Synthetic Sensor Data Generation for Activity Recognition

Ishwarya K.[1][0000-0002-1275-1229], N. Sowmya[2][0000-0002-9888-6078]*, A. Alice Nithya[3][0000-0002-3034-3536], Nandhini G.[4] and D. Devi[5]

[1] Department of Computing Technologies, School of Computing,SRM Institute of Science and Technology Kattankulathur - 603 203.
[2] Department of Electronics and Communication Engineering. , SRM Institute of Science and Technology, Kattankulathur, 603203, Tamilnadu,India
[3] Department of Computational Intelligence, School of Computing,SRM Institute of Science and Technology Kattankulathur - 603 203.
[4] Department of Artificial Intelligence and Machine Learning,,Sri Siram Engineering College,West Tambaram poonthandalam,Chennai -602109
[5] Department of Computer Science and Engineering , Sathyabama institute of science and technology,Jeppiaar Nagar, Chennai-600 119.

ishwaryk3@srmist.edu.in
sowmyan1@sr mist.edu.in*
alicenia@srmist.edu.in
devi.cse@sathyabama.ac.in
nandhini.am@sairam.edu.in

Abstract. Human Activity Recognition (HAR) is essential for a variety of applications, including assisted living, fitness tracking, and healthcare monitoring. The accelerometer, gyroscope, and magnetometer—three inertial sensors that are built into smartphones—are used in this paper's hybrid deep learning framework for sensor-based HAR. The raw sensor data goes through a thorough preparation step that includes mean/mode replacement techniques for handling missing values and Kalman Filter identification for outliers. For efficient feature extraction, the cleaned data is subsequently fed into a Modified One-Dimensional Convolutional Neural Network (1D-CNN), which captures local temporal relationships in sensor signals. A Long Short-Term Memory (LSTM) network is then fed this data in order to identify intricate human actions and learn long-range temporal patterns. Real-time, precise activity prediction is possible with the suggested method, opening the door for context-aware applications in ubiquitous computing settings. Examining the possibility of using transfer learning strategies to modify the created models for use in new activity recognition tasks or data-poor domains. Models are being optimised for low-power and resource-constrained environments, particularly for wearable technology, to guarantee prolonged use without using excessive amounts of energy.

Keywords: Kalman Filter, Convolutional Neural Network, Long Short-Term Memory , Temporal patterns.

Research Paper
DOI: https://doi.org/10.46793/BISEC25.326I
Part of ISBN: 978-86-89755-40-4

1 Introduction

Considering applications in this domain demand high-dimensional, multimodal streams of data that are characterized by a considerable variability (e.g., due to changes in the user's behavior or as a result of noise), activity detection presents a new frontier for the development of robust machine learning approaches. Nevertheless, in contrast to other applications, activity recognition lacks well-defined benchmarks [1]. Every research group usually uses experimental settings designed specifically for that purpose to test and report the performance of their algorithms on their datasets. Because of this, it is challenging to evaluate how well one methodology will work in the event that the experimental settings change, such as when a sensor fails or its location changes, or to compare the performance of many methods.

Innovative methods based on multimodal recordings, activity spots, and resilience to noise in semantic feature-based activity recognition were therefore required. Semantic features describe the intrinsic qualities of an activity, in contrast to low-level features. Semantics thereby improves the recognition task's reliability, particularly when several action executions give the identical actions various visual appearances [2]. The human body (position and pose let), qualities, linked objects, and scene context—the most common semantic features of action—are defined here, forming a semantic space. The HAR framework offers multiple approaches to leverage these semantic properties for activity recognition from still photos and video footage, as well as understanding different group activities [3].

Fig. 1. Generic HAR framework

Generic HAR framework (Fig 1) involves the following stages:

1.1 Data Acquisition

In charge of gathering data from many sorts of sensors. Sensors such as video sensors, inertial sensors, ECG signals, EEG signals, and so on generate data. Sensor data typically introduces artifacts and noise into the input data for a variety of causes, including electronic fluctuation, sensor calibration and malfunctions, acquisition in uncontrolled contexts such as non-line of sight, and so on.

1.2 Data Pre-Processing and Feature extraction

Filtering techniques are used to pre-process the noise introduced in the input data. This stage produces a set of filtered noise-free data that serves as the input for the next step. The pre-processed data is fed into the feature extraction step, where the most significant and relevant information or patterns are extracted. This stage also aids in the reduction of data dimension.

1.3 Classification

This stage involves utilization of various ML and DL and CV techniques by the model to predict the accurate label of a given input data. In classification, the model becomes fully trained using training data, and can be evaluated on test data before being applied to perform prediction on any new unseen data.

1.4 Recognition

Recognition of human activities is the last step in this process. During the training phase of the recognition process, features are given to the classifier and mapped to their respective activities like walking, running, diving, golf swing, kicking, lifting, and so on. In the testing phase, new data will be given to the trained model and activity per- formed will be recognized. Finally, the developed human activity recognition model's accuracy and efficiency are computed.

2 Literature Review

In [4] Choi et al., introduced a novel technique to data architecture for deeper features extracted in this work by concentrating on time series correlation utilizing activity data from smartphones. Data from multiple tasks were molded into single and double channels in order to discover key temporal and spatial aspects from signals. Raw data was represented using the Fourier and wavelet domains in addition to the time domain. In matching the DL classification of activities, CNN outperformed other NN models by utilizing a double-channeled time-domain input. When this method was tested again with open datasets, the outcomes were better. Lastly, a real-time analysis of the developed machine learning model's applicability produced encouraging findings.

Rodriguez et al., [5] proposed a hybrid feature selection strategy based on a filter-and-wrapper method for increased activity detection. For obtaining desirable characteristics, this strategy uses sequential floating forward search (SFFS) followed by a kernel method to construct nonlinear classifiers by feeding features into M-SVM for training and testing. Benchmark datasets were utilized to validate the performance in terms of effective activity identification while consuming the least amount of energy and hard- ware.

Ronao et al., [6] proposed a multi-scale model for feature extraction and fusion that integrates CNN with GRUs to automatically extract diverse local features and long- term dependencies from actual data and display a more detailed feature depiction by integrating convolution kernel sizes with GRU. Furthermore, by employing separable convolution rather than classical convolution, the suggested model satisfies the need to boost recognition accuracy while lowering model parameters. The suggested model ensures high recognition accuracy with less resource utilization.

Csurka et al., [7] developed straightforward activity categorization models using sensor data that uses information theory quantifiers as new features to improve computing efficiency. SHOAIB, UCI, and WISDM databases were employed to demonstrate leave-one-subject-out cross-validation approach (LOSO).

Jain, S. et al., [8] recommended automatic extraction and classification based on specific model attributes using LSTM which is well known for processing temporal sequences. The UCI-HAR dataset is used to test on a variety of human activities. A modified 1D CNN model is used for each input, and output from each input image is sent to the LSTM classifier. Tuning of hyper parameters is done by modifying the quantity of filter that maps distinct image regions. Gaussian standardization is used to demonstrate higher resilience and finer activity detection capabilities.

Zhang, Y et al., [9] came forward with a graph-based few-shot learning method with dual attention mechanism to perform HAR while taking into account the relationships between various activity data. Utilizing a feature extraction layer, the convolutional block attention module retrieves activity-related data. CNN with graph attention mechanism makes use of feature vectors to enhance recognition accuracy rates while learning to recognize new activities in novel environments.

Piergiovanni, A. J., et al., [10] proposed a framework for multi-class wearable user identification through DL model-based learning to recognize human behaviour. In order to protect the privacy of the HAR system, sensory data from wearable tri-axial gyroscopes and accelerometers collect detailed information about users' behaviors using CNN and LSTM. Biometric user identification is also used in this process.

Mukherjee, Debadyuti, et al., [11] presented hybrid architecture for HAR powered by wearable sensor data. Once the time series of sensor data is encoded into multi-channel pictures using Continuous Wavelet Transform, higher-dimensional features are extracted using Spatial Attention-aided CNN. Feature selection identifies the most crucial traits that are necessary for identifying human activities. A three filter-based approach is used to determine the suitability of features for FS namely Mutual Information, Re- lief, and minimum redundancy maximum relevance. Genetic Algorithm (GA) facilitates optimal collection of characteristics by eliminating less ranked features. K-NN classifier carries out the intended classification. Well-known, publicly available HAR datasets were used to conduct extensive experiments and overall recognition accuracy using this approach works better in comparison to other conventional methods.

Javed, Abdul Rehman, et al., [12] presented a spatiotemporal image generation practice of 3D skeletal joints for action discrimination by capturing spatial information and temporal variations. To study the influence of these strategies on human action recognition, transfer learning extracts discriminative characteristics and evaluates the proposed strategy with several fusion techniques.

Shoaib et al., [13] introduced a novel two-phase recognition system framework that made use of Deep Belief Networks (DBNs) and probabilistic generative models. RBM-based DBNs enable data reconstruction, feature generation, and classification, resulting in recognition accuracy that outperforms other state-of-the-art systems.

Table 1 presents a detailed comparative study on various pre-processing steps used in sensor-based approach. Various sensors are used to sense human activity and during the pre-processing step, noise removal and segmentation processes are performed. Kal- man filter, Linear and low pass filter, Wavelet filter and Mean filter are used to eliminate noise and other distortions. The Segmentation process makes use of techniques like Segmentations of windows based on agreed time, events and action.

3 Sensor Based HAR Framework

Within the context of sensor-based systems, a real-time lifestyle monitoring system is an advanced technical infrastructure designed to continuously track, collect, and evaluate various sensory data points related to a person's daily activities, actions, and interactions with their environment. From 2015 onwards more than 25% of individuals always carried a smartphone with them [21]. Smartphones have become much more popular since they enable consumers to access a vast array of online ser- vices. Every day, people use their smartphones for a variety of tasks, such as sending and receiving phone calls, reading their emails, accessing social media platforms like Facebook, and storing files, data, and private information on cloud storage services. In addition, smartphones have many beneficial uses in the sectors of public and medical health. Numerous themes and apps are pre-installed on smartphones and can be utilized in any area of medicine. Because the bulk of healthcare and medical applications are marketed to encourage changes in health behaviors, such as weight loss, physical fit- ness, quitting smoking, etc., relevance to public health is prioritized whenever possible. The body of relevant peer-reviewed research will increase significantly as smartphone applications particularly those that are sensor-based become more sophisticated [22]. Convolutional Neural Networks (CNNs), a deep learning method, are used in this study to identify the data collected from users via smartphones [23]. There are numerous kinds of physical activities. Our classifications focus on ambulatory sorts of activities (walking, walking upstairs, walking downstairs, sitting and standing,) [24]. The pro- posed sensor based HAR framework is shown in fig 2 with 3-axial sensor followed by preprocessing step with Kalman filter for removing outliers and next stage with modified 1DCNN-LSTM for HAR recognition.

Table 1. Pre-processing Steps in Sensor-Based Approach

Author Name and Year	Dataset and number of attributes considered	Sensors	Noising and segmentation	Inferences
Li et al., 2019 [14]	Uni MiB SHAR dataset created from mobile phones and wearable sensors of Size : 11,761	Accelerator	KF, Time driven window segmentation	Identifies and recognizes 17 different human activities
Hassan et al., 2019 [15]	UCI-HAR(581 attributes) Dataset Size : 10400	Accelerator, GPS, Magnetometer	Wavelet filter, action-driven window segmentation	Multimodal dataset collected across varied age groups, genders and origin.
Ignatov et al., 2018 [16]	HASC(500 attributes) Data Set Size: 6741	Hybrid	Mean filter, Action driven window segmentation	Dataset created through sensing and ambient sound based acceleration signals
Alma Slukh et al., 2018 [17]	Realworld (kaggle Datasets with 342 attributes) Dataset Size : 8,800	Accelerator	LPF, event-driven window segmentation	The specialised data set identifies 15 activities.
Tsinganos et al., 2017 [18]	UCI Heterogeneous Dataset with16 attributes with size: 45930257	Gyrometer, Accelerator	Linear and low pass filter, Action driven window segmentation	Heterogeneous Datasets collected for Benchmarking from subjects for activity recognition.
Kautz et al., 2017 [19]	UCIM HEALTH (570 datasets) Data Set Size: 9651	Hybrid	Low pass filter, Event-driven window segmentation	The database depicts several health ailments created by medical experts for predicting heart diseases.
Saunois, et al., 2016 [20]	UCIM HEALTH(590 datasets) Data Set Size: 13895	Accelerometer	Median filter, Time and space segmentation	Along with heart disease data, Parkinson’s and Gaucher disease symptoms are also presented.

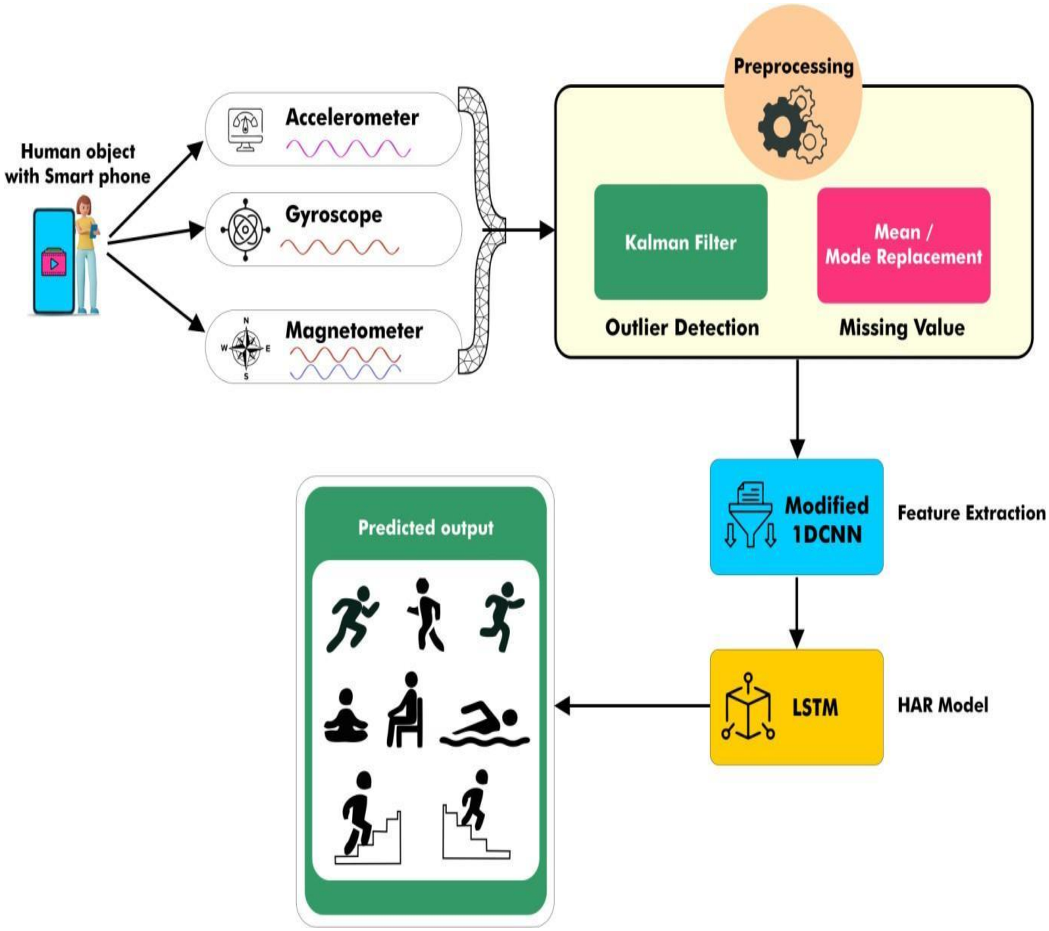

Fig 2. Proposed Sensor based HAR framework

The following were the outcomes of the research study:

- A complete framework to improve the precision and performance of HAR has been built by utilizing deep learning approaches.
- HAR datasets are more advantageous than traditional, well- known publicly available datasets for better generalization and context under- standing when used to evaluate the effectiveness of the recommended meth

- The integration of outlier a modified 1D CNN model with LSTM effectively segments the data, significantly improving recognition capabilities and ensuring accurate identification of activities.

The fundamental goal of the suggested all-inclusive technique has been driven primarily by the differences in feature engineering and scalability between deep learning and conventional methods. In order to enable the effective application of HAR, the suggested system has been created with clearly defined phases for sensor data, pre- processing, feature extraction, and classification.

There have been multiple research studies dedicated to HAR in the recent decades to develop essential methods and techniques to enhance the recognition process [9,12]. Initial studies were mostly focused on noise estimation, image classification and collaborative representation of images [15]. Modern years have been witnessing a significant shift by focusing more on experimenting with various solutions to recognize activities based on signals from inertial sensors [18]. This can be attributed to the wide-spread proliferation of mobile devices equipped with accelerators and gyrometers.

3.1 Sensor Data

Traditional HAR systems primarily rely on inertial sensors like accelerometers, gyroscopes and magnetometers to capture motion patterns associated with specific activities. This stage involves gathering of raw data from inertial sensors and from other functionalities present in the smart phones [19]. The health indicators like heart rates, sleeping patterns, temperature, and blood pressure can be captured by tracking their motion, orientation, location, and environmental conditions. The quality of the data collected is affected by variables like time, frequency, subject position, and subject direction. The collected data is then arranged chronologically into a time-series structure. Di= (xi, yi, zi), for example, is a representation of data where i= {1,2,3 …n}.

Acceleration, or the rate at which velocity changes, is measured by the accelerometer sensor included in smartphones. Moreover, it has the ability to sense changes in orientation and spin the screen [20]. Monitoring the smartphone's linear acceleration along the lateral, longitudinal, and vertical X, Y, and Z axes is the main job of this sensor. For instance, the gadget will abruptly change the amplitude along the vertical axis in response to the signal structure of the acceleration reading when the user transitions from walking to jogging [24]. Furthermore, in the difficult HAR, the acceleration data may demonstrate the motion pattern within a specific time.

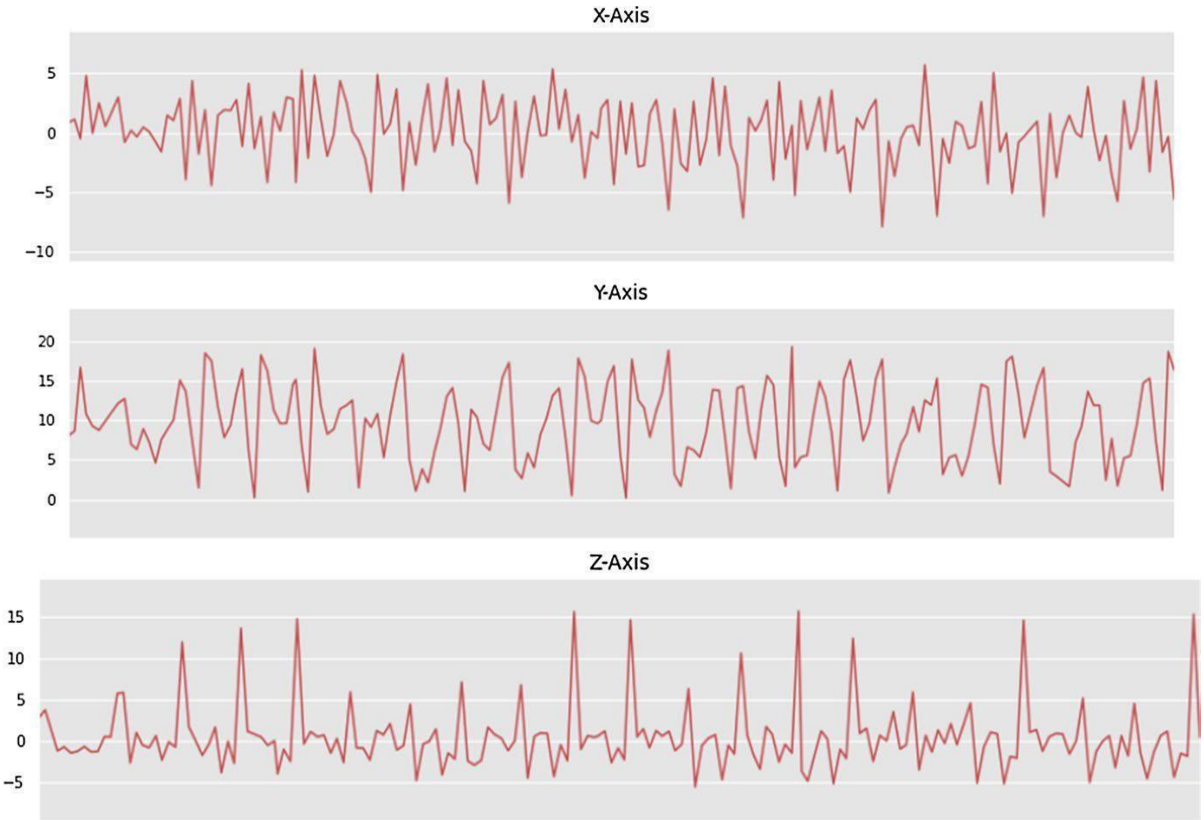

Fig. 3. Sample gyroscope data for walking

More accurately, though, a gyroscope is a device that can provide orientation data as well. The gyroscope has also been used in smartphones to ascertain the rotation rate of the device by detecting the pitch, yaw motions and roll of the device along the 3D axes, respectively. It adds another dimension to the accelerometer data by tracking twist or rotation. It also computes the rotational velocity and rate of change. The output from the accelerometer sensor can be either "noisy" and responsive, or "clean" and slow. On the other hand, when we combine a 3-axis accelerometer and gyroscope, we simultaneously get a clear and responsive output [25]. Fig 3. and fig 4 portrays the sitting and walking patterns of the gyroscope data for the sample col- lected.

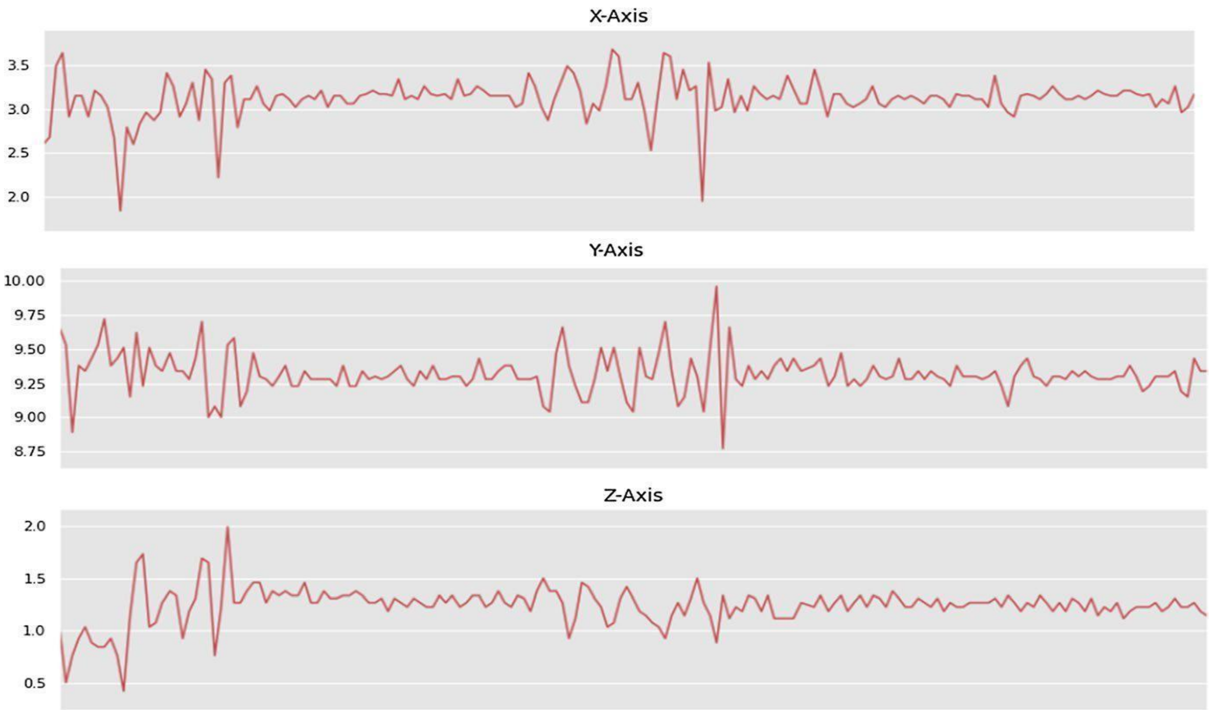

Fig. 4. Sample gyroscope data for sitting

There are different categories involved in data collection:

- Accumulated data that naturally occurs when necessary information is gathered without intervention.
- Through experimental participation, data that are semi-naturally assembled are gathered.
- Research data is a systematic gathering of information.

Due to its preset nature and ability to be used to a range of situations with comparable features, data obtained in laboratories offers particular advantages over the other two. The frequency of data acquisition is another crucial factor that affects the information related to the subject's movements. Each second's worth of data samples is indicated by the frequency rate. Getting information from people with different ages, health conditions, backgrounds, and so on is essential to enable a complex scenario. This sensor-based approach identifies some of the factors like labeling errors [14], subject variability [16], uncertainty [17], scalability [18], over fitting [19], potential bias [20], impact on variance [21], and non-linearity [22].

To overcome these factors in our proposed sensor-based approach two popular methods are performed:

1. Outlier detection using Kalman filter.
2. Imputing missing values with the mean or mode replacement.

When an ML model is either overfit or underfit, it performs poorly. Over- fitting happens when the model picks up extra information as a result of noise or any abnormality, which affects how well the model performs even with little changes or fluctuations in the data.

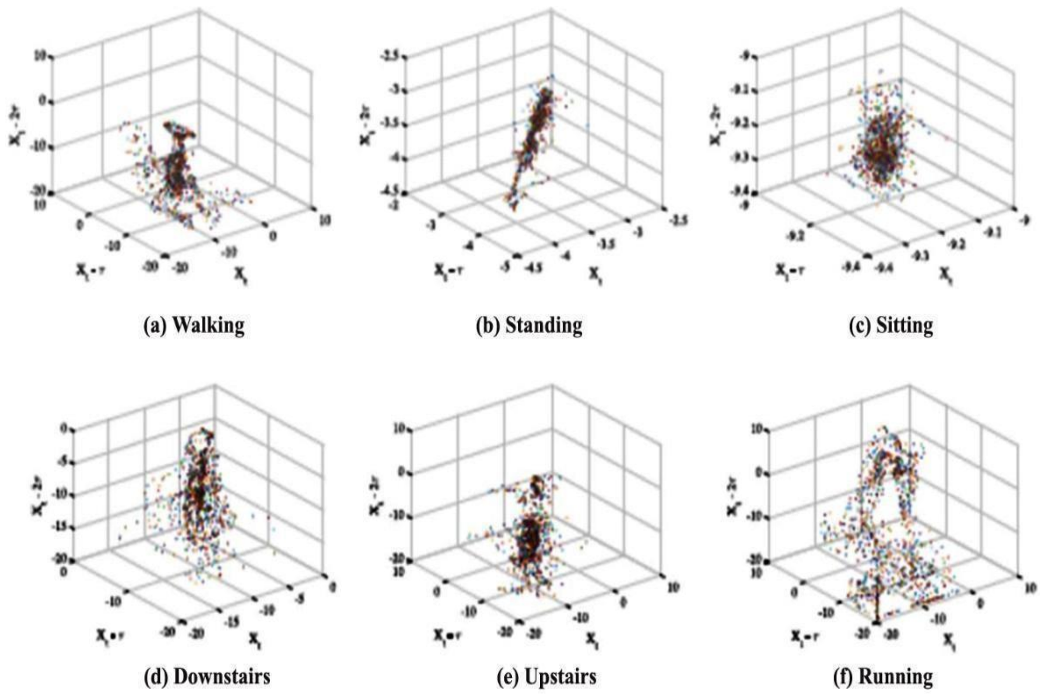

Fig. 5. Identified Activities for Outliers

A model cannot be trained without first pre-processing the input data. When a model is underfitted, it means that it was not adequately trained with sufficient data. This immediately affects accuracy and is readily identifiable (fig 5).

In order to collect data for the simulation, a group of 25 participants, ages 25 to 60, had their smartphones inserted around their waists. Data was acquired at a sampling rate of 5 Hz from accelerometers, GPS, and gyroscopes in smartphones. The following activities were assessed, including both basic and transitional measures (Table 2). The obtained data was divided into discrete actions and the time it took to complete each one. This data is then divided into various categories: training, testing and validation (Fig 6). The model was trained using the training dataset, the parameters were adjusted using the validation dataset, and the accuracy and dependability of the suggested model were evaluated using the test dataset.

Table 2. Activities included in the training dataset's list

No	Actions	Time (seconds)
0	Start	0
1	Standing	10
2	Standing to Sitting	15
3	Sitting	15
4	Sitting to lying	12
5	Walking	15
6	Jogging	10
7	Upstairs	15
8	Downstairs	12
9	Stop	15

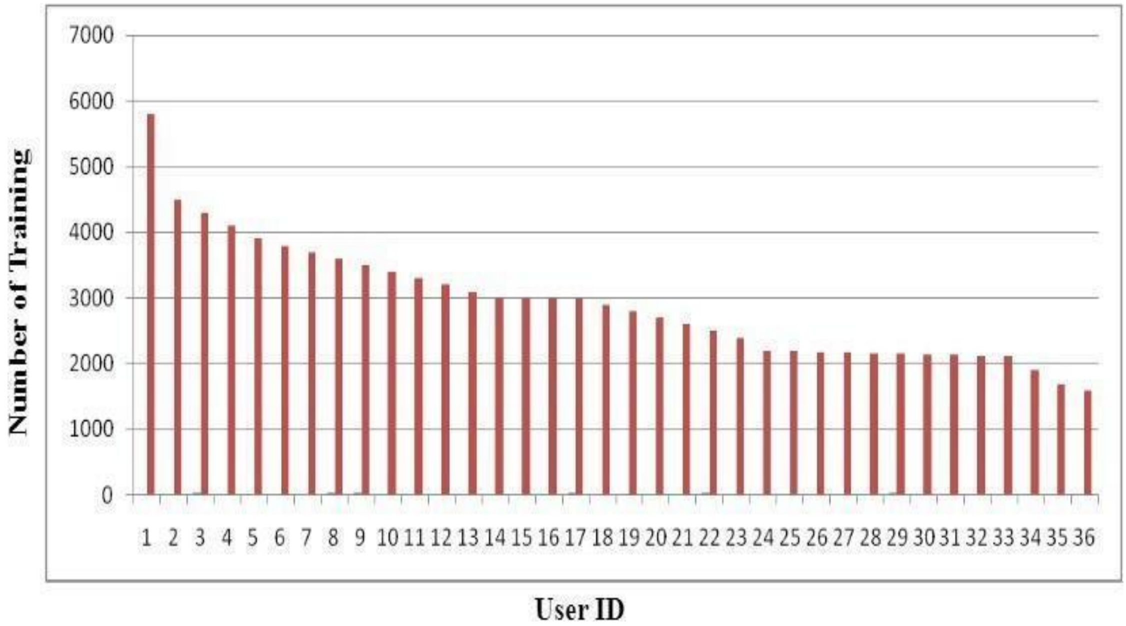

Fig. 6. Training sample dataset

Three distinct signals and axes based on the body's position and acceler- ation are included in the raw input data. From each input data series, 100 steps, or 5- second intervals, were extracted. The windows pertaining to features were converted into completed actions.

3.2 Dataset and Preprocessing

The data we utilized to monitor people was obtained using HAR with accelerometer and gyroscope sensors from the UCI Machine Learning Repository [21] (fig 7). The experiments were done out with a sample of 30 participants aged between nineteen to forty-nine years. All were engaged in seven activities: walking, standing, sitting, lying, walking downstairs, walking upwards and running. As described in (3.1), the accelerometer and gyroscope sensors at a sampling rate of 50Hz measured acceleration and angular velocity. The resulting dataset was partitioned into two sets randomly, to generate training data with 70% of the volunteers and remaining percentage for testing. The data was divided into two sections, which can be used separately.

- Inertial sensor data includes raw tri-axle readings from accelerometer and gyroscope sensors during volunteer trials, as well as activity labels.
- Activity windows are recorded with a 561-feature vector containing time and activity label, subject identifier, and frequency domain variables.

The accelerometer and gyroscope sensor data were preprocessed using noise filters before being sampled in fixed-width sliding windows with a 50% overlap (128 readings per window) for a duration of 2.56 seconds. The output of an acceleration sensor includes components related to both body motion and gravity. A Kalman filter was also used to isolate the data pertaining to body acceleration and gravity. The filter that was employed had a cutoff frequency of 0.3 Hz. Each window yielded a vector of (561) features once variables in the temporal and frequency domains were determined.

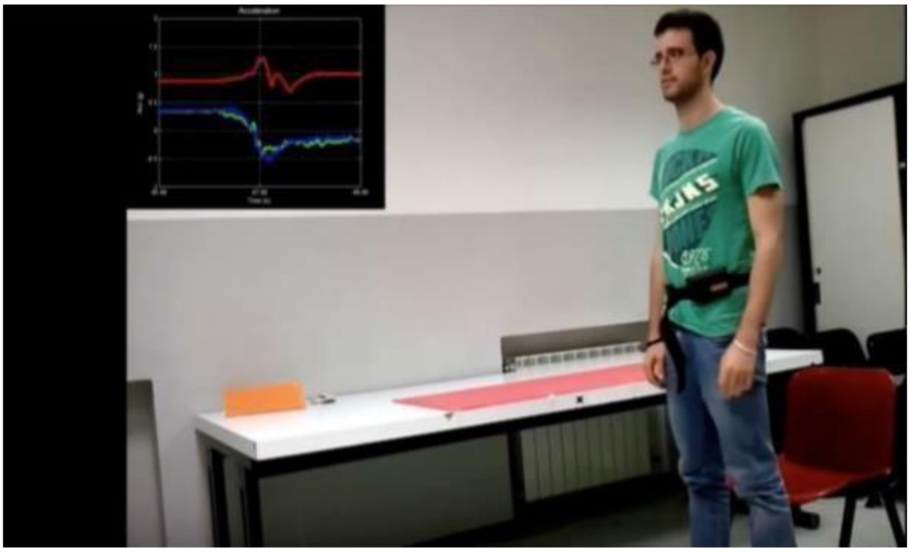

Fig 7. HAR using smart-phone sensors

Fragmentation of a continuous stream of raw sensor data into discrete segments or time intervals, where each division signifies a particular activity or action executed by the user. This process is vital towards precise labeling and analyzing of data with the aim of identifying diverse activities. Our proposed model makes use of sliding window technique due to its practical usability in real-time situations. A definite-size window slides over the sensor data, where each window is treated as a segment. Frames based window organization facilitates overlapping where transient actions that extend across multiple windows can also be captured. A sliding window event sequence is expressed using the notation $a=\{a1 \ldots an\}$, where a = the value, n = the value of the series. ws=window size, t = the point, so that $1<t<n-ws+1$, the time window can be expressed as $a'=\{at,at+1at+ws-1\}$.

Kalman filters are used in our model because they are the most commonly used pre-processing tool for estimating linear quadratic equations. They minimize the Mean Square Error (MSE) and provide an efficient computational way to establish the state of a process when given previous state information. This filter can approximate future states even while the precise nature of the studied system remains unknown. The Kal- man filter has a wide range of applications, including, guidance, navigation, vehicles, aviation and intrusion detection [18].

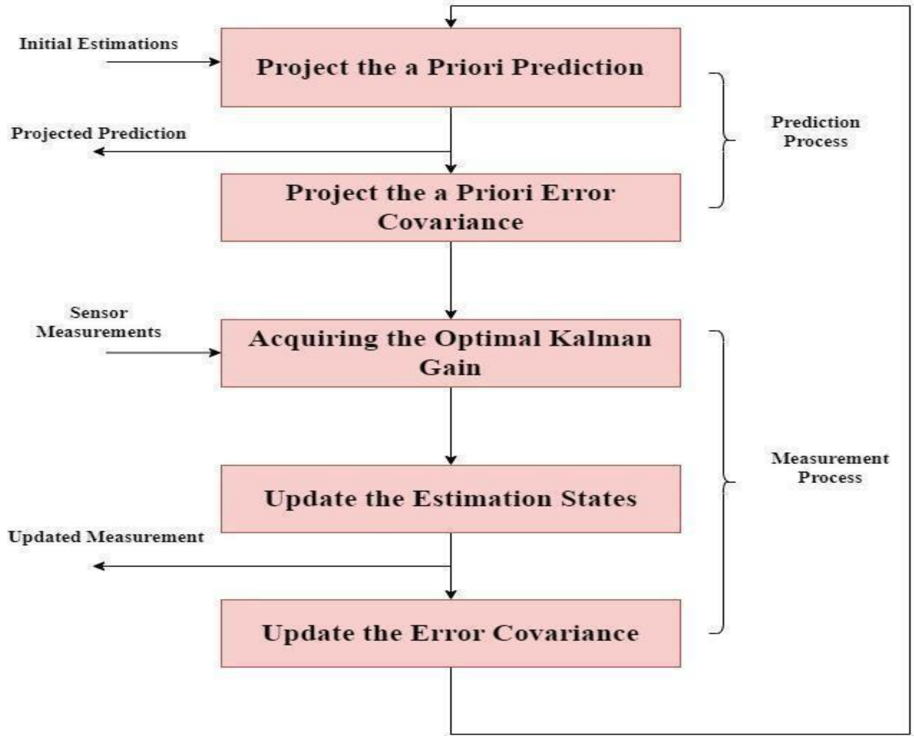

Fig. 8. Kalman Filter processes

This filter's method consists of two phases: prediction and update (Fig 8). During the prediction process, the filter first estimates the current state variables, together with their uncertainty. Once the predictions for the latter states have been generated using weighted average, they are updated with greater certainty to gain more weight. Because the filter process is recursive and does not require any additional prior information, the uncertainty matrix can only be computed using the current input measurements and previously calculated states, allowing it to run in real time. Our proposed model makes use of the Kalman filter (KF) to obtain time and measurement updates to implement human activity tracking and correction purposes [19]. The KF intends to correct the sensor noise and presents predictive guidance when tracked objects go undetected due to closure or temporary loss of signal from sensing region. Initially, a state is maintained which consists of location of human user along x and y axes. During tracking, the initial state consists of first detected location and updates the current state variables with a transition matrix by interconnected indecisiveness and estimates the new position plus the covariance based on current position. Thus, the KF algorithm calculates more accurately than those established on a single sensor measurement (fig 9).

2.1 Feature Extraction and Classification

Because of its widespread application, HAR has become a popular study topic, particularly in accordance with the advancement of DL. Many researchers believe that CNNs are best suited for feature extraction from signal inputs.

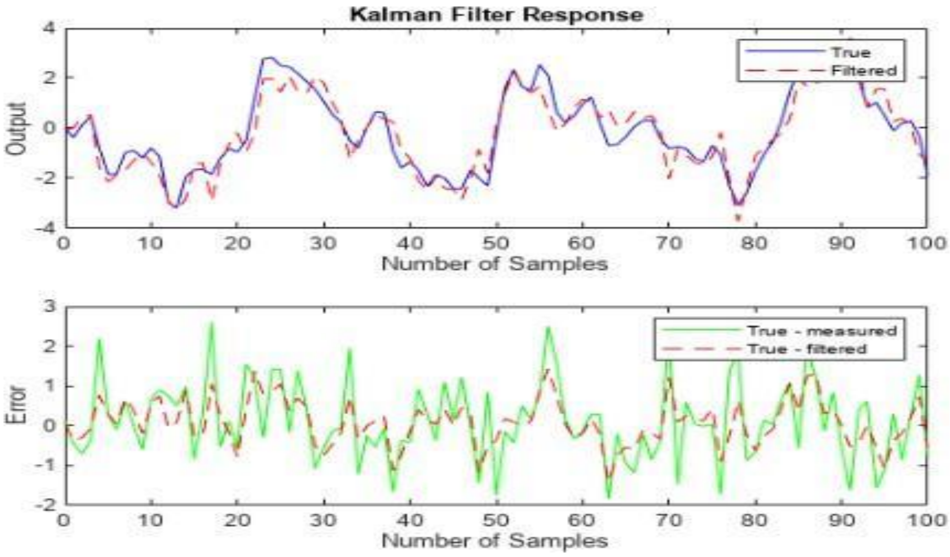

Fig. 9. Results of Proposed Kalman Filter for Raw (A) and Filtered (B) Input Samples

It has generated a lot of interest in using these methods to instantly identify the human behavior on smartphones. A DNA based on a modified 1D-CNN is suggested to identify the appropriate network connections and hyper-parameters for improving performance. A batch normalisation introduced to hasten confluence and it reduced dimensionality and model hyperparameters, which was sequenced by two densely linked layers. A node for every possible item category and a softmax activation function are present in the final dense layer [21]. The UCI-HAR dataset was utilized to assess execution based on activities mentioned above in this chapter. Automatic extraction and classification of human behaviors is part of the proposed paradigm.

3.3 Modified 1DCNN-LSTM Architecture

A recent study demonstrated that combining CNN and LSTM layers is successful in learning time series data [12]. As a result, rather than using CNN, LSTM is employed. Because of its memory function, it can trap the characteristics of time series data temporarily without experiencing diminishing gradient and bursting issues. The generator feeds the previous predictions to the subsequent LSTM cells, which generates a series of sensor data. The generator is thus able to produce time series sensor data that is more precise. The model is made up of two LSTM layers, two fully connected layers and Four 1-D CNN layers (Fig. 10).

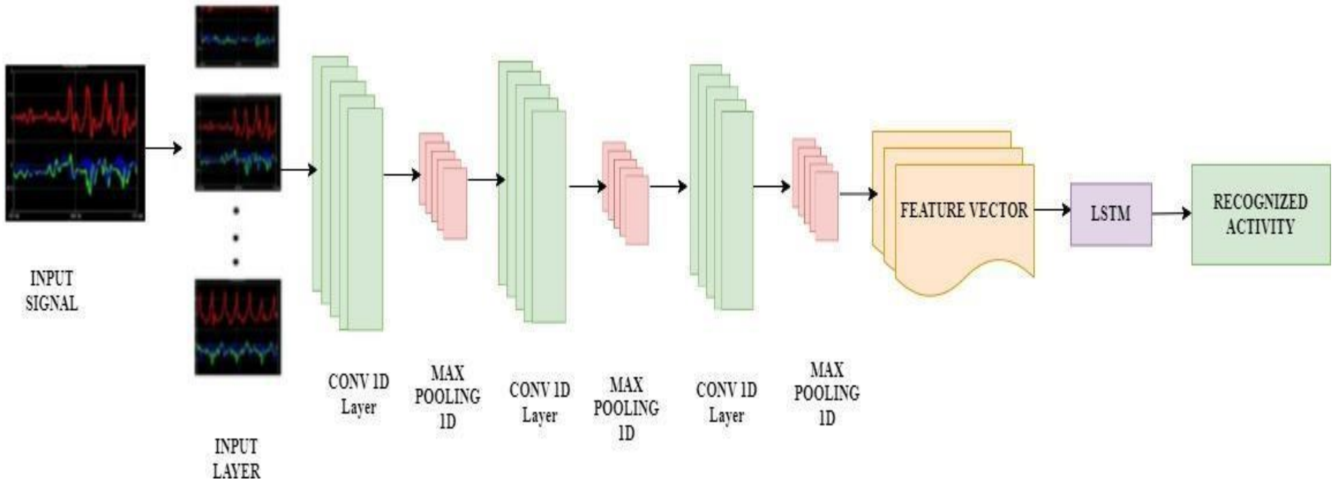

Fig. 10. Modified 1DCNN-LSTM Architecture

The generator's architecture information is displayed in the suggested model. It is important to note that the training process will not converge since the discriminator is likely to perform better than the generator. Selecting suitable model parameters that won't overload the generator is hence one of the discriminator's design factors. The discriminator's trainable parameters should be about equivalent to the generator's in order to balance the two models. The discriminator architecture used in the recommended model for this investigation is described in Table 3.

Table 3. Modified 1DCNN-LSTM Architecture

Layer (type)	**Configuration details**	**Output shape**
1D Convolutional	Filter=64, Kernel size=6 Activation=Leaky ReLU Input Shape=(None,100, 6)	None,96,64
Dropout	Rate=0.4	None, 96,64
1D Convolutional	Filter=128, Kernel size=3	None, 94,128
Dropout	Rate=0.4	None, 94,128
Max pooling	Pool size=2	None, 47,128
Flatten	–	None,6016
LSTM	Units=200	LSTM
Dense	Units=100 Activation=ReLU	Dense
Dense	Units=1 Activation=Sigmoid	Dense
Total parameters 686,060		

4 Conclusion

The investigated model addressed HAR with the goal of fusing DL with hand-crafted features to create a greater effective smartphone-based behavior identification model that puts an emphasis on an individual's safe and healthy lifestyle. Modified 1DCNN- LSTM architecture is better at actively differentiating between motions, obtaining time- series-based properties from sensor input, and identifying patterns. Basic and transitional actions are the focus of this model's application; further study on more complicated actions has been taken into consideration for the future. The research's objective focuses on the categorisation of input and use it for practical application based on HAR. For instance, activity-based analysis in health care apps might notify the appropriate authorities about patients under observation. As an outcome of the model evaluated, it was found that the accuracy was found to be 95% after many epoch iterations of the system inputs.

References

1. Wu, Jingwen, et al. "Detecting the quantitative hydrological response to changes in climate and human activities." Science of the Total Environment 586 (2017): 328-337.
2. Xu, Yang, et al. "Propagation from meteorological drought to hydrological drought under the impact of human activities: A case study in northern China." Journal of Hydrology 579 (2019): 124147.
3. Ni, Bingbing, et al. "Multilevel depth and image fusion for human activity detec- tion." IEEE transactions on cybernetics 43.5 (2013): 1383-1394.
4. Ke, Shian-Ru, et al. "A review on video-based human activity recognition." Computers 2.2 (2013): 88-131.
5. Jiménez-Bonilla, Alejandro, Manuel Díaz-Azpiroz, and Miguel Rodríguez Rodríguez. "Tectonics may affect closed watersheds used to monitor climate change and human activity effects." Terra Nova 35.1 (2023): 58-65.
6. Ronao, Charissa Ann, and Sung-Bae Cho. "Human activity recognition with smartphone sensors using deep learning neural networks." Expert systems with applications 59 (2016): 235-244.
7. Csurka, Gabriela. "Domain adaptation for visual applications: A comprehensive survey." arXiv preprint arXiv:1702.05374 (2017).
8. Jain, Yashswi, et al. "PoseCVAE: Anomalous human activity detection." 2020 25th International Conference on Pattern Recognition (ICPR). IEEE, 2021.
9. Zhang, Ying, et al. "Vegetation dynamics and its driving forces from climate change and human activities in the Three-River Source Region, China from 1982 to 2012." Science of the Total Environment 563 (2016): 210-220.
10. Piergiovanni, A. J., et al. "Adversarial generative grammars for human activity predic- tion." Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part II 16. Springer International Publishing, 2020.
11. Mukherjee, Debadyuti, et al. "EnsemConvNet: a deep learning approach for human activ- ity recognition using smartphone sensors for healthcare applications." Multimedia Tools and Applications 79 (2020): 31663-31690.

12. Javed, Abdul Rehman, et al. "A smartphone sensors-based personalized human activity recognition system for sustainable smart cities." Sustainable Cities and Society 71 (2021): 102970.
13. Shoaib, Muhammad, et al. "Complex human activity recognition using smartphone and wrist-worn motion sensors." Sensors 16.4 (2016): 426.
14. Li, Haobo, et al. "Bi-LSTM network for multimodal continuous human activity recognition and fall detection." IEEE Sensors Journal 20.3 (2019): 1191-1201.
15. Hassan, Mahmoud O., and Yasser M. Hassan. "Effect of human activities on floristic com- position and diversity of desert and urban vegetation in a new urbanized desert ecosys- tem." Heliyon 5.8 (2019).
16. Ignatov, Andrey, et al. "Ai benchmark: Running deep neural networks on android smartphones." Proceedings of the European Conference on Computer Vision (ECCV) Workshops. 2018.
17. Almaslukh, Bandar, Jalal Al Muhtadi, and Abdel Monim Artoli. "A robust convolutional neural network for online smartphone-based human activity recognition." Journal of Intelli- gent & Fuzzy Systems 35.2 (2018): 1609-1620.
18. Tsinganos, Kanaris, et al. "ERA-PLANET, a European Network for Observing Our Chang- ing Planet." Sustainability 9.6 (2017): 1040.
19. Kautz, Thomas, et al. "Activity recognition in beach volleyball using a Deep Convolutional Neural Network: Leveraging the potential of Deep Learning in sports." Data Mining and Knowledge Discovery 31 (2017): 1678-1705.
20. Saunois, Marielle, et al. "The growing role of methane in anthropogenic climate change." Environmental Research Letters 11.12 (2016): 120207.
21. Ishwarya, K., and A. Alice Nithya. "Performance-enhanced real-time lifestyle tracking model based on human activity recognition (PERT-HAR) model through smartphones." The Journal of Supercomputing 78.4 (2022): 5241-5268.
22. Nithya, A. Alice, et al. "CNN based Identifying Human Activity using Smartphone Sen- sors." 2022 International Conference on Edge Computing and Applications (ICECAA). IEEE, 2022.
23. Kumar, Pranjal, Siddhartha Chauhan, and Lalit Kumar Awasthi. "Human activity recogni- tion (har) using deep learning: Review, methodologies, progress and future research directions." Archives of Computational Methods in Engineering 31.1 (2024): 179-219.
24. Khan, Danyal, et al. "Advanced IoT-based human activity recognition and localization using Deep Polynomial neural network." Ieee Access 12 (2024): 94337-94353.
25. Yang, Xiaoshan, et al. "Cross-modal federated human activity recognition." IEEE Transactions on Pattern Analysis and Machine Intelligence 46.8 (2024): 5345-5361.