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Enhancing Health Monitoring using Efficient Hyperparameter Optimization

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Abstract

Nowadays, healthcare problems among elders have been increasing at an unprecedented rate, and every year, more than a quarter of the elderly people face weakening injuries such as unexpected falls, etc. resulting in broken bones and serious injuries in some cases. Sometimes, these injuries may go unnoticed, and the resulting health consequences can have a considerable negative impact on their quality of life. Constant surveillance by trained professionals is impossible owing to the expense and effort. The detection of physical activities by different sensors and recognition processes is a key topic of research in wireless systems, smartphones and mobile computing. Sensors document and keep track of the patient's movements, to report immediately when any irregularity is found, thus saving a variety of resources. Multiple types of sensors and devices are needed for activity identification of a person's various behaviours that record or sense human actions. This work intends to gather relevant insights from data gathered from sensors and use it to categorize various human actions with machine learning using appropriate feature selection and hyperparameter tuning, and then compare the implemented models based on their performance. Understanding human behaviour is very useful in the healthcare industry, particularly in the areas of rehabilitation, elder care assistance, and cognitive impairment.

Keywords: Health monitoring, hyperparameter optimization, rehabilitation, elder care, activity monitoring

1. Introduction

It is well known that several researchers have recently been focusing on the detection, identification, and monitoring of human actions across a variety of sectors. Human Activity Recognition (HAR) is a term used frequently to describe the automated identification of

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human bodily motions. Monitoring human activity is crucial to the population's overall mental and physical health. Chronic conditions including obesity, diabetes, and cardiovascular disease may be automatically detected and controlled by doctors through close observation of individuals' daily tasks. As part of their therapy, these patients are typically asked to adhere to a strict physical activity regimen. Offering an activity identification system will help patient understand their lifestyles and enable their doctors to easily track them and, as a result, make the best suggestions. Human activity tracking over time will shorten hospitalisation, increase the accuracy of diagnoses, and improve patients' life expectancy. Based on an understanding of human behaviour, several healthcare systems are operational. This includes sensor-based strategies, which may be divided into wearable and device sensors.

The monitoring work carried out by people or some cutting-edge recognition model additionally uses 3D and depth cameras. The user's activity data can also be collected by placing RFID passive tags nearby and utilising RFID readers to scan the tags. Hence, the HAR duties can be classified into two fundamental methods. The first of these strategies is known as the computer vision strategy, while the other is known as the sensor-based strategy. In lab settings, the computer vision-based technique often performs well. However, in real-world circumstances, computer vision-based methods can be ineffective because of a variety of potential disruptions such as clamour or fluctuating light power. By using devices that are affixed to an individual's body and constant assessment of several bodily signals that show the status of human behaviours, HAR devices that employ sensors seek to learn data about the condition of the human's surroundings. Research in this field has seen a tremendous improvement, particularly with the growth of newly entrenched sensors and the prevalent use of smartphones in behaviour identification applications.

Smartphones are a necessity in our daily lives since they use a range of sensors to enhance the user experience. There are two such sensors used in this work, namely accelerometers and gyroscopes. An electromechanical instrument that monitors acceleration forces is known as an accelerometer. Acceleration is determined by dividing speed by time, or by the differences in velocity. These forces can be either static, like the constant pull of gravity, or dynamic, like the movement or vibrations experienced by many mobile gadgets. On the other hand, a gyroscope is a tool used to measure or maintain rotational speed. It is a revolving wheel or disc having a freely rotatable spin axis. In line with the principle of conservation of angular momentum, this axis maintains its orientation even when the mounting spins or tilts. In addition to the Hubble Telescope, gyroscopes are also used in inertial navigation systems and submerged submarine steel hulls. Gyrocompasses may be made using gyroscopes, and they can be added to or used in place of magnetic compasses in ships, aeroplanes, and other kinds of vehicles. They might also be included in inertial guidance systems or used to help stabilize ships, motorcycles, and other types of vehicles. Since they are used for everyday tasks like fitness bands, accessories, and smartphone applications, modern society urgently requires these sorts of technological advancements.

Therefore, to understand the real-world uses of machine learning, this paper has studied this relevant issue that is now developing and becoming more popular. Users wore their phones around their waists as they engaged in various activities to get the required readings. As a result, one of the six human activities was predicted using the features developed using data from the accelerometer and gyroscope. To find the model with the optimal level of accuracy using the features and data provided, a variety of different models were used and compared during the study. The main aim is to deploy the smartphone sensors and use a mechanism that can also be used in fitness applications and bands, which are fairly popular these days.

2. Related Works

The majority of the evaluated literature indicates that HAR is used in placing medical equipment in a home setting, hospitals and rehab facilities. HAR is frequently used to track the activities of elderly patients residing in rehabilitation facilities for the management and prevention of chronic diseases [1]. HAR is also used for monitoring the activities of the elderly in smart homes [2] [3]. Additionally, HAR is employed in rehabilitation facilities to promote physical activity among patients with dysfunction and psychomotor slowness [4], children with motor impairments [5], post-stroke motor patients [6], and exergaming [7]. Apart from that, the HAR is used to monitor patients at home, including lifelogging [8] and the calculation of energy expenditure to help prevent and manage obesity [9]. It has been used often in the field of human-computer interaction in games and exergames like Kinect [10][11][12], Nintendo Wii [13], [14], and full-body motion-based games for older individuals [15] and those with neurological impairment [16]. Through HAR, human body motions are identified to provide computer instructions on how to carry out specific jobs. HAR is also utilized in observing additional behaviours, such as stereotyped movements, illnesses that affect kids with autism spectrum disorders abnormalities, for cardiac patients at home [17], and discovery of early disease symptoms [18] and it also gives the doctors the chance to intervene. Additional healthcare related HAR applications include geriatric fall detection and intervention [19][20]. Wearable sensors, including an accelerometer, gyroscope, and magnetometer, are used in motion activity detection. Sensing devices may be used to detect a variety of data, including natural features, movement, position, and other physiological functions [21][22][23].

According to Hassan et al. [24], the major goal of their work was to create a reliable HAR mechanism using the information from sensing devices. Since cell phones are used so frequently in our everyday lives for several purposes, including healthcare, they claimed that employing smartphones for augmented reality is an extremely wise move. According to the researcher's investigation, adjusting for 12 different physical activities led to an average detection rate of 89.60% and an absolute accuracy rate of 95.80%.

HAR equipment is employed in a wide range of industries, particularly in the defence, surveillance, and medical sectors [25]. The condition of human activities may be determined by employing extrinsic (non-homogenous) sensors in HAR devices as a consequence of technology studies and applications made in recent years. Sensing devices are frequently used in systems for assessing daily activities in human activity identification research due to their affordable fee, compactness, and low usage of energy. Human action recognition programmes' primary goal is to get specific details about motions with the use of wearable sensors [26]. In HAR deployments, there are two crucial parts. The inputs measured by the sensor are first broken down into their parts, or characteristics. In the following phase, a machine learning technique classifies the extracted characteristics. The useful characteristics acquired in the initial step are those that determine the system's effectiveness [27].

A brand-new continuous feature-based approach that relies on Triple Patterns and Discontinuous Wavelets (TP-DWT) was developed by Tuncer et al. [28]. The projected TP-DWT-based extraction of features network-based technique for sEMG signal identification was provided. The proposed TP-DWT-based sEMG signal identification technique included channel merging, TP-DWT network extraction of features, 2-level extraction of features, and conventional classifier categorization. The TP-DWT-based sEMG classification technique achieved an average accuracy of 99.14% for all strength levels using the K-Nearest Neighbour (KNN) classification with tenfold cross-validation. Tuncer et al. [29] claimed to have established a brand-new technique for identifying gender and everyday sports events using detector inputs. To put the suggested MK-LDP and RFNCA-based HAR technique into the trial, three examples were developed. These three conditions included categorization by gender, classification by activity, and categorization by both gender and behaviour. According to the researchers, the HAR investigation that used sensory inputs from the suggested MK-LDP and RFNCA-based architecture was effective. In another research, Tuncer et al. [30] used transfer deep learning algorithms for their AR approach. The authors reported that 1,000 characteristics per system were recovered using the characteristic extractors ResNet18, ResNet50, and ResNet101. Combining the retrieved characteristics yielded 3000 traits. During the feature stage of selection, the most unique 1000 characteristics were chosen using Relief-F, and these chosen characteristics were then fed into the Support Vector Machine (SVM) with third-order polynomial (cubic) activation. The suggested technique recognised gender and activity with classification performance rates of 99.96 and 99.61%, respectively.

Numerous supervised learning methods were employed for the deployment of HAR in [31] where algorithms were employed to divide the result into three main categories: sitting, jogging, and walking. This was accomplished by keeping track of modifications every 20 occurrences and employing a constant window length during the feature extraction step without any overlap. When HAR is continuously being implemented using ML and DL models, [32] provided additional details regarding HAR. SVM, KNN, and Convolutional Neural Networks (CNN) were used to build the models, where it was discovered that despite the addition of dimension reduction, SVM’s and CNN's performance were quite close. Another study [33] employed a one-Dimensional (1D) CNN and emphasized mostly the specific deep learning component for HAR implementations. The acceleration data for x, y, and z are transformed into vector magnitude information that may then be utilised as the source for training the 1D CNN. This outperformed the Random Forest (RF) approach's accuracy of 89.10% and produced an accuracy of 92.71%. As a result, although both Machine Learning (ML) and Deep Learning (DL) techniques have highly accurate rates, additional research reveals that fluctuations exist.

Study [34] demonstrated why machine learning methods fall short of deep learning. Deep Learning approaches, in contrast to ML techniques, learn by developing a more abstract data encapsulation as the network expands; thus, the modelling approach obtains deeper characteristics and produces outcomes with more precision. It merely replicates brain activity, with several levels of neural connections arranged in a stack, much like the traditional brain model. Multiple human activity databases from cell phones and/or smartwatches have been reported in the literature, including WISDM v1 and v2, UCI-HAR, and UniMiB SHAR surveyed by Demrozi et al. [35]. Baldominos et al. [36], carried out a comparison of various techniques using machine learning (deep and shallow). The four sensors already stated were employed to take readings. The group of randomly selected Decision trees fared better than both shallow classifiers like RF, MLP, NB, KNN and CNN. Deep learning neural networks and Deep Stacked Autoencoders (DSAE) were two deep learning models that Alo et al. [37] studied. In both systems, only accelerometer readings were taken into account. The magnitude vector, pitch and roll angle vectors, and observations were also employed for model training.

A novel HAR model based on convolutional and LSTM recurrent units was created in [38]. Relying on Google's Inception-ResNet architecture, the proposed iSPLInception was created in [39]. The performance it displayed when utilising various HAR datasets was adequate. The researchers of [40] investigated the uses of various techniques for deep learning and discovered that the combination CNN-BiGRU model delivered the best results for recognizing activities using wrist-worn wearable sensors. The existing solutions were mostly focused on using different human activities and did not put much emphasis on tuning the hyperparameters. In this framework, appropriate hyperparameter optimization has been implemented to modify the model's parameters, which is essential to regulate the behavior of the model to produce an improvised model with the best possible performance.

3. Proposed Methodology

This section discusses the methodology proposed in this study.

3.1 Data Source

This work made use of an open-source dataset from the UCI Machine Learning Repository. [21] To collect the accelerometer and gyroscope measurements needed for this study, thirty participants participated in the following six different activities.

- Walking
- Walking upstairs
- Walking downstairs
- Sitting
- Standing
- Lying

The count of readings taken for each activity has been given below.

Table 1. Frequency distribution of all activities present in the dataset [41]

S. No.	Activity	Count
1	Standing	1374
2	Sitting	1286
3	Lying	1407
4	Walking	1226
5	Walking Downstairs	986
6	Walking Upstairs	1073

The dataset recorded three axial linear accelerations and three axial angular velocities at a steady rate of 50Hz using the device's installed accelerometer and gyroscope. To identify important data and eliminate background noise, feature extraction was used. After using noise reductions to the different sensors, they were recognized in frames of 2.6 seconds with an overlapping probability of 0.5 to get 128 samples in each frame. The acceleration data was split into signals for body and gravity. All of the accelerometers and gyroscopes are tri-axial, which means that they detect acceleration and angular velocity in the X, Y, and Z axes [41]. The below figure shows the signals obtained and their corresponding statistical properties present in the dataset.

Table 2. Signals obtained and their corresponding statistical properties [42]

S. No.	Signals	Statistical properties estimated on every signal
1	Total Body Acceleration-XYZ	Mean value
2	Total Gravity Acceleration-XYZ	Standard deviation
3	Time domain Body Jerk Acceleration-XYZ	Median absolute deviation
4	Time domain Body Gyro XYZ	Largest value in array
5	Time domain Body Gyro Jerk-XYZ	Smallest value in array
6	Time domain Body Acceleration Magnitude	Signal magnitude area
7	Time domain Gravity Acceleration Magnitude	Energy measure. Sum of the squares divided by the number of values.
8	Time domain Body Acceleration Jerk Magnitude	Interquartile range

9	Time domain Body Gyro Magnitude	Signal entropy
10	Time domain Body Gyro Jerk Magnitude	Auto-regression coefficients with Burg order equal to 4
11	Frequency domain Body Acceleration-XYZ	Correlation coefficient between two signals
12	Frequency Body Acceleration Jerk-XYZ	Index of the frequency component with the largest magnitude
13	Frequency domain Body Gyro-XYZ	Weighted average of the frequency components to obtain a mean frequency
14	Frequency domain Body Acceleration Magnitude	Skewness of the frequency domain signal
15	Frequency Body Acceleration Jerk Magnitude	Kurtosis of the frequency domain signal
16	Frequency Body Gyro Magnitude	Energy of a frequency interval within the 64 bins of the FFT of each window.
17	Frequency domain Body Gyro Jerk Magnitude	Angle between two vectors.

3.2 Data Pre-processing

The duplicate and null values in the data were removed first. Also, it was checked if there is any imbalance in data. The balance in data was visualized by plotting the graphs for the count of different activities undertaken by each subject ID and the count of different human activities. SMOTE was implemented which generates minority class samples at random and duplicates them, thereby balancing the distribution of classes. For the minority class, it produces virtual training data using linear interpolation. The motion was categorized into two categories - Static and Dynamic. Static included activities such as sitting, standing, and lying while Dynamic included walking upstairs, walking downstairs and normal walking.

3.3 Data Exploration and Visualization

Data exploration was carried out to examine and study data to get important insights and to spot potential regions or trends for further investigation. The plots obtained have been depicted in the following figures.

tBodyAccMagmean: It is the magnitude of the mean of body acceleration in the time domain determined by an accelerometer. From Figure 1, it can be observed how effectively "tBodyAccMagmean" can distinguish static activity from a dynamic activity from the tBodyAccMagmean v/s Accelerator Body Mean plot. In Figure 2, Accelerator Gravity Mean on x-axis (t.gravity.acc.mean.x) represents the mean of time domain signal of gravity acceleration in X axis. In Figure 3, Mean Body Acceleration (t.body.acc.mean) represents the mean of time domain signal of acceleration experienced by the body of an individual.

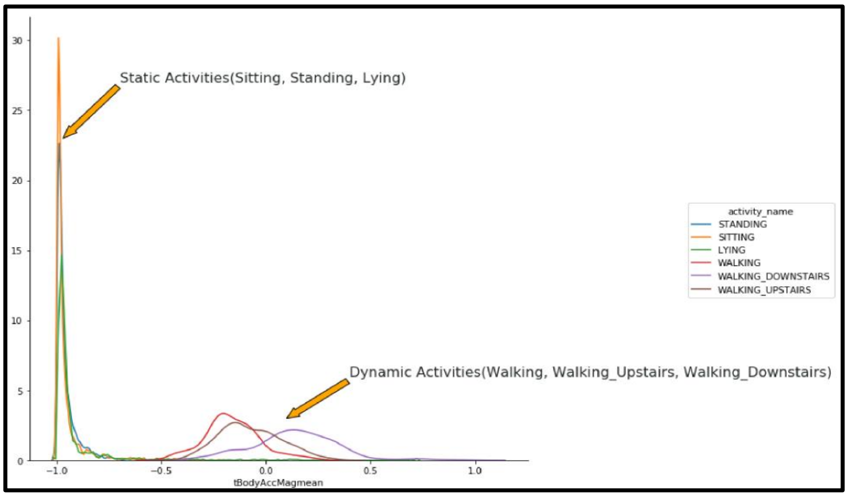

Figure 1. tBodyAccMagmean for all activities

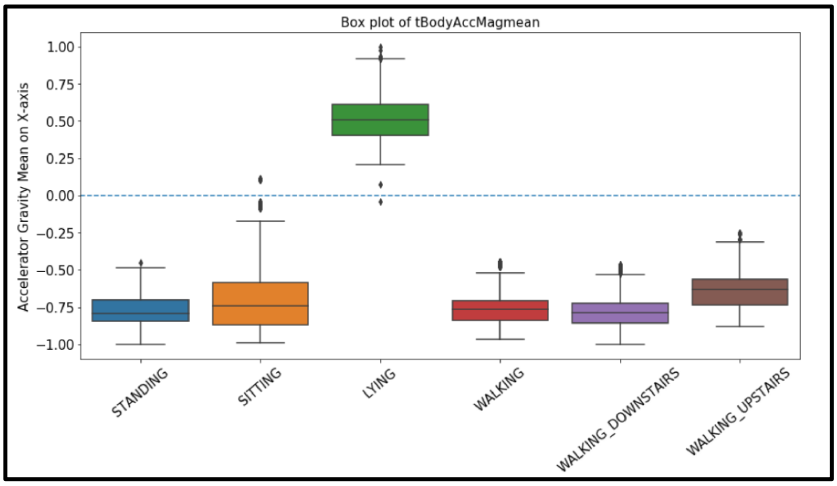

Figure 2. Box plot of tBodyAccMagmean with Accelerator Gravity Mean on X-axis

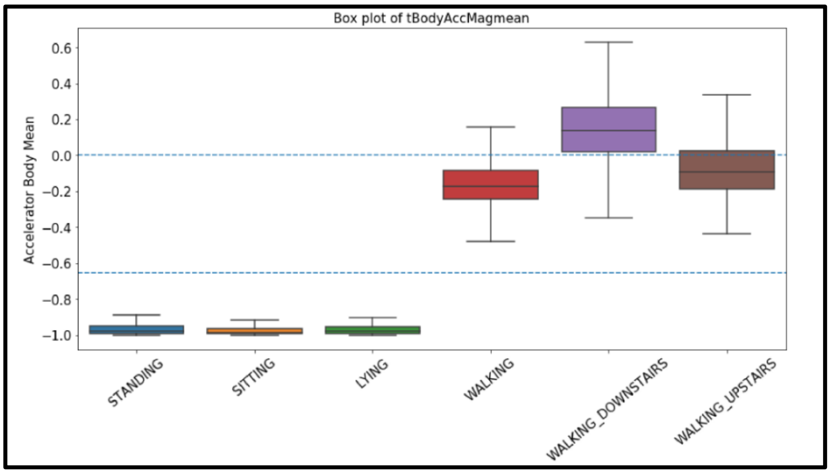

Figure 3. Box plot of tBodyAccMagmean with Accelerator Body Mean on X-axis

Following conditions can be inferred from Figure 2 and Figure 3.

- When *Accelerator Gravity Mean on X-axis > 0.2,* it can be inferred that the activity will most likely be lying.
- When *Accelerator Gravity Mean on X-axis < 0.0,* it can be inferred that the activity can be anything but lying.
- When *Mean Body Acceleration < -0.85,* it can be inferred that activities are either standing, sitting or lying.
- When *Mean Body Acceleration > -0.5,* it can be inferred that activities are either walking or walking downstairs or walking upstairs.
- When *Mean Body Acceleration > 0.0,* it can be inferred that the activity is walking downstairs.

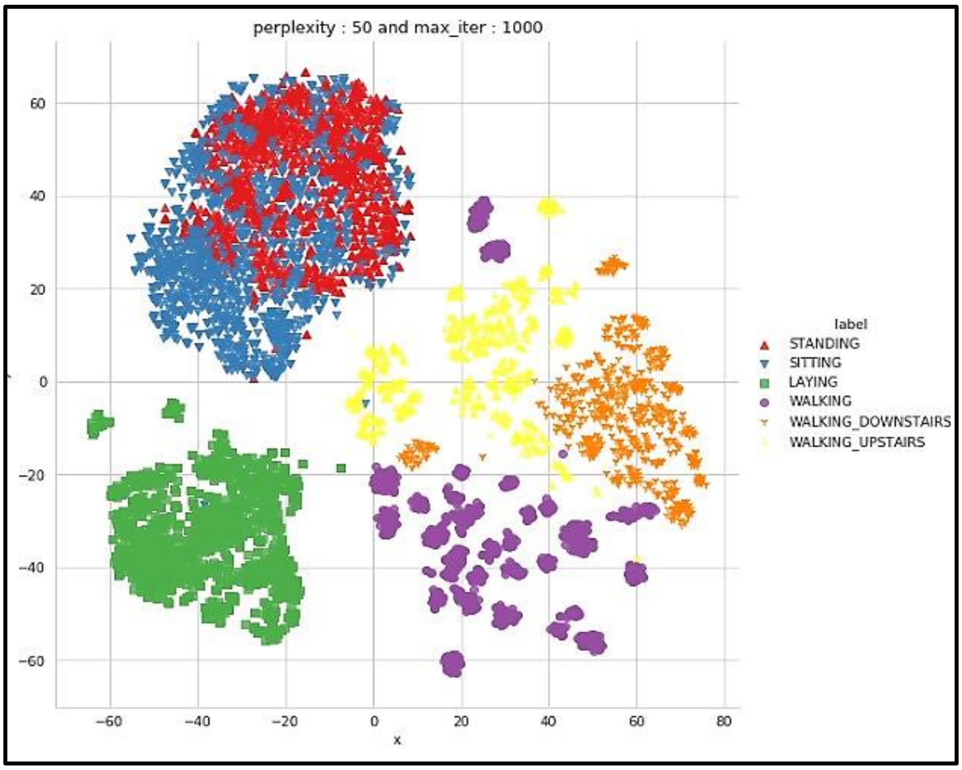

Figure 4. T-SNE Plot depicting separability between different activities

The T-SNE plot was implemented to data for better visualization and to get a better perplexity. Using this, different sets of data points corresponding to different human activities were obtained. From the T-SNE plot in Figure 4, it can be observed that except for Standing and Sitting, all other activities are separated fairly well.

3.4 Model Implementation

Data was split into 70% training data and 30% testing data. For better understanding, various machine learning models - Logistic Regression, Linear Support Vector Machine, RBF Support Vector Machine, Decision Tree, Random Forest and a deep learning LSTM Model were implemented using raw readings obtained from accelerometer and gyroscope signals as features to train the model. The results obtained from all the models were then compared.

Hyperparameter Tuning: The following best hyperparameters were determined using GridSearchCV optimization while training the models:

Table 3. Tuned Hyperparameters obtained after optimization

Model	Tuned Hyperparameters
Logistic Regression	*C parameter: 10, penalty: L2 regularization, cv:3 and n_jobs:1, solver: liblinear, tol:0.0001*
Linear SVM	*C parameter: 1, cv:3, loss: squared hinge, max_iter:100, tol:0.0001*
RBF SVM	*C parameter: 100, gamma: auto, kernel, degree:3, decision_function_shape: ovr, cache_size:200, cv:3*
Decision Tree	*criterion: gini, max_Depth: 7, min_samples_leaf:1, min_samples_split:2, splitter: best*
Random Forest	*cv:3, n_estimators:200, min_samples_leaf:1, min_samples_split:2, n_jobs:1*
Gradient Boosted Decision Trees	*Criterion: friedman_mse, max_depth:1, learning rate:0.1, n_estimators:100, persort: auto*
LSTM	*batch_size: 32, epochs: 8, optimizer: adam, Dropout rate: 0.69 and Dropout_1 rate: 0.21*

4. Results and Discussion

The results obtained on implementing different models are given in the table below.

Table 4. Results obtained on implementing the models for classifying different human activities

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	96.20 %	0.97	0.96	0.97
Linear Support Vector Machine	96.53 %	0.97	0.96	0.97
RBF Support Vector Machine	96.46 %	0.96	0.96	0.96

Decision Tree	85.42%	0.87	0.86	0.87
Random Forest	92.57 %	0.93	0.92	0.93
Gradient Boosted Decision Trees	90.59 %	0.91	0.91	0.91
LSTM	87.75 %	0.89	0.88	0.89

The above table shows that Linear SVM provided the best accuracy of 96.53 % while Decision Tree gave the worst accuracy of 85.42 % as it tends to overfit and does not generalize well on the data. LSTM was able to give an accuracy of 87.72% even without engineered features. Also, Logistic Regression and Linear SVM produced the best F1 Score (0.97) while the Decision Tree gave the least score (0.87).

5. Conclusion

Recognizing human activity in time series is a difficult problem for categorization. Efficient feature extraction generally requires extensive domain understanding and methodologies from signal processing. It entails predicting a person's motion based on sensor data. In this paper, a smartphone sensors-based recognition system has been built to identify human activity using efficient hyperparameter tuning. It is observed that Logistic Regression, Linear SVM, and RBF SVM achieved an accuracy above 96% which is significantly better than the existing solutions. The features used in them were well-engineered by domain experts in signal processing. Also, deep learning helps to build models such as LSTM, even when there is no domain expert-engineered features, and produces comparable results. In the real world, having domain knowledge and feature engineering is one of the most vital facets of modelling as observed from the results of this work. Future work in this area might incorporate more activities and even look to develop a real-time smartphone system. Other search techniques include density-weighted techniques and variance reduction to improve the effectiveness of active learning. Also, the results can be further improved by using high powered GPU and by evaluating it while tuning hyperparameters.

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