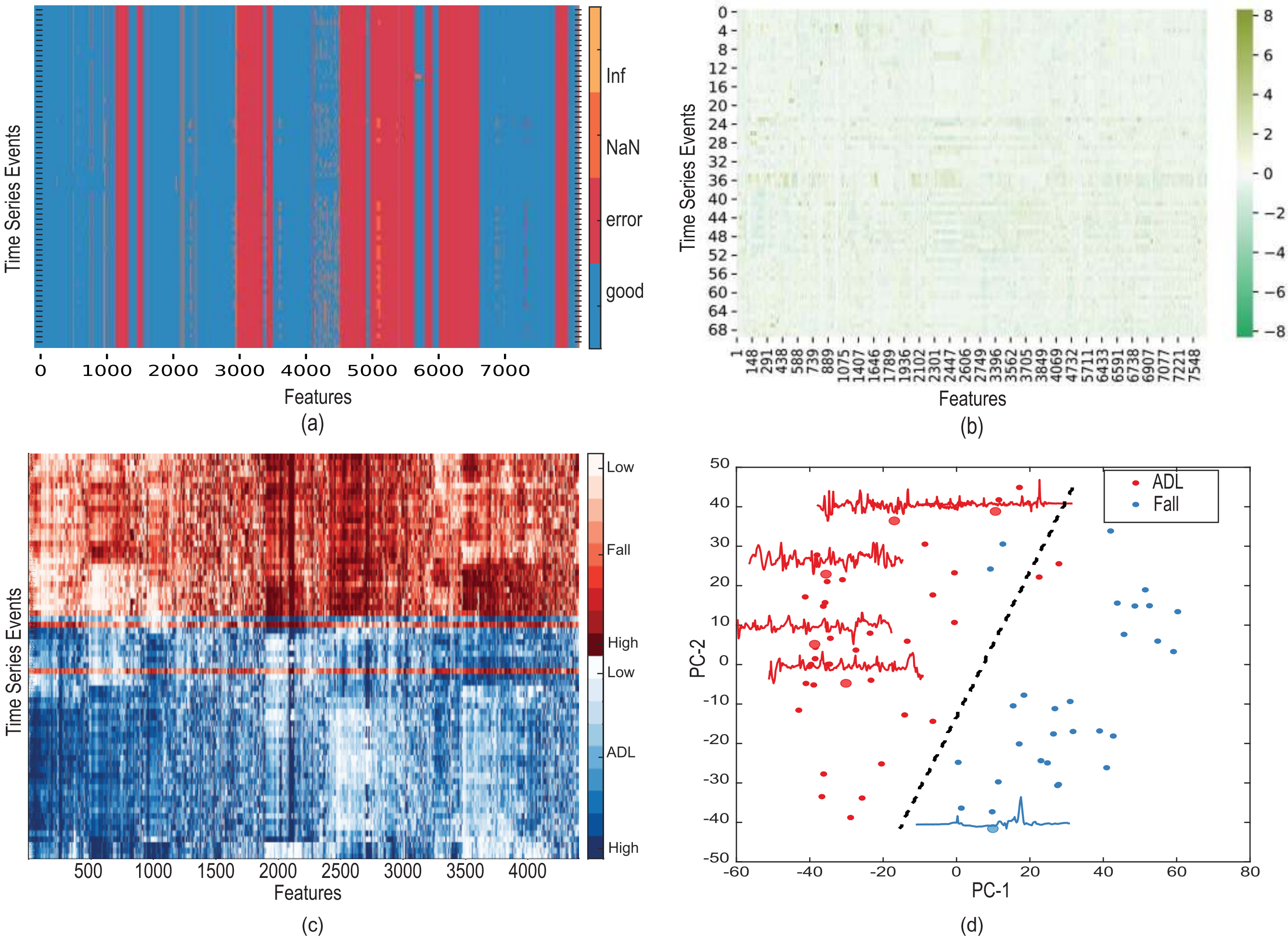

FIGURE 4. **(a) Distribution of special value of each feature for the UR fall dataset where special value contains infinity, error and NaN. Blue color represents good value of each feature. (b) Cleaned and normalized feature matrix of the UR fall dataset where every feature converted to a same scale ranges between -8 and 8. The z-score normalization method have applied to bring the all feature value in an unified scale. Horizontal axis represents features having good value while vertical axis represents each time series event in the UR fall dataset. (c) Clustered feature matrix where red colour group represents fall samples and blue colour group represents ADL samples. Hierarchical linkage clustering approach was used to group related features and time series events by calculating euclidean distance between time-series features. High color intensity represents low value and low color intensity represents high value. It also depicts that first 1500 features have low value for ADL samples whereas, fall samples have high value. (d) Low dimensional representation of the UR fall dataset using principal component analysis. The horizontal axis represents principle component-1 and vertical axis represents principal component-2. Red dot represents ADL sample while blue dot corresponds to the fall samples. The black dotted line have used to indicate the separation of falls and ADLs sample. It clearly shows that if we reduce the dimension of the extracted features matrix, our extracted features can easily distinguish the fall samples from the ADL samples.**

one variable by another variable. It is closely related to the concept of entropy, where entropy measures the uncertainty of a random variable. The mutual information between two random variables X and Y can be defined as the following Eq. 2

$$\begin{aligned} MI(X;Y) &= H(X) + H(Y) - H(X,Y) \\ &= H(X) - H(X|Y) \\ &= H(Y) - H(Y|X) \\ &= -\sum_{x \epsilon X, y \epsilon y} p(x,y) * \log_2 \frac{p(x,y)}{p(x)p(y)} \end{aligned} \tag{2}$$

Here, $MI(X;Y)$ represents mutual information between X and Y. The top 500 features were selected from extracted feature matrix those have higher mutual information score.

2) REMOVE HIGHLY CORRELATED FEATURES USING PEARSON CORRELATION COEFFICIENT

In this step, we will reduce the feature set obtained from the mutual information feature selection algorithm. There is a high chance of redundant features or highly correlated and anti-correlated features present in the feature matrix. We first computed the Pearson correlation coefficient [36] of every feature and clustered the correlated features. The Pearson correlation coefficient is denoted by r, which is expressed as follows:

$$r = \frac{Covariance(X,Y)}{\sigma_X . \sigma_Y} \tag{3}$$

Here, X and Y are two random variables. σ_X and σ_Y denotes the standard variation of X and Y, respectively.

TABLE 3. Accuracy, Sensitivity and Specificity of Different Classifiers for Individual Dataset Based on our Proposed Method.

Dataset	Algorithm	Accuracy	Sensitivity	Specificity
UR Fall	RF	0.99	0.97	1.00
	SVM	0.97	0.94	1.00
	NB	0.99	0.97	1.00
	LR	0.97	0.94	1.00
	KNN	0.97	0.94	1.00
	DT	0.97	0.97	0.98
UP Fall	RF	0.98	0.98	0.97
	SVM	0.98	1.00	0.97
	NB	0.97	1.00	0.94
	LR	0.99	1.00	0.99
	KNN	0.98	1.00	0.97
	DT	0.96	0.95	0.97
MOBIFALL	RF	0.99	0.99	0.99
	SVM	0.99	0.99	0.99
	NB	0.99	0.99	0.99
	LR	0.99	0.99	0.99
	KNN	0.99	0.99	0.99
	DT	0.99	0.98	1.00

TABLE 4. The Hyper-Parameter of the Selected Classifiers Used in the Work.

Classifier	Hyper-parameter
RF	The number of trees= 100; The function to measure the quality of a split= gini impurity
SVM	Regularization parameter, C = 1.0; Kernel = RBF
LR	penalty='L2'; Regularization parameter, C = 1.0; Tolerance for stopping criteria = 1e-4
DT	The function to measure the quality of a split = gini; The strategy used to choose the split at each node = 'best'; The minimum number of samples required to split an internal node =2
KNN	distance metric = 'minkowski'; leaf_size=30; Number of neighbors=5; Power parameter for the Minkowski metric=2
NB	var_smoothing = 1e-9

Legend: RBF–Radial Basis Function

After that, we have taken all the uncorrelated features with correlation coefficient less than 0.85. Furthermore, from the rest of the correlated clusters, we have calculated the feature importance of each cluster's features. Most important features of each cluster were kept, where rest of the features were discarded. In this way, we have got an uncorrelated feature set, where the number of features is almost halved.

3) BORUTA ALGORITHM

The Boruta algorithm [37] arises from the spirit of the RF. It uses feature selection, which is a fundamental step in ML. By this algorithm, we cope with problems and solve them by adding more randomness to the system. Features are removed periodically in every iteration from the dataset, which is considered under-performed by the RF model. As it lessens the error found by using the RF model, this method leads to a minimal optimal feature subset. It occurs by choosing a shortened version of the input dataset that, as a result, can remove some essential features. It categorizes the features into three groups, such as confirmed, rejected, and tentative. We have taken only confirmed features for the next step.

4) SELECTION OF TOP FIVE FEATURES USING FEATURE IMPORTANCE

After getting confirmed features from the Boruta algorithm, we selected the top five features by calculating the feature importance. Fig. 5 depicts the top twenty features selected by Boruta algorithm. These features were ranked based on the importance value, which is calculated by Eq. (4).

$$fi = \frac{\sum_j nfi_{i,j}}{\sum_{j \in af, k \in af} nfi_{j,k}} \tag{4}$$

Here, fi is the feature importance of a feature in the set, nfi is the normalized feature importance, and af is all the features considered. Based on these feature importance value, the higher value represents better relevance with the target class. Finally, we selected the top five features for our fall

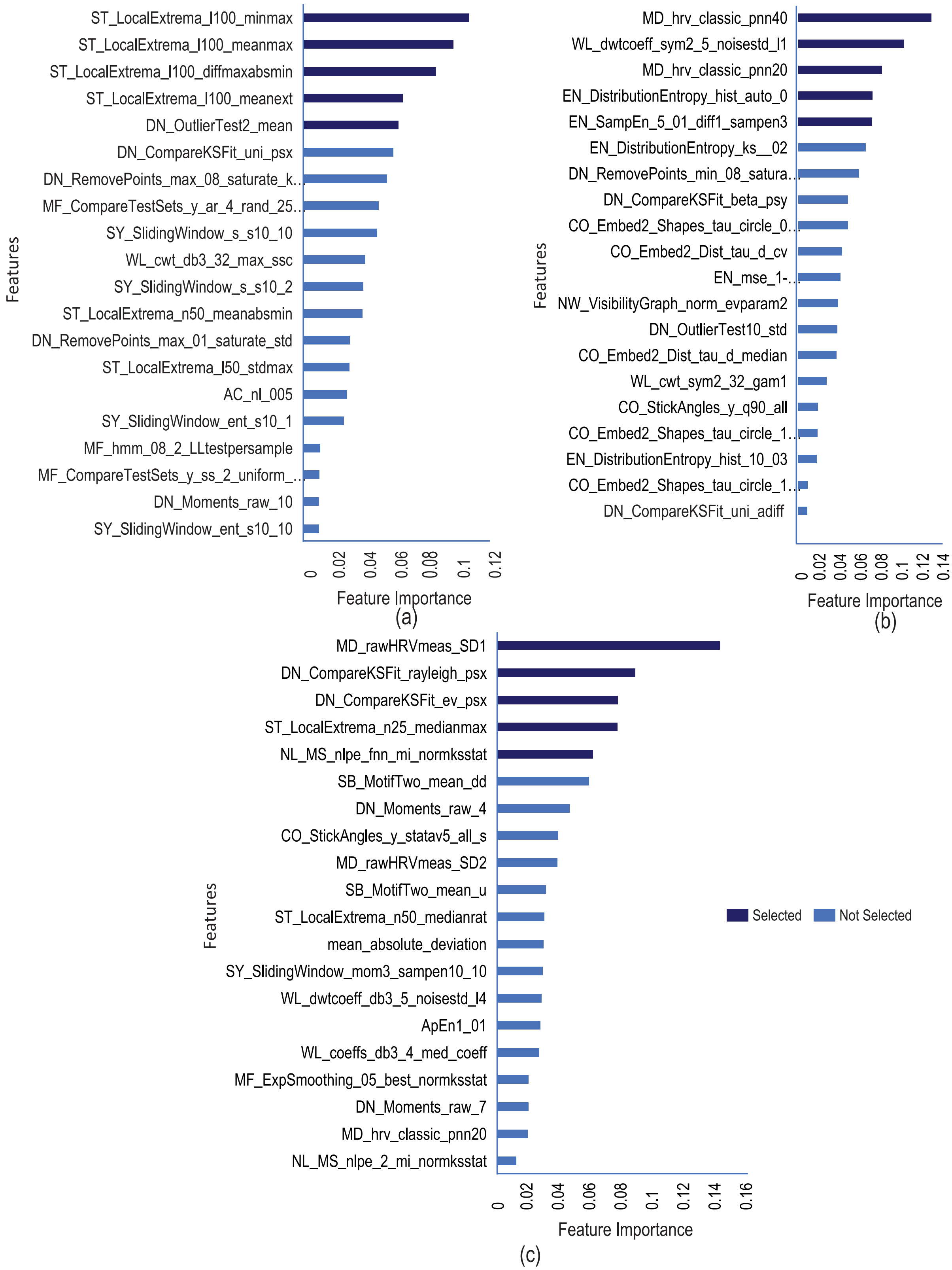

FIGURE 5. Feature importance of dominant features of UP Fall, MOBI Fall, and UR Fall dataset. The selected and not selected features were represented using darker blue and lighter blue, respectively. (a) A feature importance bar chart of dominant features for UP fall dataset, where top five features were selected based on higher feature importance value. (b) A feature importance graph of relevant features for MOBIFALL dataset, where top five features were selected based on the superiority of feature importance. (c) A feature importance chart of dominant features for UR fall dataset. The top five features were selected for this study.

TABLE 5. Name and Interpretation of the Top Five Selected Features for Three Pulicly Available Datasets.

Dataset	Name	Interpretation
MOBIFALL	MD_hrv_classic_pnn40	It measures the acceleration rate variability by calculating the variation of acceleration peak to peak interval.
	EN_DistributionEntropy_hist_auto_0	Distributional entropy. Estimates of entropy from the distribution of a data vector
	WL_dwtcoeff_sym2_5_noisestd_l1	Discrete wavelet transform coefficients. Decomposes the time series using a given wavelet and outputs statistics on the coefficients obtained up to a maximum level.
	MD_hrv_classic_pnn20	It measures the acceleration rate variability by calculating the variation of acceleration peak to peak interval.
	EN_SampEn_5_01_diff1_sampen3	Sample Entropy of a time series
UP Fall	DN_OutlierTest2_mean	How distributional statistics depend on distributional outliers.
	ST_LocalExtrema_l100_meanmax	How local maximums and minimums vary across the time series.
	ST_LocalExtrema_l100_minmax	Finds maximums and minimums within given segments of the time series and analyses the results.
	ST_LocalExtrema_l100_diffmaxabsmin	Finds maximums and minimums within given segments of the time series and analyses the results.
	ST_LocalExtrema_l100_meanext	Finds maximums and minimums within given segments of the time series and analyses the results.
UR Fall	DN_CompareKSFit_ev_psx	Fits an extreme value distribution to the given data.
	DN_CompareKSFit_rayleigh_psx	Fits a Rayleigh distribution to the given data.
	MD_rawHRVmeas_SD1	It calculates the acceleration variability of a given time-series event.
	ST_LocalExtrema_n25_medianmax	How local maximums and minimums vary across the time-series.
	NL_MS_nlpe_fnn_mi_normksstat	Normalized drop-one-out constant interpolation nonlinear prediction error.

detection model. Table 5 describes the name and interpretation of the selected top five features for MOBIFALL, UP Fall, and UR Fall datasets.

G. SELECTION OF PROPOSED FEATURES

We have analyzed the confirmed features obtained from the Boruta feature selection algorithm for the three mentioned datasets separately. The common features from all the datasets are taken into account and we obtained about 39 dominant features for all the datasets. Table 8 provides the name and corresponding HCTSA ID of the newly selected dominant features set.

H. ML CLASSIFIER

We have incorporated six ML classifiers (SVM, LR, DT, RF, KNN, NB) to distinguish fall events from other daily activities. The used hyper-parameter of these classifiers have given in Table 4. The top five selected features are used to train the ML algorithm. K-fold cross-validation was performed to evaluate performance in every case.

III. RESULTS

We have performed three different experiments to see our data analysis pipeline's performance in terms of accuracy, sensitivity, and specificity. We have performed all the experiments in ''HP Probook 450 G4'' laptop. The size of the ram was 8 GB and SSD was 128 GB. A brief details of each experiment are given below.

Experiment 1: We observed performance of our data analysis pipeline using widely used shallow ML algorithms (such as RF, SVM, NB, LR, KNN, DT) using three publicly available datasets.

Experiment 2: We trained our fall detection model with two datasets and tested by another unseen dataset to obtain the generalization capability of our model.

Experiment 3: The ML classifiers were trained by the top 39 features selected from the top essential features of all datasets.

A. RESULTS OF EXPERIMENT 1

Result of experiment 1 is summarized in Table 3. We have obtained the performance of three publicly available datasets to validate our data analysis pipeline. After performing all the feature reduction techniques depicted in Section II-F, the most dominant five features were selected for each of the datasets as mentioned earlier. After performing K-fold validation, where k was set to 3, RF and NB achieved the highest average accuracy (99%) in the UR Fall dataset. Sensitivity was 97%, and specificity was 100% in both cases. All the other ML classifiers were also performed at a satisfactory level. In the UP fall dataset, LR achieved the highest average accuracy of 99%, where sensitivity was 100%, and specificity was 99%. All the other ML classifiers achieved accuracy within a range of 96% to 98%. In the MOBIFALL dataset, all the datasets achieved 99% average accuracy, which is a remarkable result. Sensitivity and specificity were close to 100% in all of the ML algorithms.

Fig. 6 shows the violin plot of selected dominant features of all three databases. From the plot, it can be clearly said that these features were capable of classifying events very effectively as they are not much overlapped with each other.

B. RESULTS OF EXPERIMENT 2

In experiment 2, we used three publicly available datasets. The results of this experiment are illustrated in Table 6. We

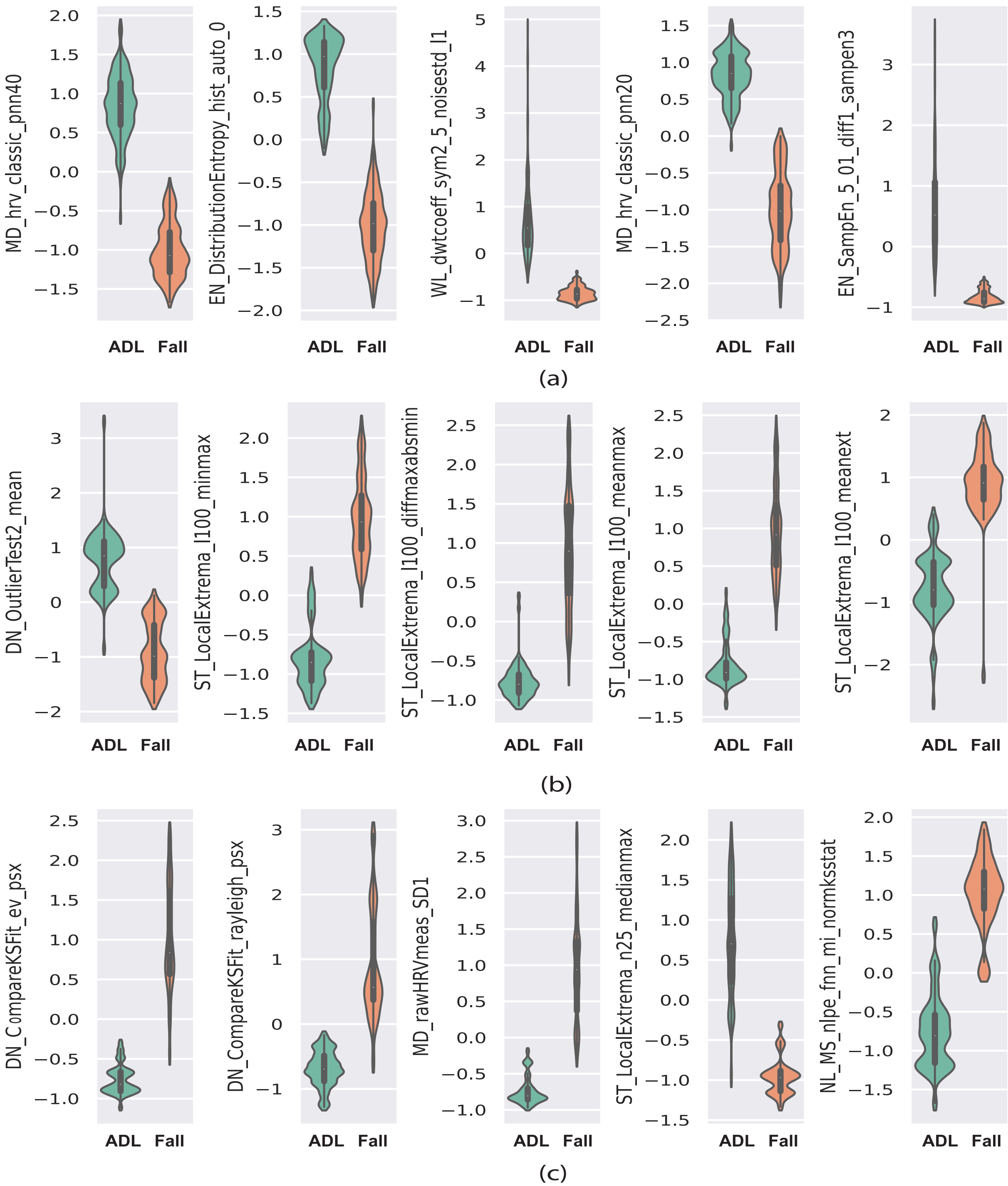

FIGURE 6. **Violin plot of top features which have been selected by our data analysis pipeline. Violin plots of top five features of MOBIFALL dataset (a), UP fall dataset (b), and UR fall dataset (c).**

used MOBIFALL and UR Fall dataset as the training set and UP Fall as the test set in the first case. We have followed the full feature reduction pipeline and finally selected 5 most important features as the input of ML classifiers. We have found out that KNN, NB and LR classifiers were the most efficient ones in this case. KNN achieved at most 92% average accuracy where both NB and LR achieved accuracy of 91%. However, the NB and KNN classifier achieved the highest sensitivity (98%), where LR had the highest specificity (88%). All the other classifiers achieved accuracy in the range of 88% - 89%. Then we used UP Fall and UR Fall as the training set where MOBIFALL was used as the test set. Here, SVM achieved 98% average accuracy where sensitivity was 100%, and specificity was 96%. Other classifiers achieved

TABLE 6. Accuracy, Sensitivity and Specificity of Different Classifiers Based on the Proposed Method While Two Datasets Were Used as the Training Set and Another One Was Kept as the Test Set.

Dataset		Algorithm	Accuracy	Sensitivity	Specificity
Train	Test				
MOBIFALL UR Fall	UP Fall	RF	0.89	0.97	0.82
		LR	0.91	0.95	0.88
		SVM	0.89	0.90	0.88
		DT	0.88	0.97	0.81
		KNN	0.92	0.98	0.88
		NB	0.91	0.98	0.85
UP Fall UR Fall	MOBIFAL	RF	0.97	0.98	0.96
		LR	0.97	1.00	0.95
		SVM	0.98	1.00	0.96
		DT	0.94	0.98	0.91
		KNN	0.97	0.99	0.94
		NB	0.97	1.00	0.95
MOBIFALL UP Fall	UR Fall	RF	0.89	0.77	0.98
		LR	0.93	0.83	1.00
		SVM	0.90	0.77	1.00
		DT	0.84	0.63	1.00
		KNN	0.93	0.97	0.90
		NB	0.89	0.73	1.00

average accuracy in the range of 94% - 97%. In another case, MOBIFALL and UP Fall datasets used as the training set, and UR Fall used as the test set. KNN and LR achieved the best average accuracy (93%). The highest sensitivity was 97% which was achieved by KNN. In terms of sensitivity, all the classifier achievd more than 98% specificity except KNN. Other classifiers achieved average accuracy in the range of 84% - 90%.

C. RESULTS OF EXPERIMENT 3

In the final experiment, we used a standard feature set for all the datasets. These feature sets had in total 39 features, where they were selected from the top features of all three datasets. The result of this experiment is described in Table 7. A list of all the selected features is given in Table 8. In the UR Fall dataset, NB, RF, and LR achieved the highest accuracy (96%), where SVM achieved 94% average accuracy. NB achieved the highest 98% average sensitivity, and RF and LR got the best specificity (98%). LR outperformed the other algorithms in the UP Fall dataset, where it achieved 97% average accuracy, 98% average sensitivity, and 98% average specificity. However, KNN achieved highest sensitivity of about 99%. Other classifiers achieved average accuracy in the range of 93% - 96%. LR achieved 100% accuracy in the MOBIFALL dataset, where it achieved 99% sensitivity and 100% specificity. Fig. 7 provides an overview of the result of all three experiments. From the Fig.7, it can be said that the proposed method achieved excellent fall detection performance in all experiments.

IV. DISCUSSIONS

This section presents a brief discussion of the proposed fall detection data analysis pipeline and discusses the outcome of the research. The significance of this research is described in this section.

A. EFFECTS OF OUR DATA ANALYSIS PIPELINE ON INDIVIDUAL DATASET

The results of experiment 1 indicate the effect of the proposed data analysis pipeline on different publicly available datasets. It can be seen that our data analysis pipeline performed significantly well for each dataset and yielded exceptional results. Our proposed method achieved more than 97% accuracy for the UR fall dataset using different classifiers that are described in Table 3. We obtained a maximum of 100% accuracy, sensitivity, and specificity for all datasets using the proposed data analysis pipeline. It is assumed that there was no overfitting occurred because the model provided good performance for all datasets. Moreover, the top five dominant features of each dataset had significant effects on performance. It was observed that the selected features of each dataset can easily separate the falls and ADLs that can be seen in Fig. 6.

However, different datasets had different dominant features due to the different characteristics of datasets such as data

TABLE 7. Accuracy, Sensitivity and Specificity of Different Classifiers for Individual Dataset Based on the Proposed Feature Set.

Dataset	Algorithm	Accuracy	Sensitivity	Specificity
UR Fall	RF	0.96	0.96	0.98
	SVM	0.94	0.96	0.96
	NB	0.96	0.98	0.94
	KNN	0.94	0.97	0.92
	LR	0.96	0.96	0.98
UP Fall	RF	0.96	0.98	0.96
	SVM	0.93	0.95	0.94
	NB	0.95	0.98	0.94
	KNN	0.95	0.99	0.94
	LR	0.97	0.98	0.98
MOBIFALL	RF	0.99	0.98	1.00
	SVM	0.99	0.99	0.99
	NB	0.98	0.97	0.99
	KNN	0.99	0.99	1.00
	LR	1.00	0.99	1.00

acquisition pattern, range of accelerometer sensor, sampling rate, number of fall types and ADLs. Although a lot of characteristics differences among the existing datasets was observed, the proposed pipeline was successful in identifying meaningful features and achieved an almost perfect fall detection accuracy in all the mentioned datasets. We can hope that our data analysis pipeline can obtain dominant features set in any dataset and it could be different from the mentioned datasets. In production, characteristics of all devices remain quite similar. Therefore, our pipeline will find out the same set of dominant features for all the devices which are alike in characteristics that could be used furthers for detecting fall events with almost perfect accuracy.

B. GENERALIZATION CAPABILITY OF THE PROPOSED METHOD

We have conducted experiment 2 to see the generalization capability of our data analysis pipeline. The performance of our fall detection method significantly decreased in this case. We trained our model with two datasets and tested by another dataset to obtain our method's generalization capability. Our data analysis pipeline generalizes well while the fall detection model is tested with the MOBIFALL dataset and trained with UP fall and UR fall dataset. The highest performance was obtained by the SVM classifier that achieved accuracy, specificity, and sensitivity of 98%, 96%, and 100%, respectively. The second best case was while our model was tested by the UR fall dataset and trained by MOBIFALL and UP fall dataset. The maximum specificity of about 100% was achieved by all ML classifiers except RF. However, it yielded lower sensitivity for all classifiers on the UR fall dataset. If we compare the performances of experiment 1 and experiment 2, it is notable that the performance was significantly decreased in experiment 2. The main reasons for decreased performance are the characteristics of individual datasets. If we analyze each dataset individually, the accelerometer sensor, acquisition pattern, number of participants, experimental setup, types of fall category, sampling rate, accelerometer range, the physical condition of participants subject, sensor placement were different. The sampling rate of UR fall dataset was 256 Hz which is very high compared to the other two datasets. UP fall had sampling rate of 18.4 Hz only while MOBIFALL had sampling rate of 100 Hz. MOBIFALL dataset consists of four different types of falls. On the other hand, the UR fall dataset had three types of falls. In the case of UP fall dataset, there was five different types of falls while ADL was six different types. Moreover, the number of samples was different. UR fall had only 30 fall sample while MOBIFALL had 288 fall sample. Therefore, it was expected that the performance could be decreased. However, the performance shows that our method achieved at least 92% accuracy all the cases considered in the experiment 2. Thus, we can say that the proposed method provides a very good performance, and it can generalize well against different datasets having different characteristics. However, there are still rooms for future researchers to make a more generalized method.

C. EFFECTS OF SELECTED FEATURE SET

The performances of the selected feature set were described in Table 7 . The results showed that all ML models performed significantly well against all datasets. It is one of the major achievements of our work. We have introduced these new features that performed better towards the MOBIFALL dataset, UP fall dataset and UR fall dataset. It is a good indicator of the proposed method, and we can say that the proposed feature

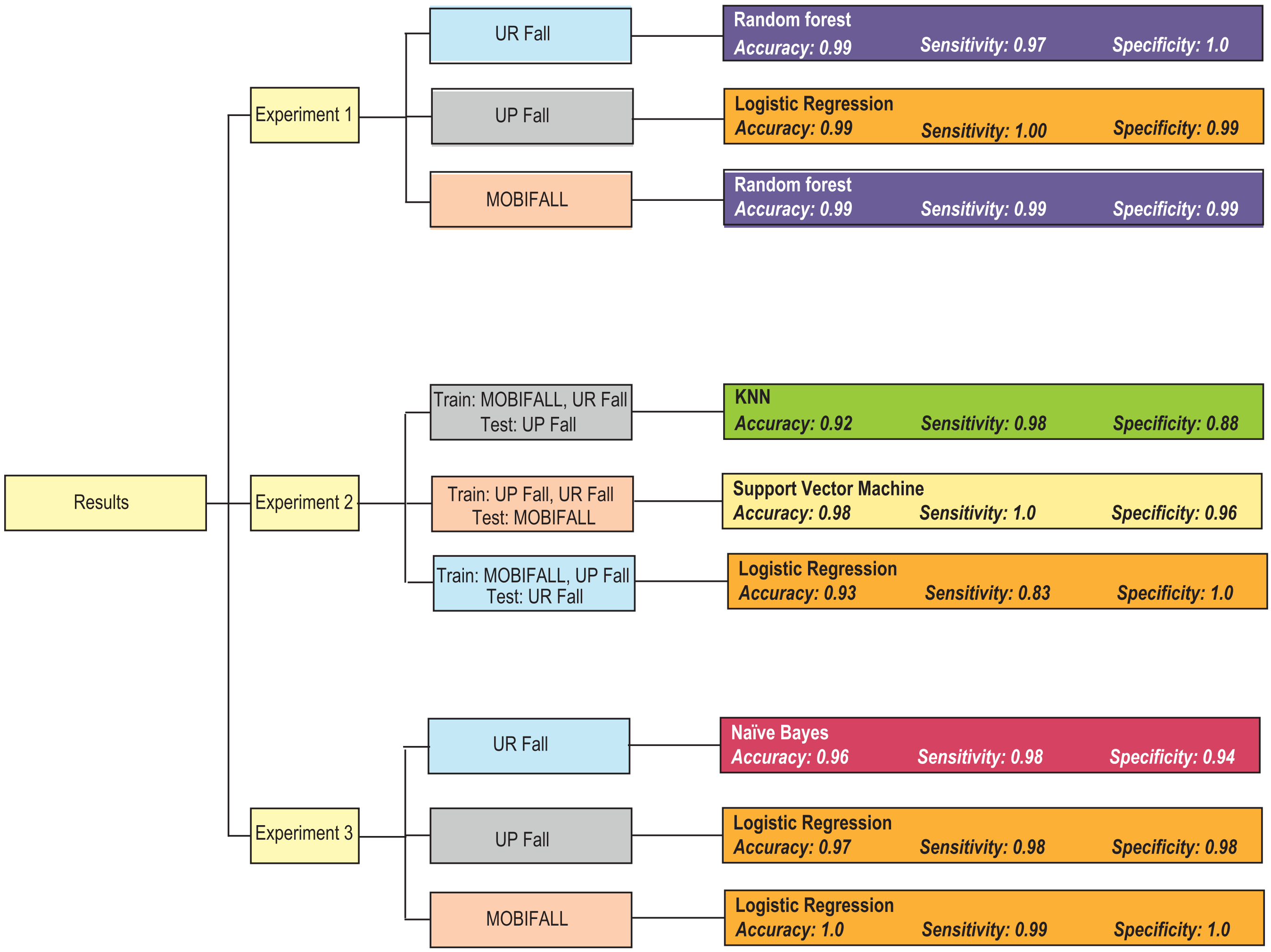

FIGURE 7. Dataset wise highest performing classifiers based on accuracy, sensitivity, and specificity throughout the different experiments.

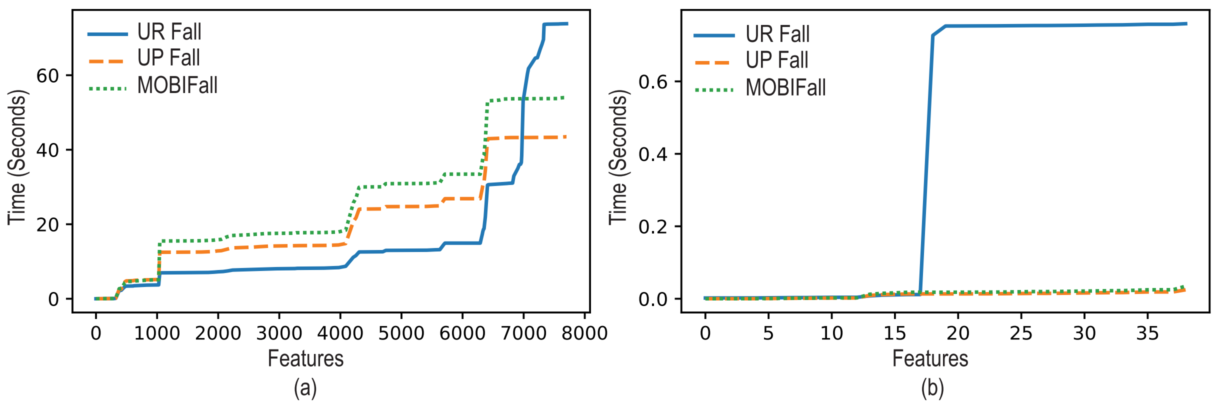

FIGURE 8. Average feature calculation time for a single event of the three publicly fall datasets where blue colour represents UR fall dataset, orange colour represents UP fall dataset and green colour represents MOBIFall dataset. The calculation time in seconds is presented in vertical axis and horizontal axis presents the number of features being calculated. (a) The average required time for calculation of 7700 features for a single event of three datasets. Maximum time required for UR Fall dataset. (b)The average required time for calculation of selected 39 features for a single event of three datasets.

set will play a significant role in the fall detection research community. We have extracted a massive number of cross-disciplinary time-series features that required an enormous amount of time and increased complexity. That is why we

TABLE 8. Name and HCTSA ID of Selected Features. HCTSA IDs are Used to Obtain Detail Information of Each Feature Which is Given in the Following Link: https://hctsa-users.gitbook.io/hctsa-manual/.

Features Name	HCTSA ID
NL_MS_nlpe_2_mi_normksstat	6686
SB_MotifTwo_mean_dd	3595
ST_LocalExtrema_n25_stdmin	3427
ST_LocalExtrema_n50_medianabsext	3453
EN_DistributionEntropy_hist_20_0	895
WL_coeffs_db3_4_med_coeff	6521
FC_Surprise_dist_20_tau_m2quad_500_tstat	2532
DN_RemovePoints_min_08_saturate_mean	1812
MD_pNN_raw_pnn100	7698
SY_SlidingWindow_mom3_ent10_1	672
SY_SlidingWindow_mom4_ent5_1	692
ST_LocalExtrema_n25_maxabsext	3436
ST_LocalExtrema_l100_meanext	3400
MF_hmm_CompareNStates_06_24_meanLLtest	7577
SY_SlidingWindow_ent_s10_1	613
WL_cwt_sym2_32_std_ssc	6463
WL_cwt_db3_32_std_ssc	6437
skewness_pearson	42
MF_FitSubsegments_arma_2_2_uniform_25_01_fpe_std	6970
MF_StateSpace_n4sid_3_05_1_maxonmean	7172
CO_HistogramAMI_std1_2_1	210
SB_MotifTwo_mean_uuu	3605
SB_MotifTwo_mean_h	3594
quantile_70	75
DN_RemovePoints_min_05_saturate_std	1801
DN_RemovePoints_absclose_08_remove_kurtosisrat	1727
DN_RemovePoints_min_08_saturate_std	1813
SY_DriftingMean50_mean	2227
CO_Embed2_tau_eucds1	1987
CP_ML_StepDetect_l1pwc_02_rmsoffpstep	7626
SY_SlidingWindow_mom4_ent10_1	695
DN_FitKernelSmoothzscore_entropy	934
DN_RemovePoints_min_05_saturate_kurtosisrat	1803
CO_Embed2_Dist_tau_d_cv	2022
EN_DistributionEntropy_ks__02	885
WL_cwt_sym2_32_medianabsC	6446
DN_Moments_raw_5	35
SY_SlidingWindow_s_s10_1	590
NW_VisibilityGraph_norm_gaussnlogL	2119

have proposed the new dominant feature set to overcome this limitation, that requires a minimal amount of time. It is observed from Fig. 8 (b) that the feature extraction time was significantly reduced for all the datasets if we have calculated only these selected feature set compared to the computation of all features shown in Fig. 8(a). The computation time for all the features was more than 40 seconds in all dataset where it required less than 1 second in the case of selected features set. Whilst comparing the performance between experiment 1 and experiment 3, the performance of experiment 3 has been decreased substantially as of experiment 1. This is due to the selection of common features in all datasets in experiment 3, and selection of the top 5 features from each datasets in experiment 1. Another reason was the curse of dimensionality as higher number of features considered in experiment 3 compared to the experiment 1.

D. COMPARISON WITH EXISTING RESEARCH WORKS

As falls can be life-threatening, fall detection models should be robust. False alarms should be reduced as much as possible, and sensitivity should be close to 100%. After considering 7,700 cross-disciplinary features, our proposed pipeline successfully achieved close to perfect accuracy and sensitivity using simple ML classifiers in all the databases, which required lower computational cost than deep learning models. The proposed pipeline showed satisfactory performance in reducing false alarms. Fig. 9 provides a performance comparison of our proposed pipeline with some existing research works.

Our proposed architecture achieved 99% accuracy, 97% sensitivity, and 100% specificity using the RF classifier in the UR Fall database. Theodoridis *et al.* [38] achieved 96% accuracy, 97% sensitivity and 95% specificity in the same dataset. The model of Boruke *et al.* [38], [39] and Kwolek B. *et al.* [26] achieved 93% accuracy, where Kwolek B. *et al.* found 90% sensitivity in UR Fall dataset by their proposed architecture. Therefore, it can be said that, our proposed architecture showed better performance and robustness in UR fall dataset.

Ponce *et al.* achieved 97% accuracy, 89% sensitivity, and 99% specificity in UP Fall dataset using a supervised ML method [40]. Martinet *et al.* [27] and Casilari *et al.* [41] could

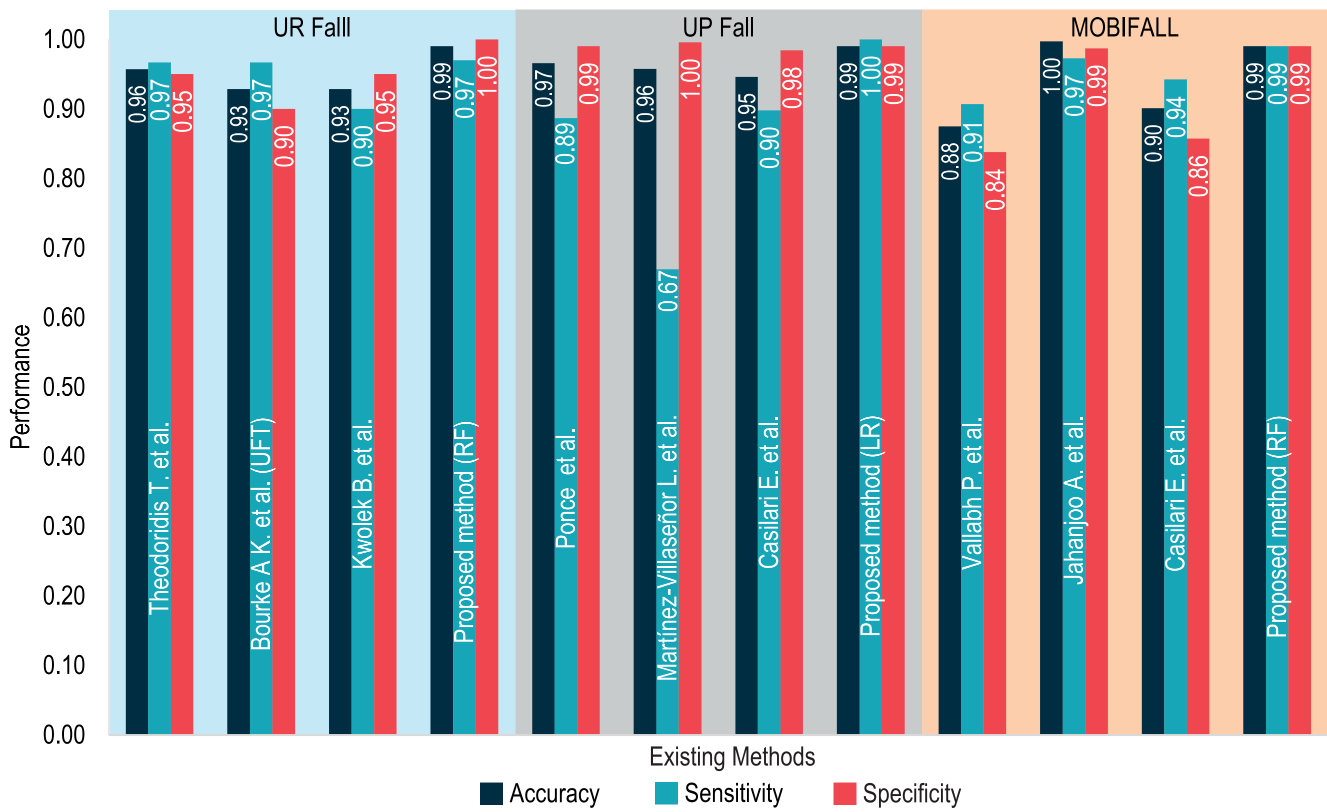

FIGURE 9. Performance comparison of our proposed method with existing methods those used the same publicly available datasets.

achieve 98% and 95% accuracy, but their sensitivity was less than 90% in the same dataset. Our proposed method achieved 99% average accuracy, 100% average sensitivity, and 99% average specificity after doing K-fold validation in the UP fall dataset using the LR classifier. So, our proposed method significantly improved sensitivity and accuracy in the case of the UP Fall dataset.

In the case of the MOBIFALL dataset, Jahanjoo A *et al.* [42] achieved 100% accuracy, 97% sensitivity, and 99% specificity, where Vallabh P *et al.* [43] and Casilari *et al.* [41] achieved just more than 90% accuracy. The proposed pipeline achieved 99% average accuracy, 99% average sensitivity, and 99% average specificity in the MOBIFALL dataset that is the most significant performance in sensitivity and accuracy among the motioned works. Therefore, the proposed method showed great promise in fall detection as it has provided excellent robustness and significant performance in three publicly available datasets.

E. LIMITATIONS

This main limitation of this article is that we did not test the proposed method in real-world fall events to ensure that the method can detect falls in the real world scenario. Another limitation was that we extracted a massive number of cross-disciplinary time-series features that are more than 7,700 in number, requiring a tremendous amount of time and increasing complexity. The key drawback is that we have not tested the proposed system's performance in real-world fall scenarios.

F. FUTURE WORKS

This article proposed a new pipeline to identify fall events using cross-disciplinary time-series features. The pipeline can process time-series events collected using accelerometer placed in any position of the human body. This system can be deployed on a cloud based engine as well as on portable devices such as smartphone, micro-controller, and smart wearable. Portable embedded devices can be properly calibrated and trained to detect fall in real time, which may be convenient for the elderly. On the other hand, detection of fall in real-time can be troublesome because of high latency on cloud-based devices. Therefore, in future, we intend to deploy the proposed structure on the resource-constrained embedded devices to test the model's robustness.

V. CONCLUSION

Falls lead to death among older people worldwide. This article aimed to develop an effective fall detection system that can detect elderly falls at home or outside. We proposed a fall detection data analysis pipeline to detect potential elderly fall events using an accelerometer sensor. We extracted cross-disciplinary time-series features from the accelerometer signal and proposed a new set of features to detect elderly falls. Although, the proposed system selects different features for different training sets, a thorough training before production can solve this issue. This is the first work in fall detection research that analyzed a vast amount of cross-disciplinary time-series features to the best our knowledge in the fall detection research. Three publicly available datasets were used to validate the proposed method. We have performed three different experiments with these datasets and achieved improved performance in all the cases. We have also compared our results with the existing works that used the same datasets and found that the proposed architecture outperformed the existing research works. Finally, we hope that our newly proposed feature set might be a good starting point for upcoming research in the fall detection task.

COMPLIANCE WITH ETHICAL STANDARDS

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Conflicts of Interest: All authors declare that they have no conflict of interest.

Ethical Approval: No ethical approval required for this study.

Informed Consent: This study used secondary data, therefore, the informed consent does not apply.

Authors and Contributors: This work was carried out in close collaboration between all co-authors.

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