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A New Approach for Human Activity Recognition (HAR) Using A Single Tri-axial Accelerometer Based on a Combination of Three Feature Subsets

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Abstract: Human Activity Recognition (HAR) is focused on Activities of Daily Living and developed in the health and human security fields. The HAR concept was introduced in previous research using multi-sensor devices. In their implementation, wearable devices require computational and real-time environmental limitations. This paper proposed a new approach for HAR using a machine learning-based single-sensor accelerometer. This research aimed to determine the performance of machine learning in HAR using three Feature Subsets: Feature Subset Signal Vector Magnitude (SMA), Feature Subset Fast Fourier Transform (FFT), and Feature Subset Value-Crossing. In features selection, ANOVA was used to reduce feature dimensionality. The experimental results have been assessed using the confusion matrix to prove that the proposed model can achieve an optimal accuracy of 0.97, higher than several state-of-the-art approaches. The optimal sensitivity and specificity values have been 0.98 and 0.99 and are partially higher than previous studies using similar testing scenarios.

Keywords: Human activity recognition (HAR), Activities of daily living (ADL), Single triaxial accelerometer, ANOVA.

1. Introduction

Human Activity Recognition (HAR) is a field that has received quite a lot of attention because it can be applied for several purposes, such as elderly care, health care, rehabilitation, entertainment, monitoring, and human interaction with computers [1-3]. Various techniques have been developed for activity recognition, both computer vision-based and sensor-based [2]. Computer vision usage requires a camera device to capture human activities [3, 4]. This computer vision technique can provide good results, but lighting, privacy, processing complexity, and fixed camera positions still need to be solved [1, 2, 6]. Therefore, sensor-based techniques can be an option to overcome the shortcomings of camera-based techniques.

Sensor-based activity recognition generally uses sensors integrated into smartphones [7], and wearable devices, such as watches [8-10], bracelets [11, 12], clothing [13], and some are even attached to the mouth or teeth [14]. The use of sensors for this purpose is called wearable sensors [1]. Wearable sensors have several advantages compared to a camera, such as [6]: it can be placed on the observed object precisely and does not interfere with privacy because there is no image or video capture. In addition, its position can follow the observed object.

The wearable sensor data requires appropriate processing tools and prediction algorithms to identify activities. Previous research introduces the use of machine learning algorithms for activity recognition, both using traditional techniques and using deep learning [1, 3, 8, ,13, 15]. HAR model using deep learning can automatically extract salient features through different filters to perform recognition [16, 17]. However, this deep algorithm requires many datasets and sufficient computation and has no easy explanation because the algorithm is a black box [18]. Traditional algorithms focus on handcrafted feature extraction [17], so the main

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challenge is performing the feature extraction process. Features generated from sensor data can be categorized based on the time domain and frequency domain [18, 19]. These features can be sourced from various sensors, such as accelerometer, gyroscope, and magnetometer sensors [1, 20-22]. These sensors can be used singly or as a combination of homogeneous or heterogeneous sensors [21]. Using multi-sensors generates more complex data and requires special attention to data dimension [3]. In addition, in wearable sensors, the use of multi-sensors can increase computational costs [23].

This paper proposed a new Human Activity Recognition (HAR) detection approach by applying a single sensor and a machine learning-based classifier. A single sensor usage for HAR is challenging and interesting because it can overcome heavy pre-processing [23]. Optimization is done using multiple techniques in the feature extraction and selection process. The proposed model aims to accurately detect routine human activities based on activity patterns from a single accelerometer sensor. This detection can help in the healthcare field, for example, as supporting data for patient medical records that are seen based on routine patient activities. The proposed research has research contributions, namely as follows.

(1) This research uses data sourced from a single accelerometer sensor. It aims to overcome pre-processing problems.
(2) Feature extraction uses a combination of time domain, frequency domain, and value-crossing. The result of feature extraction consists of three subsets: Feature Subset Signal Vector Magnitude (SMA), which is the time domain; Feature Subset Fast Fourier Transform (FFT), which is the frequency domain; and Feature Subset Value-Crossing.
(3) The resulting features are selected using ANOVA, and each combination of feature selection results is evaluated using several machine learning algorithms: Extreme Gradient Boosting, AdaBoost, Gradient Boosting, Random Forest, Decision Tree, and Support Vector Machine.

This research is organized as follows. Section 2 discusses related research. The proposed model is described in Section 3, which consists of Signal Vector Magnitude (SVA), Fast Fourier Transform (FFT), ANOVA, and equations to calculate feature extraction. Section 4 discusses the experiment setup: setup parameters of the machine learning used, datasets, and confusion matrix to evaluate the machine learning model. The results and discussion of the proposed paper are described in Section 5. Lastly, the discussion of conclusions and future research in Section 6.

2. Related Work

Machine learning algorithms have been used for Human Activity Recognition (HAR) using traditional and deep learning [24]. Some examples of traditional machine learning were K-Nearest Neighbours (KNN) [18, 25, 26], Random Forest (RF) [26, 27], Support Vector Machine (SVM) [18, 26], Multi-Layer Perceptron [28], and AdaBoost [29]. While deep learning algorithms, such as CNN [19], LSTM [30], RNN [31], and others. Previous research showed [32, 33], that some machine learning algorithms produced different performances, even with the same dataset. Deep learning was still an issue for a limited amount of data, so traditional machine learning was still an option [18]. Generally, ensemble-based machine learning was used to improve activity recognition accuracy [19]. The main focus in HAR with traditional machine learning was on the feature extraction process before the classification process [17, 24]. The features generated at the feature extraction stage could be categorized into shallow and deep features [34]. One of the techniques for extracting shallow features was handcrafted feature extraction, which had a specific domain [17]. This research used the handcrafted feature extraction technique.

Vidya [3] proposed a model for recognizing daily activities such as bending, cycling, lying, sitting, standing, and walking, with features derived from multi-sensor accelerometer data and RSS from WSN. Feature extraction was performed in the time and frequency domains using Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD). The results from DWT and EMD were further extracted into entropy, energy, and statistical features, including mean, mean absolute deviation, median absolute deviation, standard deviation, and L2 norm. Subsequently, all generated features were selected using Pearson's correlation and classified with a Support Vector Machine (SVM), K-nearest Neighbour (KNN), Ensemble Classifier (EC), and Decision Tree (DT). The extraction method used enhanced machine learning performance, specifically Decision Tree (DT) classifier. Human Activity Recognition (HAR) was applied to identify daily activities, including the recognition of table tennis, as demonstrated by Hegazy et al. [33]. This research incorporated a combination of accelerometer, gyroscope, and IR depth camera sensors. The features used included magnitude, standard deviation, peak-to-peak amplitude, mean, median, minimum, and maximum. Meanwhile, the extracted features were evaluated using machine learning algorithms such as FastDTW, K-nearest Neighbour (KNN), Support Vector Machine (SVM), Naive Bayes (NB), and RNN. The experimental results showed that the combination of accelerometer, gyroscope, and IR depth camera sensors could enhance classifier performance, with RNN showing the highest average performance.

Ehatisham-Ul-Haq et al. used an RGB-D camera, accelerometer, and gyroscope combination to recognize 27 activities [35]. RGB-D camera data were extracted using Bag-of-Words (BoWs), while accelerometer and gyroscope data were converted into Signal Vector Magnitude (SMA) for further extraction into statistical values, specifically the mean. The results were classified using a Support Vector Machine (SVM) and K-nearest Neighbour (KNN), where optimal performance was achieved when all features from the RGB-D camera, accelerometer, and gyroscope were used for classification. Previous research recognized Activities of Daily Living (ADL) and falls using RGB, depth, and accelerometer sensors [36], where 3 public datasets were evaluated with Logistic Regression (LR) algorithms. The proposed model achieved the accuracy of 0.93 and features extracted from both time and frequency domains included skewness, fuzzy entropy, temporal moment, and geometric (skeleton).

Geravesh et al.[37] also conducted similar research to classify daily activities such as sitting, standing, walking, cycling, climbing stairs, and descending stairs. A total of 6 features were extracted from the combination of accelerometer and gyroscope sensors. These features were evaluated using various machine learning algorithms, including Multi-Layer Perceptron (MLP), K-nearest Neighbour (KNN), Random Forest (RF), Decision Tree (DT), and Logistic Regression (LR). Among the algorithms, MLP showed the best performance. Additionally, recognizing cyclist activities was explored through accelerometer, gyroscope, and magnetometer sensors, as showed in previous research [38]. The research used a SVM for accident classification, extracting 24 features in the time domain including mean and standard deviation. Principal Component Analysis (PCA) was used to reduce the features count, resulting in a model with the accuracy, sensitivity, and specificity of 0.95, 0.96, and 0.94, respectively.

Previous research [39] combined heart rate and accelerometer sensors to classify fall and non-fall activities. Several machine learning methods were used, including a SVM, DT, KNN, NB, and Gaussian Mixture Models (GMMs). Data from the sensors were extracted into candidate features such as mean, median, standard deviation, mean absolute deviation, skewness, kurtosis, signal magnitude area, data maximum, and spectral entropy. Furthermore, data included summation of time-domain energy, activity count, root mean square, successive normal sinus, deceleration capacity, acceleration capacity, fastest heart rate, and triangular index. These features were selected using Fisher Score with Mutual Information and the results showed a significant effect on fall detection due to the combination of heart rate and accelerometer sensors. HAR for scaffolding activities had also been explored [40], classifying a total of 15 activities. The sensors used included electromyography (EMG), gyroscope, and accelerometer (IMU). Subsequently, the extraction process was based on the time domain with a total of 38 features, where 6 were extracted from IMU and 32 from EMG. The classification algorithm used was Artificial Neural Network (ANN), showing that the combination of EMG and IMU outperformed single-sensor setups with the accuracy of 0.94.

The use of multiple sensors such as accelerometer, gyroscope, magnetometer, heart rate, and camera has also been investigated [3, 33, 35, 36, 40]. The results showed that the use of multiple sensors could enhance the performance of machine learning classifiers. However, the increase in data dimensions with the number of sensors used posed challenges in preprocessing complexity [41]. Previous attempts to reduce data dimensions used various method including Signal Vector Magnitude [35, 42], Principal Component Analysis (PCA) [38], Chi-square and ANOVA [43]. The effectiveness of using a single sensor to reduce data dimensions still requires investigation. Regarding features usage, investigations have been carried out focusing on time and frequency domains, producing entropy, energy, and statistical features, including mean, median, standard deviation, average, minimum, maximum, skewness, and other statistical values [3, 33, 35, 36, 38, 39]. Moreover, the combination of these mentioned features with others required exploration.

In this research, the proposed model focused on using a single accelerometer sensor to reduce preprocessing complexity. The Feature Subset Signal Vector Magnitude (SMA) was used as the time domain, while the frequency domain was the Feature Subset Fast Fourier Transform (FFT), with the Feature Subset Value-Crossing.

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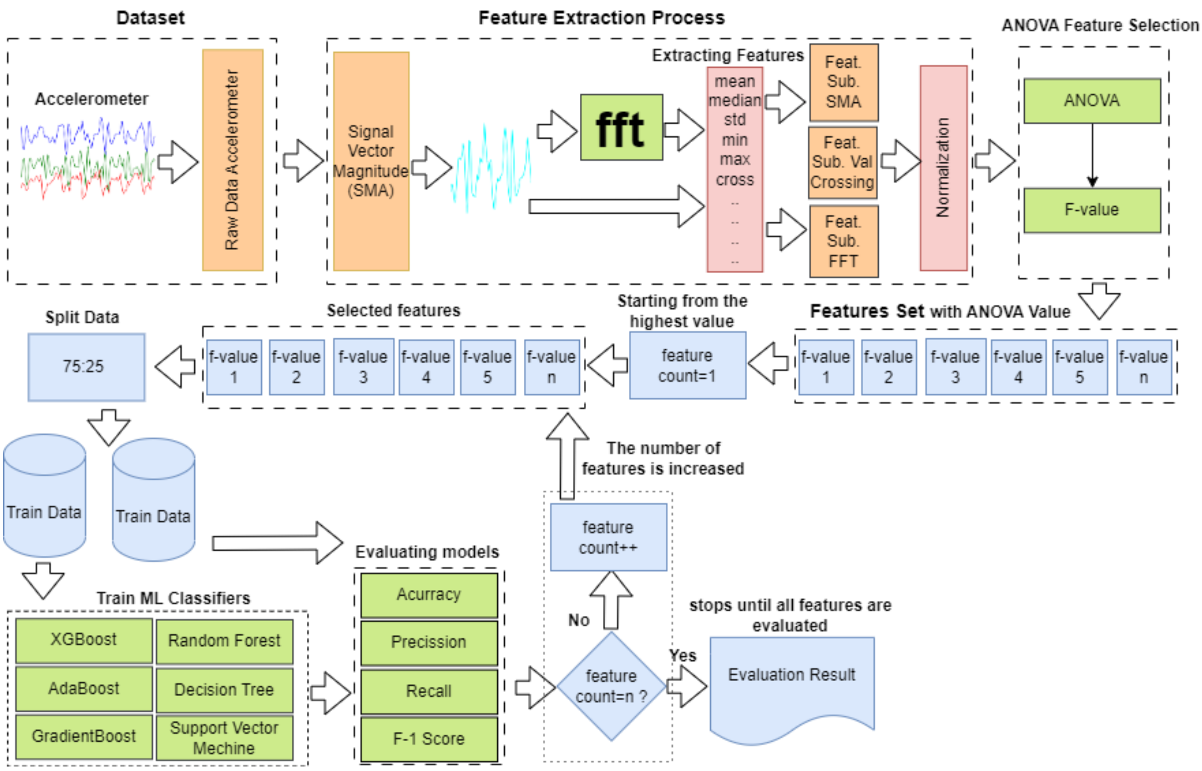

Figure. 1 Proposed Method

3. Proposed Method

This section describes the proposed model, as shown in Fig. 1. A series of accelerometer sensor values consisting of 3 axes (x,y,z) were converted into Signal Vector Magnitude (SMA). Signal Vector Magnitude values were extracted into three Feature Subsets using the equations in Table 1. The resulting features consisted of three subsets: Feature Subset SMA, Feature Subset FFT, and Feature Subset Value-Crossing. Especially for Feature Subset FFT, it was an extraction of Signal Vector Magnitude and converted into Fast Fourier Transform (FFT) values. Furthermore, each feature value was normalized to the same scale. All generated features were given an F-value using ANOVA. Features that have obtained the F-value were selected into a feature combination. Feature selections into a feature combination started from the feature with the largest F-value to the feature with the next smaller F-value. There would be 1 to n feature combinations. Each combination had a different number of features. The number of features of the current feature combination was an increment of the number of features of the previous feature combination. Data consisting of several feature combinations was divided into training and testing data. Furthermore, it was used to train and evaluate the machine learning algorithm. This research used six shallow classifiers or traditional machine learning: Extreme Gradient Boosting (XGBoost), AdaBoost, Gradient Boosting, Random Forest, Decision Tree, and Support Vector Machine. The resulting machine learning model was evaluated using accuracy, precision, recall, and F-1 score.

3.1 Signal Vector Magnitude (SVA) and Fast Fourier Transform (FFT)

The accelerometer sensor had three axes: x, y, and z, where each of these axes produced a serial value in m/s^2. A larger number of axes could result in a larger data dimension but also require more complex pre-processing [41]. The acceleration in the three-dimensional axis could be converted into Signal Vector Magnitude (SVA) values. Thus, the number of dimensions became smaller and increased the efficiency of the feature extraction process [44]. In previous research [39, 40, 41], Signal Vector Magnitude was calculated using Eq. (1). A_x, A_y, and A_z were accelerometer acceleration values for the x, y, and z axes, while SVA was the square root of the sum from the squares of each axis.

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

Table 1. Feature Extraction Formula

Feature Definition	**Mathematical Definition**	**Feature Subset SMA (Time Domain)**	**Feature Subset FFT (Frequency Domain)**	**Feature Subset Value Crossing**
Mean	$\frac{1}{n}\sum_{i=1}^{n}(acc_i)$	MEA	MEF	
Standard Deviation	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(acc_i-\overline{acc})^2}$	SDA	SDF	
Min	$\min(acc_i)$	MNA	MNF	
Max	$\max(acc_i)$	MXA	MXF	
Difference min max	$\max(acc_i)-\min(acc_i)$	DIA	DIF	
Median	$\begin{cases} acc_{\left[\frac{n+1}{2}\right]}, if\ n\ odd \\ \frac{1}{2}\left(acc_{\left[\frac{n}{2}\right]}+acc_{\left[\frac{n+1}{2}\right]}\right), if\ n\ even \end{cases}$	MDA	MDF	
Interquartil	Q_3-Q_1	IQA	IQF	
The sum of values that are greater than mean	$\begin{cases} \sum_{i=1}^{n} f(acc_i) \\ f(acc_i)=\begin{cases} acc_i, if\ \ acc_i > \frac{1}{n}\sum_{i=1}^{n}(acc_i) \\ 0,\ \ else \end{cases} \end{cases}$	GMA	GMF	
The sum of values that are less than mean	$\begin{cases} \sum_{i=1}^{n} f(acc_i) \\ f(acc_i)=\begin{cases} acc_i, if\ \ acc_i < \frac{1}{n}\sum_{i=1}^{n}(acc_i) \\ 0,\ \ else \end{cases} \end{cases}$	LMA	LMF	
Number of peak above (median+std)	$\begin{cases} \sum_{i=1}^{n} f(acc_i) \\ f(Xpeak_i)=\begin{cases} 1, if\ \ Xpeak_i > M+S \\ 0,\ \ if\ Xpeak_i = 0 \end{cases} \\ Xpeak_i=\begin{cases} acc_i, if\ \ acc_{i-1} < acc_i > acc_{i+1} \\ 0,\ \ else \end{cases} \end{cases}$	PPA	PPF	
Number of peak above (median-std)	$\begin{cases} \sum_{i=1}^{n} f(acc_i) \\ f(Xpeak_i)=\begin{cases} 1, if\ \ Xpeak_i > M+S \\ 0,\ \ if\ Xpeak_i = 0 \end{cases} \\ Xpeak_i=\begin{cases} acc_i, if\ \ acc_{i-1} < acc_i > acc_{i+1} \\ 0,\ \ else \end{cases} \end{cases}$	PMA	PMF	

Skewness	$\frac{1}{nS^3}\sum_{i=1}^{n}(acc_i - \overline{acc})^3$	SKA	SKF	
Kurtosis	$\frac{1}{nS^4}\sum_{i=1}^{n}(acc_i - \overline{acc})^4$	KUA	KUF	
signal magnitude area	$\sum_{i=1}^{n}\left(\frac{\lvert Ax_i\rvert}{n}\right) + \sum_{i=1}^{n}\left(\frac{\lvert Ay_i\rvert}{n}\right) + \sum_{i=1}^{n}\left(\frac{\lvert Az_i\rvert}{n}\right)$	SMA	SMF	
Number of mean-crossings	$\begin{cases} \sum_{i=1}^{n} f(acc_i) \\ f(acc_i) = \begin{cases} 1, if \;\; acc_{i-1} > \frac{1}{n}\sum_{i=1}^{n}(acc_i) > acc_i \\ 1, if \;\; acc_{i-1} < \frac{1}{n}\sum_{i=1}^{n}(acc_i) < acc_i \\ 0, else \end{cases} \end{cases}$			MEC
Number of median-crossings	$\begin{cases} \sum_{i=1}^{n} f(acc_i) \\ f(acc_i) = \begin{cases} 1, if \;\; acc_{i-1} > M > acc_i \\ 1, if \;\; acc_{i-1} < M < acc_i \\ 0, else \end{cases} \end{cases}$			MDC
Number of Standard Deviation - crossings	$\begin{cases} \sum_{i=1}^{n} f(acc_i) \\ f(acc_i) = \begin{cases} 1, if \;\; acc_{i-1} > S > acc_i \\ 1, if \;\; acc_{i-1} < S < acc_i \\ 0, else \end{cases} \end{cases}$			SDC
Number of Gravity - crossings	$\begin{cases} \sum_{i=1}^{n} f(acc_i) \\ f(acc_i) = \begin{cases} 1, if \;\; acc_{i-1} > g > acc_i \\ 1, if \;\; acc_{i-1} < g < acc_i \\ 0, else \end{cases} \end{cases}$			GRC

A series of Signal Vector Magnitude (SVA) values became Fast Fourier Transform (FFT) values. In this research, the FFT was obtained using the *numpy.fft.fft* function found in the Python programming language library.

3.2 ANOVA Feature Selection

The extensive data dimension was challenging for researchers in machine learning, especially classical machine learning [45, 46]. Feature selection provided an effective way to overcome this problem by removing irrelevant and redundant data, thereby reducing computation time, and improving the performance of machine learning models [45, 47, 48]. One of the feature selections that has been successfully applied in machine learning was the analysis of variance (ANOVA) [49, 50, 51, 52, 53].

ANOVA was calculated by dividing the variance between groups by the variance within groups, as shown in Eq. (2).

$$F_{value} = \frac{s_{btw}^2}{s_{with}^2} \tag{2}$$

s_{btw}^2 is the variance between groups, while s_{with}^2 is the variance within groups. Both were calculated using Eq. (3) through Eq. (7).

$$\overline{A}_i = \frac{1}{n_i}\sum_{j=1}^{n_i} g_{ij} \quad (3)$$

$$\overline{A} = \frac{1}{K}\sum_{m=1}^{K} G_m \quad (4)$$

$$g_{ij} \in G_m \quad (5)$$

i is the value of 1 to k, where k is the number of groups grouped from all data samples. While $\overline{A}_i$ is the mean of each group, starting from $\overline{A}_1$ to $\overline{A}_k$, g_{ij} is the sample data of each group, with the length of each group is n_i. $\overline{A}$ is the mean of all samples, while G_m is all sample data with K number of samples.

$$s^2_{btw} = \frac{1}{df_{btw}}\sum_{i=1}^{k} n_i\left(\overline{A}_i - \overline{A}\right)^2 \quad (6)$$

$$s^2_{with} = \frac{1}{df_{with}}\sum_{i=1}^{k}\sum_{j=1}^{n_i}\left(g_{ij} - \overline{A}_i\right)^2 \quad (7)$$

Formula df_{btw} is the degree of freedom from sample variance between groups, $df_{btw} = k - 1$. Whereas df_{with} is the degree of freedom of sample variance within groups, $df_{with} = K - k$.

3.3 Feature-Based Classifier

In this paper, the feature extraction approach used was on Signal Vector Magnitude (SVA) and Fast Fourier Transform (FFT) values, as shown in Table 1. Feature Subset SVA is extracted directly from the Signal Vector Magnitude value. Feature Subset FFT is a feature extracted from SVA values converted into FFT frequency domain values. Meanwhile, Feature Subset Value-Crossing is a feature extracted from the SVA value that intersects with the mean, standard deviation, and gravity values. Meanwhile, Feature Subset Value-Crossing is a feature extracted from the SVA value that crossing with the mean, standard deviation, and gravity values. The n notation refers to the number of data, M is the median, S is the standard deviation, A_x is the acceleration on the x-axis, A_y is the acceleration on the y-axis, Az is the acceleration on the z-axis, g is the gravitational acceleration of 9.81 m/s^2, $Xpeak$ is the peak value, Q_1 is the 1st quartile, and Q_3 is the 3rd quartile. The acc notation refers to the Signal Vector Magnitude (SVA) value for the Feature Subset SMA. For Feature Subset FFT, the notation acc refers to the FFT value. The accelerometer sensor value is serial data, so the i notation is the data in the i-th order.

4. Experiment Setup

This section will explain the preparation and testing requirements, including parameter setup, dataset, and confusion matrix evaluation.

4.1 Parameter Setup

In this paper, the proposed model used six machine learning algorithms to classify data that has been reduced to features. The machine learning algorithms used the Python programming language to refer to the Scikit-Learn framework. Table 2 shows each classifier parameter during the experiment.

4.2 Dataset

The data used was a public dataset [54]. The human activity data movements were recorded using magnetometer (HMC5883L, Honeywell, USA), accelerometer (ADXL345, Analog Devices, USA), and gyroscope (ITG-3200, InvenSense Inc., USA) sensors mounted on the subject's waist. It was collected from 8 subjects, consisting of 2 females and six males, and each subject performed three times of simulation. The dataset consisted of 13 falls (4 forward, four backward, two lateral right, two lateral left, and one syncope) and five actions of daily living. This research focused on Activities of Daily Living (ADL) using a single accelerometer sensor. Thus, the data used consisted of five

Table 2. Parameter Setup

Classifier	Function	Setting & Paramater
Extreme Gradient Boosting	XGBClassifier()	n_estimators=100,eval_metric='mlogloss'
AdaBoost	AdaBoostClassifier()	n_estimators=50,base_estimator=svc,learning_rate= 0.2, random_state=0
Gradient Boosting	GradientBoostingClassifier()	n_estimators=100
Random Forest	RandomForestClassifier()	n_estimators = 100, criterion = 'entropy', random_state = 42
Decision Tree	DecisionTreeClassifier()	default
Support Vector Mechine	svm.SVC()	kernel='rbf'

Table 3. Activities of Daily Living (ADL)

Activities of Daily Living (ADL)	Number of Activities
lying on a bed then standing	24
walking a few meters	24
sitting on a chair then standing	24
climbing three steps	24
standing after picking something	24

Table 4. ANOVA F-value

Index	Feature	F-value	Index	Feature	F-value	Index	Feature	F-value
0	MEA	28.63	11	SKA	5.13	22	LMF	22.13
1	SDA	49.55	12	KUA	1.68	23	PPF	28.53
2	MNA	10.33	13	SMA	7.14	24	PMF	21.22
3	MXA	8.73	14	MEF	31.75	25	SKF	29.91
4	DIA	11.4	15	SDF	27.96	26	KUF	25.44
5	MDA	41.94	16	MNF	1.28	27	SMF	30.92
6	IQA	61.71	17	MXF	24.11	28	MEC	30
7	GMA	20.07	18	DIF	24.12	29	MDC	25.85
8	LMA	40	19	MDF	13.29	30	SDC	0.75
9	PPA	22.27	20	IQF	56.43	31	GRC	30.42
10	PMA	36.79	21	GMF	54.67			

activities, as shown in Table 2.

4.3 Confusioin Matrix

The machine learning algorithm's performance was evaluated using accuracy, precision, recall, and F-1 score. TP represents true-positive, TN is true-negative, FP is false-positive, and FN is false-negative. The accuracy shown in Eq. (8) represents how accurately the model can classify correctly. Accuracy is the ratio of TP to the overall data. Precision is the ratio of TP predictions compared to all positive predicted results, as shown in Eq. (9). Recall is the ratio of TP predictions compared to the overall true positive data, which was calculated using Eq. (10). Meanwhile, the F1 Score is a comparison of weighted average precision and recall, which was calculated using Eq. (11).

$$accuracy = \frac{TP}{TP+TN+FP+FN} \tag{8}$$

$$precision = \frac{TP}{TP+FP} \tag{9}$$

$$recall = \frac{TP}{TP+FN} \tag{10}$$

$$F1\ score = \frac{precicion \times recall}{precicion + recall} \tag{11}$$

5. Result and Discussion

This research analysed the combination of features that could provide the best performance in six machine learning algorithms. The combination was based on ANOVA feature selection. In experiments using the public dataset [61], the ratio of training data and training data was 75:25. It used five classes, as shown in Table 3. Each feature had an F-value calculated using Eq. (4). Each F-value is shown in Table 4. Feature IQA had the highest F-value, which was the Interquartile value of Signal Vector Magnitude (SVA), while the smallest F-value was SDC, which is the sum of the crossing values between Signal vector Magnitude (SVA) and standard deviation. The feature with the highest F-value would always be present in every feature combination evaluated using machine learning. However, the feature with the smallest F-value was only present in the feature combination with the largest number, namely 32 features.

In this paper, the model extracted 32 features because each feature combination was based on the number of features, resulting in 32 feature combinations. Each combination had a different number of features used for the classification process. Fig. 2 shows the accuracy results for each machine learning classifier. Depending on the

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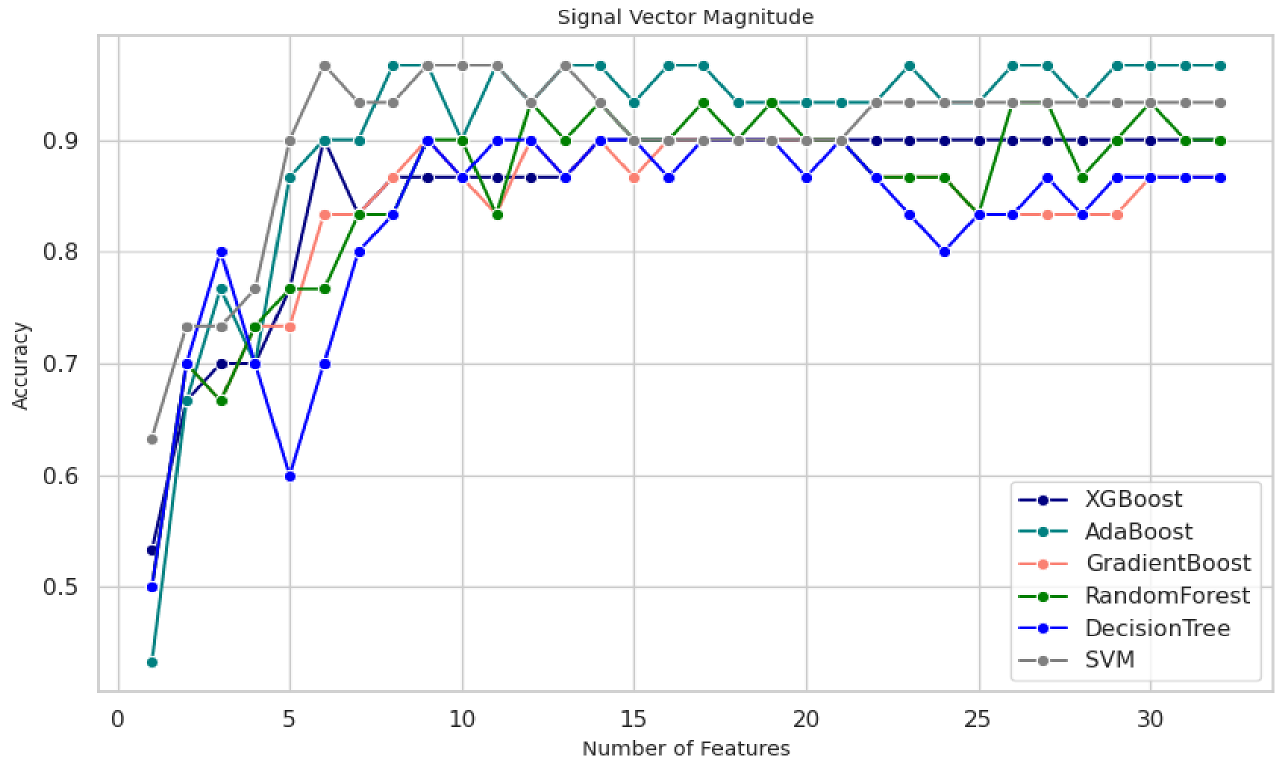

Figure. 2 Accuracy Comparison Based on the Number of Features

Table 5. Performance Comparison between All Features with Feature Selection

Classiffiers	**Metrics**	**Performance in all features**	**Anova Feature Selection**		
			Number of Features	**Combination of features based on index**	**Best Performances**
eXtreme Gradient Boosting	Accuracy	0.9	6	1,5,6,8,20,21	0.9
	Precision	0.9			0.9
	Recall	0.92			0.92
	F-score	0.9			0.9
AdaBoost	Accuracy	0.97	26	0,1,2,4,5,6,7,8,9,10,14,15,17,18,19,20,21,22,23,24,25,26,27,28,29,31	**0.97**
	Precision	0.97			**0.98**
	Recall	0.96			**0.96**
	F-score	0.96			**0.97**
Gradient Boosting	Accuracy	0.87	9	1,5,6,8,10,14,20,21,27	0.9
	Precision	0.87			0.9
	Recall	0.88			0.92
	F-score	0.86			0.9
Random Forest	Accuracy	0.9	26	0,1,2,4,5,6,7,8,9,10,14,15,17,18,19,20,21,22,23,24,25,26,27,28,29,31	0.93
	Precision	0.9			0.94
	Recall	0.91			0.95
	F-score	0.9			0.94
Decision Tree	Accuracy	0.87	9	1,5,6,8,10,14,20,21,27	0,9
	Precision	0.88			0.91
	Recall	0.88			0.92
	F-score	0.87			0.9
Support Vector Mechine	Accuracy	0.93	6	1,5,6,8,20,21	**0.97**
	Precision	0.93			**0.97**
	Recall	0.95			**0.98**
	F-score	0.94			**0.97**

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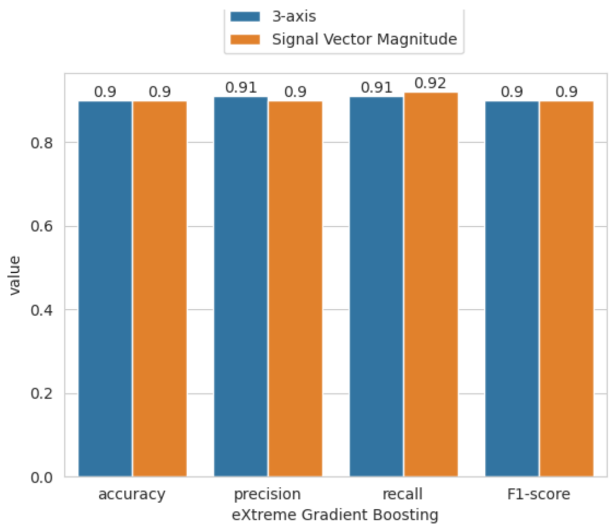
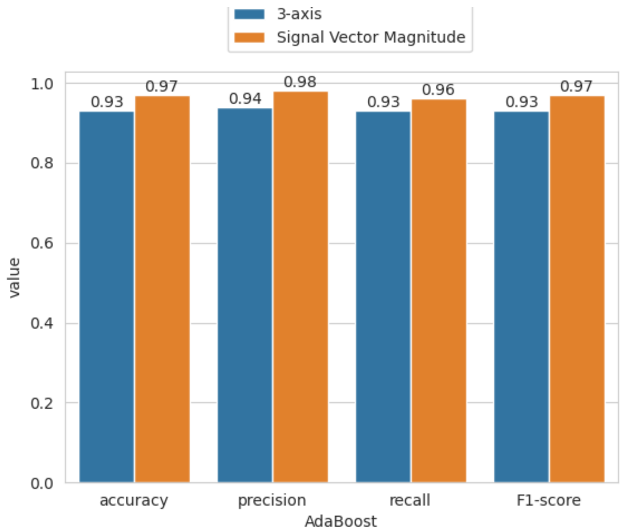
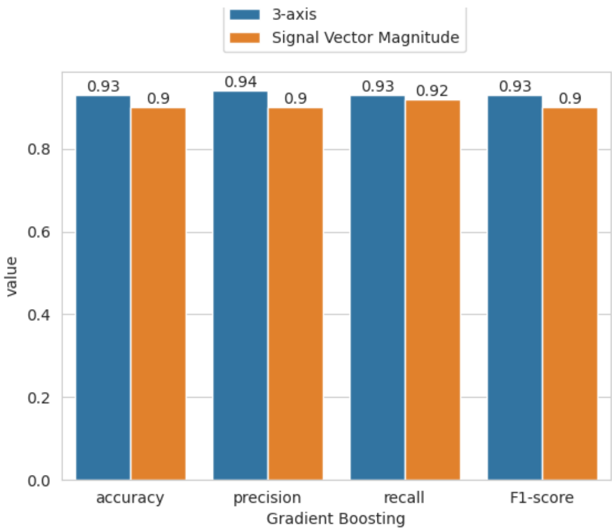


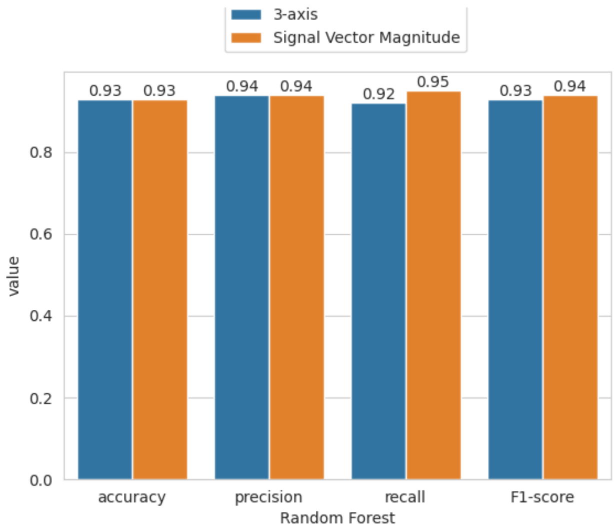
(a) Extreme Gradient Boosting



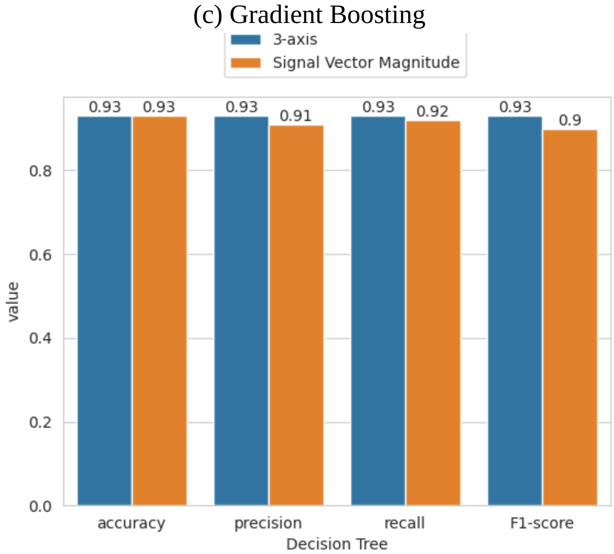
(b) AdaBoost



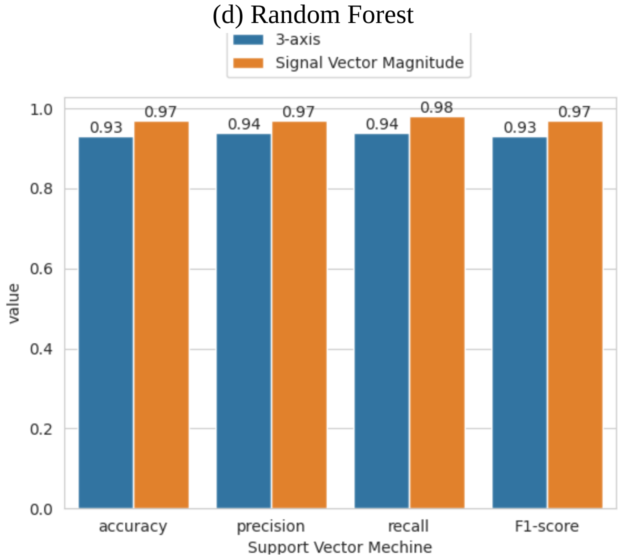
(c) Gradient Boosting



(d) Random Forest



(e) Decision Tree



(f) Support Vector Machine

Figure. 3 Comparison of 3-axis and Signal Vector Magnitude

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Table 6. Performance comparison of the proposed model and state-of-art approches

Reference	***Classiffier***	***Sensor***	***Feature Extraction***	***Acc***
Vidya [3]	KNN	Accelerometer sensor and RSS of WSN	Handcrafted	0.96
Ehatisham-Ul-Haq et al [35]	SVM	Accelerometer, gyroscope, depth sensor	Handcrafted	0.95
Hafeez [36]	Logistic Regression (LR)	RGB, depth, and Accelerometern sensor	Handcrafted	0.93
Geravesh *et al.*[37]	KNN	Gyroscope and accelerometer sensor	Handcrafted	0.94
Tabei et al. [38]	SVM	Accelerometer, gyroscope, and magnetometer sensor	Handcrafted	0.95
Nho et al [39]	KNN	Heart rate and accelerometer sensor	Handcrafted	0.94
Bangaru et al. [40]	ANN	Electromyography sensor (EMG), Gyroscope and accelelrometer sensor	Handcrafted	0.94
Proposed Model	XGBoost	Accelerometer	Handcrafted	0.90
	AdaBoost			**0.97**
	Gradient Boosting			0.90
	Random Forest			0.93
	Decision Tree			0.93
	SVM			**0.97**

combining features used, several feature combinations could have the same accuracy value or higher in each classifier. Table 5 shows the performance comparison of each classifier for using all features and feature selection. Using feature selection ANOVA could improve performance compared to not using it. As shown in Fig. 2, the best performance of each classifier could be achieved using several feature combinations. Thus, the feature combinations presented were only those with the smallest number of features but having the best performance. AdaBoost and Support Vector Machine (SVM) performed best among the six classifiers. The performance could be achieved using 26 and 6 features, respectively. AdaBoost's accuracy, precision, recall, and F-1 scores were 0.97, 0.98, 0.96, and 0.97, respectively, while the Support Vector Machine was 0.97, 0.97, 0.98, and 0.97. The feature combinations presented in Table 5 were presented in the index. More details on the feature names can be seen in Table 4.

This research also compared Signal Vector Magnitude (SVA) with 3-axis sensors. Using 3-axis sensors certainly resulted in more features, three times more than using Signal Vector Magnitude (SVA). The experimental scenario used the same equations as the proposed model. Fig. 3 shows the performance comparison for each classifier. For 3-axis usage, the AdaBoost, Random Forest, and Support Vector Machine (SVM) classifiers performed better than the other classifiers. Consecutively, the three classifiers had the same accuracy, precision, recall, and F-1 score values of 0.93, 0.94, 0.93, and 0.93. In this research, Signal Vector Magnitude (SVA) performed better than the 3-axis, especially in the AdaBoost and Support Vector Machine (SVM) classifiers.

Table 6 shows a comparison between the proposed model and other state-of-the-art approaches, which were selected based on several similarities, such as HAR classification, handcrafted feature extraction method, and the use of traditional machine learning. The accuracy (acc) in state-of-the-art approaches ranged from 0.93 to 0.96 [3][35]-[40], while the optimal accuracy (acc) in the proposed model was 0.97, surpassing the state-of-the-art approaches used for HAR classification.

A comparison was also conducted with 3 previous investigations sharing similarities, particularly in terms of dataset and HAR topic. Section 4.2 elaborated on the details of the dataset used by Santoyo-Ramon et al. [55], Santoyo-Ramón et al. [56], and Martins et al [57]. Specifically, for Martins et al. [57], the dataset described in Section 4.2 was combined with other public datasets, increasing the total amount of data used. The values compared included accuracy (Acc), sensitivity (Sen), and specificity (Spe), as shown in Table 7. For a SVM and AdaBoost classifiers, the proposed model showed a higher specificity (0.99) compared to

Table 7. Comparison with Previous research (Same Dataset)

Reference	***Classiffier***	***Sensor***	***Feature Extraction***	***Acc***	***Sen***	***Spe***
Santoyo-Ramon et al. [55]	Fully connected layer	Accelerometer, gyroscope, orientation, magnetometer	CNN	-	1.00	0.97
Santoyo-Ramón et al. [56]	SVM (linear kernel)	Accelerometer, gyroscope, orientation, magnetometer	Handcrafted	-	0.99	0.98
	KNN (Euclidean, 10 neighbors)			-	0.98	0.98
	SVM (quadratic kernel)			-	0.99	0.97
Martins et al. [57]	KNN	Accelerometer, gyroscope	CNN	0.94	0.84	0.99
	Ensemble Learning			0.94	0.82	0.99
Proposed Model	XGBoost	Accelerometer	Handcrafted	0.90	0.92	0.98
	AdaBoost			**0.97**	**0.96**	**0.99**
	Gradient Boosting			0.90	0.92	0.98
	Random Forest			0.93	0.95	0.98
	Decision Tree			0.93	0.92	0.98
	SVM			**0.97**	**0.98**	**0.99**

Santoyo-Ramon et al. [55] and Santoyo-Ramón et al. [56]. Meanwhile, the accuracy (0.97) and sensitivity (0.98) values were better than the model proposed by Martins et al. [57]. Partially, the accuracy, specificity, and sensitivity values of the proposed model showed better performance compared to previous research. The proposed model used a single accelerometer sensor, while the 3 previous investigations applied multiple sensors to reduce processing complexity without compromising performance. Therefore, the proposed model could serve as an alternative for implementation on limited computing devices, as its performance was capable of balancing the use of multiple sensors conducted in previous research.

6. Conclusion

Wearable sensors have limitations in computational capabilities. Thus, using a single accelerometer sensor was one option to overcome heavy pre-processing and a larger number of features. Feature consisted of three Feature Subset parts: Signal Vector Magnitude (SMA) Feature Subset, Fast Fourier Transform (FFT) Feature Subset, and Value-Crossing Feature Subset, resulting in 32 features in total. By using feature selection ANOVA, a combination of features was obtained. The feature combination was evaluated using six machine learning algorithms: Extreme Gradient Boosting, AdaBoost, Gradient Boosting, Random Forest, Decision Tree, and Support Vector Machine. In the experiment, the best performance was obtained from the AdaBoost and Support Vector Machine classifiers, which could be achieved using 26 and 6 features, respectively. The accuracy, precision, recall/sensitivity, F-1 scores, and specificity for AdaBoost were 0.97, 0.98, 0.96, and 0.97, 0.99 respectively, while those for Support Vector Machine were 0.97, 0.97, 0.98, 0.97, and 0.99. Partially, the accuracy, specificity, and sensitivity values of the proposed model showed better performance compared to previous research.

Future research directions can focus on applying the proposed model to real-time systems on wearable sensor devices. In addition, investigating the impact of using various other feature selection techniques can provide insights to optimize the proposed model performance.

Conflicts of Interest

The author declares no conflict of interest.

Author Contributions

Conceptualization, Liandana; methodology, Liandana; software, Liandana, Hostiadi, and Pradipta; validation, Liandana, Hostiadi, Pradipta; formal analysis, Liandana, Hostiadi, Pradipta; investigation, Liandana, Hostiadi, Pradipta; resources, Liandana, Hostiadi, Pradipta; data curation, Liandana, Hostiadi, Pradipta; writing—original draft preparation, Liandana, Hostiadi, Pradipta; writing—review and editing, Hostiadi, Pradipta; visualization, Liandana, Hostiadi, Pradipta; supervision, Hostiadi, Pradipta; project administration, Liandana. All authors have read and approved the final manuscript.

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