TABLE I
BASIC CHARACTERISTICS OF PUBLIC DATASETS OF FALLS AND ACTIVITIES OF DAILY LIVING (ADLS)

Dataset Name	**Subjects (Age Range)**	**Device Used**	**Sampling Rate**	**Number of Types of ADLs/Falls**	**Position of Sensing Points**
MobiFall [5] [6]	25 (22–47 years)	Samsung Galaxy S3, A-BMA220, G-MPU-6050	50 Hz	9/4	Waist-mounted using belt clip
HAR [16]	30 (19–48 years)	Samsung Galaxy S II smartphone, Accel, Gyro	50 Hz	6/NA	Smartphone attached via a belt or pouch
mHealth [18]	10 (N/A)	Shimmer2 wearable sensors, Accel, Gyro	50 Hz	12/NA	Chest Sensor, Left Ankle Sensor, Right Lower Arm Sensor
HARTH [19]	22 (NA)	Accel, Gyro	50 Hz	12/NA	Sensors were attached to the right thigh and lower back
HAR70+ [21]	15 (70-95 years)	Accel, Gyro	50 Hz	8/NA	Sensors were attached to the Lower back and thigh
WEDAFALL [25]	15 (70-95 years)	Fitbit Sense smartwatch sensor data, Accel, Gyro, HR, EE, Orientation Sensor	5–50 Hz	350 fall trials from young participants and 157 fall trials from elderly participants, totaling 507 falls/619 activities of daily living (ADLs)	Wrist
SmartFallDataSet [26]	7 Smartwatch, 7 Notch, Multiple Farseeing (21–55 years Smartwatch, 20–35 years Notch, Elderly Farseeing)	Microsoft Band 2 smartwatch, Notch Motion Sensors, Farseeing Sensors, Skin Temp Sensor, GPS Sensor	31.25 Hz (Smartwatch), Variable (Notch), 20–100 Hz resampled to 31.25 Hz (Farseeing)	91 falls + 90 ADLs (Smartwatch), 107 falls + 2,456 ADLs (Notch), 23 falls + 27,412 ADLs (Farseeing)	Wrist (Smartwatch and Notch), Torso (Farseeing)
Sisfall [28]	38: 23 young adults (19–30 years), 15 elderly (60–75 years)	Smartphones Custom-built embedded device with Accel (ADXL345, MMA8451Q) and Gyro (ITG3200)	200 Hz	19/15	Waist
FARSEEING [30]	2000 (19–30 years young adults, 60–75 years elderly)	Samsung Galaxy S3, Accel, Gyro, and Mag	100 Hz (73%) and 20 Hz (27%)	NA/208	Lower back (L5 vertebrae, 72%) and thigh (28%)
UPFall [32]	17 (18-24 years)	Mbientlab MetaSensor IMUs, NeuroSky MindWave EEG Headset, Microsoft LifeCam Cinema Cameras	100 Hz (73%) and 20 Hz (27%)	6/5	Left wrist, under the neck, right pocket, waist (belt), left ankle, Forehead

Dataset Name	Subjects (Age Range)	Device Used	Sampling Rate	Number of Types of ADLs/Falls	Position of Sensing Points
FALLAID [33] [34]	15 (NA)	Accel, Gyro, Mag, Baro	Accel and Gyro: 238 Hz, Mag: 80 Hz, Baro: 10 Hz	44/35	Waist, Wrist, and Neck
UMAFALL [36]	17 (19–48 years)	IMUs and an Optical Motion Capture System	50 Hz	5/4	Chest, Waist, Wrist, Ankle
Mendeley data [37]	1 (NA) (Millions of sensor readings collected at a frequency of 1 Hz over six months)	PIR Sensors, FSR, Reed Switches, Photocell Light Sensors, Temp and Humidity Sensors, Smart Plugs	1 Hz	6/5	Installed in rooms and hallways to detect movement, Placed on beds, couches, and chairs to monitor pressure variations, Mounted on doors, cabinets, and the fridge to record usage patterns, Distributed throughout the home for environmental monitoring.
Ecare [38]	NA (NA)	Smartphone, Fitbit Smartwatch, ESP32 for IPS	NA	6/4	Smartphone (placed in the trouser pocket), 4 SensorTags placed on: Ankle (foot motion and fall detection), Wrist (hand and upper body movement tracking), Chest (central body orientation reference), Waist (core movement detection for balance monitoring)

TABLE II
OVERVIEW OF DATASETS

Dataset Name	ML Algorithm	DL Algorithm	Feature Extraction	Evaluation Measures	Limitations
MobiFall [5] [6]	Decision Trees, RF,SVM,k-NN,NB,Gradient Boosting	CNN,RNN,LSTM,Transformers Autoencoders,CNN+LSTM	Time-Domain Features, Frequency-Domain Features	Accuracy, Sensitivity,Specificity ,F1-Score	Participant Diversity and Variability,Overfitting Risks,Data Imbalance
HAR [16] [17]	RF,KNN, Decision Trees,Gradient Boosting	CNN,RNN,LSTM	Time-domain signals (mean, standard deviation, skewness, kurtosis) Frequency-domain features (energy, entropy, correlation),Derived Features(Jerk, angular acceleration, magnitude of acceleration.)	Accuracy P, R, and F1-Score, Confusion Matrix, Cross-Validation	Device Dependency,Restricted Activity Range, missing the variety seen in real-world scenarios. Sensor NoisE, Fixed Position
mHealth	SVM,RF,KNN,DT	CNNs, RNNs/LSTM, Transformers, Autoencoders	TDF,FDF,Posture Analysis	Accuracy P, R, and F1-Score,ROC-AUC Score,Latency	Noise Sensitivity,User Variability,Real-time Constraints
HARTH [20]	SVM,RF,KNN,Logistic Regression	CNN, RNN, LSTM	TDF,FDF,Posture Analysis	Accuracy P, R, and F1-Score,ROC-AUC Score,Latency	Noise Sensitivity,User Variability,Real-time Constraints
HAR70+ [21] [24]	SVM,RF,KNN,DT	CNNs, BiLSTM, ResNet	TDF,FDF,Posture Analysis	Accuracy P, R, and F1-Score,ROC-AUC Score,Mean Absolute Error (MAE),False Alarm Rate (FAR)	Data Imbalance ,Noise,Computational Complexity and Energy Constraints,False Alarms and Privacy Issues
WEDAFALL [25] [7]	SVM,RF,KNN,DT	CNNs, BiLSTM, Hybrid CNN-LSTM,Transformer-Based Models,Stacked Autoencoders	TDF,FDF,Statistical Features: Correlation between movements, zero-crossing rates	Accuracy P, R, and F1-Score,ROC-AUC Score,MAE,False Alarm Rate	Only One Sensor ,Staged Falls,Limited Participants,Class Imbalance
SmartFallDataSet [26] [27]	SVM,NB	RNN with GRU	TDF,FDF	Accuracy P, R, and F1-Score,ROC-AUC Score,MAE,False Alarm Rate ,statistical features	Class Imbalance,Environmental Noise,User-Specific Differences
Sisfall [29]	SVM,KNN,RF,DT	CNN,LSTM	TDF,FDF	Accuracy P, R, and F1-Score,ROC-AUC Score	Variability in Falls,Data Imbalance,Sensor Placement

Dataset Name	ML Algorithm	DL Algorithm	Feature Extraction	Evaluation Measures	Limitations
FARSEEING [30] [31] [6]	Decision Trees, RF,SVM,k-NN,XGBoost,LightGBM,LR	CNN,RNN,LSTM,Autoencoders	TDF, FDF,Statistical Features,Temporal Features	Accuracy,P,R Sensitivity,Specificity ,F1-Score	Limited Data Quantity,Data Imbalance,Variability in Sensor Placement,Noise and Missing Data,Lack of Standardization
UPFALL [32]	SVM,KNN, Decision Trees,	CNN,RNN,LSTM,Autoencoder	Time-domain signals (mean, standard deviation, skewness, kurtosis) Frequency-domain features (energy, entropy, correlation),Activity-Specific Features	Accuracy P, R, and F1-Score, Confusion Matrix, Cross-Validation	Noise Sensitivity,User Variability,Computational Cost,Real-time Constraints,False Alarms
FALLAID [34]	SVM	CNN,LSTM	Horizontal Acceleration Magnitude,Dynamic Thresholding	Sensitivity, Specificity	Simulated Falls,Sensor Placement,Battery Life,False Positives
UMAFALL [36]	SVM,RF,DT,KNN	CNN,RNN,LSTM	TDF,FDF,Posture and Transition Analysis	Accuracy,F1-score Sensitivity, Specificity	Sensor Data Quality ,Computational Complexity,Generalization Issues
Mendeley data [37]	K-Means Clustering ,DBSCAN,Isolation Forest,DT,RF,SVM	CNN,LSTM	Extracted Features: Sensor activation patterns, duration, frequency, and contextual interactions	Accuracy P, R, and F1-Score,ROC-AUC Score	Single Participant,Limited Activity Scope,No Multi-User Data,Data Labeling Challenges
Ecare [38]	KNN,DT,RF,SVM	CNN,LSTM	mean, standard deviation, and signal magnitude vector	accuracy, precision, recall, and F1-score.	sensor placement constraints, lack of diverse participants, and real-world noise interference

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