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Developing a GA-optimized EWMA feature engineering method for real-time human activity recognition

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ABSTRACT

Real-time human activity recognition (HAR) is garnering attention across various fields, such as healthcare, fitness and sports, security and surveillance, occupational safety, smart environments, and more. This is largely attributed to the rapid development of mobile devices, which enable users to record human activity signals using accelerometers. In this study, we found that the recognition rates were poor when tri-axial activity signals collected from accelerometers were directly fed into classifiers, including decision trees (DT), discriminant analysis (DA), logistic regression (LR), Naïve Bayes classifiers, support vector machines (SVM), ensemble learning (EL), and neural networks (NN). The recognition rates improved from 75% to 94% when the three-axis signals were transformed into statistical signal features (SSF). Despite the improvement in accuracy, the increase in the number of input variables from 3 to 66 has burdened the computation time. Furthermore, a higher recognition rate is needed to have an effective decision making. Therefore, this study develops a novel feature engineering method by using genetic algorithm (GA) and exponentially weighted moving average (EWMA). The EWMA is not only used to capture the characteristics of time sequences derived from the activity signals but also to eliminate redundant SSFs. GA is employed to optimize EWMA weights for each SSF. The results demonstrate that the Ensemble Bagged Trees classifier, using the proposed GA-optimized EWMA features, achieves a testing recognition rate of 95.2% with a prediction time of less than 0.01 s, making it suitable for the field of real-time HAR.

Keywords: Human activity recognition, Feature engineering, Statistical signal features, Exponentially weighted moving average, Genetic algorithm.

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1. INTRODUCTION

With the development of technology, more and more people are using smartphones and wearable devices for personal exercise and health management. When applied in the medical field, human activity recognition (HAR) is a key area of artificial intelligence and machine learning. Machine learning methods such as deep learning and integrated models are further used to identify and classify activities through data collected by various devices. Human activities can be accurately identified and classified. Machine learning techniques have significantly advanced HAR in recent years, especially in fields such as healthcare and human-computer interaction (Gumaei et al., 2019; Irfan et al., 2021; Khan et al., 2022). These methods enable the extraction of high-level knowledge from raw sensor inputs, allowing for precise identification of different activities. The fusion of machine learning methods, wearable technology and deep learning models provides more effective development for accurate HAR, and the use of sensor-equipped wearable devices and smartphones facilitates real-time monitoring of human activities (Devarakonda and Božić, 2022), contributing to the development of personalized healthcare systems and health monitoring. The integration of deep learning models has changed the way of analyzing large medical data sets and also provided new developments for health promotion (Purushotham et al., 2018). Therefore, a more effective prediction model of the deep learning model is proposed, which can further develop complex health promotion models suitable for individual users, and also help enhance public health and social well-being.

Due to the advancement of technology, wearable devices are equipped with sensors that can be used to collect, monitor and analyze users' physiological data, movement activities and location information. In the realm of HAR, sensors can be mainly divided into three categories: movement, environment and location. The movement sensors, including accelerometers, gyroscopes and gravity sensors can be utilized to track titling, shaking, rotating or swinging. The environment, such as barometer and thermometer can be used to monitor humidity, pressure and temperature. The location sensors like magnetometers can provide a device's location relative to a global reference point.

In this research, the accelerometer will be employed, as it detects the acceleration forces exerted on the device along the three physical axes (X, Y, and Z), capturing both movement and gravitational forces. If we can further analyze these large amounts of signals to find out the hidden correlations and patterns in users' daily activities, and then plan and provide relevant derivative health promotion service activities, only then can real value be generated for wearable devices. As the use cases of wearable devices increase, the value of the data generated becomes more and more valuable. Through big data analysis of users' general daily physical activity information, it can be used to improve the accuracy and reminder efficiency of physical activity and health promotion analysis. It is expected that in the future, people will use wearable devices to find out about health promotion, physical enhancement and medical care, and will bring greater contributions to the fields of public health and health promotion.

Recent studies have focused on smartphone-based HAR using accelerometer data (Kwapisz et al., 2011; Zhang and Sawchuk, 2012; Bayat et al., 2014; Ortiz and Luis, 2015). In these studies, the authors employed various classification methods to analyze accelerometer data effectively. The primary classifiers used in their study include decision trees (DT), support vector machines (SVM), and k-nearest neighbors (KNN). For example, Zhang and Sawchuk (2012) employs DT, SVM, and KNN classifiers to effectively recognize human activities using data from wearable accelerometers in walk forward, walk left, walk right, go upstairs, go downstairs, jump up, run, stand, sit activities. Ortiz and Luis (2015), Bayat et al. (2014), and Kwapisz et al. (2011) also utilized DT, SVM, and KNN as classifiers, with a strong emphasis on feature extraction to enhance the performance of HAR using smartphone accelerometer data. Feature extraction from accelerometer signals is a crucial step in HAR. Miluzzo et al. (2008), Dengel et al. (2016), Figo et al. (2010), Kose et al. (2012),Siirtola and Röning (2012), Shoaib et al. (2013) Dengel et al. (2016),Yin (2016) and Hsu et al. (2015) employed Decision Trees and SVMs as classifiers, highlighting the importance of feature extraction in enhancing HAR performance using accelerometer data from smartphones and smartwatches. The findings of Dengel et al. (2016), Yin (2016), Hsu et al. (2015), and Shoaib et al. (2013) suggest that SVM generally achieved higher accuracy than DT, aligning with other studies that have demonstrated the superior effectiveness of SVM in activity recognition tasks.

In healthcare, high-accuracy HAR systems can significantly enhance decision-making by healthcare professionals. For example, accurately recognizing activities such as walking, sitting, or lying down can help assess a patient's mobility and recovery progress, leading to more informed treatment plans. In this study, eight classifiers—DT, discriminant analysis (DA), logistic regression (LR), Naïve Bayes classifier, SVM, ensemble learning (EL), and Neural Network (NN)—will be employed to recognize six activities: walking, going upstairs, going downstairs, standing, sitting, and lying down, based on accelerometer data. To build upon previous research, this study specifically integrates eight classifiers and improves the feature extraction method to enhance efficiency. Feature selection is pivotal in this process because it directly influences the effectiveness of the recognition system. By identifying the most pertinent features, it not only decreases computational load but also improves the accuracy of activity classification by removing redundant and irrelevant information.

The following features will be used as inputs for these classifiers and a thorough comparison will be provided in this study, including:

(1) Original X, Y, Z three-axis data.
(2) Statistical signal features (SSF), including mean, root mean square error (RMSE), autocorrelation, peak analysis, and time-frequency analysis.
(3) GA-optimized EWMA features

The GA-optimized EWMA features are the proposed feature engineering method that takes the time sequence of the acquired data into consideration. In the past research, the characteristic of time sequence is ignored for analysis, potentially leading to the low recognition accuracy. The EWMA assigns exponentially decreasing weights to past observations as it moves through time. This means that the most recent observations have the most influence on the average, while older observations have less impact. Thus, this study will apply the EWMA to the SSF to memorize the past observations.

The following issue needed to be addressed is the determination of EWMA weights for each SSF, as each SSF has different dynamics. Since GA can explore the entire search space by using a population of potential solutions, which reduces the risk of getting trapped in local optima, this study will use GA to search for the optimal EWMA weights for each SSF, aiming to maximize the true positive rate for each activity.

This study is organized as follows: Section 2 introduces eight classifiers: DT, DA, LR, Naïve Bayes classifiers, SVM, EL, and NN. Section 3 presents the proposed GA-optimized EWMA implementation and provides a comparison, and Section 5 offers the conclusion.

2. LITERATURE REVIEW

2.1 Decision Trees

DT is a widely used machine learning algorithm that utilizes a hierarchical, tree-like model for decision-making in classification and regression tasks (Quinlan, 1986). The algorithm recursively partitions data into subsets based on feature values, allowing for intuitive interpretation and visualization (Breiman et al., 1984). This tree-like structure allows for easy visualization and understanding of the decision-making process, making DT particularly valuable in various applications including HAR (Xiao et al., 2013). In the context of health promotion, decision trees can significantly enhance HAR by enabling the automatic identification and classification of physical activities performed by individuals. This capability is crucial for developing interventions aimed at promoting physical activity and improving overall health outcomes. For instance, decision trees can analyze data collected from wearable sensors to classify activities such as walking, running, or sitting, thereby providing insights into an individual's activity levels and patterns (Xiao et al., 2013). By accurately recognizing these activities, public health practitioners can tailor health promotion strategies to encourage more active lifestyles among specific populations (Sánchez and Skeie, 2018). Moreover, decision trees can be integrated into smart home environments to monitor the physical activities of older adults or individuals with disabilities. This application not only enhances safety by detecting falls or unusual inactivity but also supports the development of personalized health interventions that promote physical activity and independence (Sánchez and Skeie, 2018). The ability of decision trees to handle various types of data, including time-series data from sensors, makes them particularly suitable for HAR tasks, where the temporal aspect of activities is essential for accurate classification (Hendriks et al., 2019). Additionally, decision trees can be combined with other machine learning techniques, such as support vector machines or genetic algorithms, to improve classification performance and robustness in HAR applications (Chen et al., 2011; Li and Fan, 2014). This hybrid approach can lead to more accurate predictions and a better understanding of the factors influencing physical activity, ultimately informing public health initiatives aimed at enhancing community health and well-being. In summary, decision trees are a powerful tool for HAR offering a structured and interpretable method for analyzing physical activities. Their application in health promotion can lead to more effective interventions that encourage active lifestyles and improve health outcomes, particularly in vulnerable populations.

2.2 Discriminant Analysis

DA is a statistical classification method that constructs linear or quadratic functions to differentiate between predefined groups by maximizing the separation among them (Fisher, 1936). It allows the researcher to assess whether significant differences exist between the groups based on the predictor variables. Additionally, it evaluates the accuracy of the classification. The discriminant analysis is widely used in the field of healthcare. (Tintorer et al., 2015) employed the discriminant analysis to explore the factors affecting the adoption of clinical communities of practice among healthcare professionals. Kabir (2021) evaluated factors that influence maternal healthcare service utilization. Ciucă et al. (2020) distinguished between individuals who undergo screening and those who do not for colorectal cancer. Rivenbark and Ichou (2020) found that exploring discrimination in healthcare as a barrier to access for socially disadvantaged populations. In healthcare, discriminant analysis has been utilized to evaluate the discriminatory properties of enabling factors on healthcare service utilization (Rivenbark and Ichou, 2020), determine the ability of variables to discriminate between different groups such as screeners and non-screeners for colorectal cancer (Ciucă et al., 2020), and understand how discrimination acts as a barrier to care for vulnerable populations (Chen et al., 2011). By utilizing this statistical technique, researchers can gain valuable insights into the complex interplay of factors influencing healthcare utilization, trust, and disparities among diverse populations.

2.3 Logistic Regression

LR is a fundamental statistical technique for modeling binary outcomes by estimating the probability of an event occurring based on predictor variables (Cox, 1958). The logistic function enables the transformation of linear combinations of independent variables into probabilities, making it particularly useful in disease prediction and healthcare studies (Hosmer et al., 2013). For example, in a study comparing screeners and non-screeners for colorectal cancer, logistic regression could be utilized to identify the factors significantly influencing the likelihood of being a screener (Sherchan et al., 2022). In healthcare research, logistic regression has been employed to explore various aspects of healthcare delivery and patient outcomes (Hosmer et al., 2013; Sherchan et al., 2022).

2.4 Naïve Bayes Classifiers

Naïve Bayes classifiers are probabilistic models that apply Bayes' theorem under the assumption of independence between predictor variables (Duda and Hart, 1973). Sherchan et al. (2022) optimized the Naïve Bayes classifier method to improve accuracy in diagnosing the disease. Affandi (2023) applied the Naïve Bayes classifier in sentiment analysis of student experiences during online learning, demonstrating high accuracy in classifying sentiments related to online lectures during the COVID-19 pandemic. In conclusion, Naïve Bayes classifiers play a significant role in healthcare research by enabling accurate predictions, sentiment analysis, and classification tasks. Their simplicity, efficiency, and ability to handle categorical data make them valuable tools for various healthcare applications, ranging from disease diagnosis to sentiment analysis and community question classification.

2.5 Support Vector Machines

SVMs are supervised learning models that identify the optimal hyperplane to separate data into distinct classes (Cortes and Vapnik, 1995). SVMs have been utilized in the development of an intelligent health monitoring system using IoT and advanced machine learning techniques to provide accurate predictions and assist healthcare workers in giving appropriate interventions (Chandra et al., 2023). SVMs have been employed in the efficient diagnosis of liver disease, where the algorithm was optimized with a row Search Algorithm to enhance diagnostic accuracy (Devikanniga et al., 2018). SVMs have been used in knowledge discovery for hospital-acquired catheter-associated urinary tract infections, demonstrating their utility in analyzing and predicting healthcare-associated infections (Park et al., 2019). Moreover, SVMs have been applied in the field of voice pathology assessment, where they were used as a classifier in a healthcare big data framework to assess voice disorders efficiently (Hossain and Muhammad, 2016). Additionally, SVMs have been employed in the context of COVID-19 outbreak prevention, where sentiment analysis was conducted to predict individuals' awareness of precautionary procedures using machine learning models, including SVM (Aljameel et al., 2020). In conclusion, SVMs play a crucial role in healthcare applications by enabling accurate predictions, disease diagnosis, infection forecasting, and sentiment analysis. Their ability to handle complex data and classify information efficiently makes them valuable tools for improving healthcare outcomes and decision-making processes. Based on these previous related researches on HAR (Shoaib et al., 2013; Hsu et al., 2015; Dengel et al., 2016; Yin, 2016), the findings indicated that SVMs generally provided higher accuracy compared to decision trees, which is consistent with findings from other studies that have demonstrated the effectiveness of SVMs in activity recognition tasks.

SVMs has a great impact on transforming the input data into a higher-dimensional space, making it easier for the SVMs to find a hyperplane that separates the classes effectively. Common SVMs kernel functions are:
Common SVMs kernel functions are:

(1) Linear kernel: $K(x_i, x_j) = x_i x_j$, which is called "linear SVM" in this study.

(2) Polynomial kernel: $K(x_i, x_j) = (x_i \cdot x_j + c)^d$, where c is a constant to control the influence of higher-order terms and d denotes the degree of the polynomial, with d=2 is called "Quadratic SVM" and d=3 is called "cubic SVM" in this study.

(3) Gaussian kernel: $K(x_i, x_j) = exp\left(-\gamma \|x_i - x_j\|^2\right)^d$, where γ controls the width of the Gaussian function. A larger γ focus on local points, while a smaller γ captures global patterns. With $\gamma = 0.5$, $\gamma = 1$ and $\gamma = 2$ would be called "fine Gaussian SVM", "medium Gaussian SVM," and "coarse Gaussian SVM" in this study.

2.6 Nearest Neighbor

KNN algorithm is a non-parametric classification technique that assigns a data point to the class most common among its nearest neighbors (Cover and Hart, 1967). The Nearest Neighbor (NN) method, particularly in its KNN form, is a widely utilized algorithm in machine learning and data mining, characterized by its simplicity and effectiveness in classification and regression tasks. In the context of public health, KNN has been applied to various domains, including disease prediction, patient classification, and health outcome analysis. One notable application of KNN in public health is in the detection and classification of diseases. For instance, utilized the K-Nearest Neighbor method to develop an expert system for detecting immunodeficiency, demonstrating its effectiveness in predicting health conditions based on patient data (Ramadhan et al., 2019). Additionally, research on large-margin nearest neighbor classifiers provides insights into enhancing classification performance, which is crucial for accurate health assessments (Domeniconi et al., 2005). In summary, the Nearest Neighbor method, especially through its KNN variant, has significant applications in public health, ranging from disease detection to environmental health assessments. Its ability to handle complex datasets and provide accurate classifications makes it a vital tool in the ongoing efforts to improve health outcomes and inform public health policies. Despite its simplicity and efficiency, KNN's accuracy is sensitive to the choice of distance metric and the number of neighbors used, which necessitates careful parameter tuning.

2.7 Ensemble Learning

EL is a machine learning paradigm that combines multiple classifiers to improve prediction accuracy and reduce overfitting (Dietterich, 2000). EL involves combining multiple individual machine learning models to create a more robust and accurate predictive model by leveraging the diversity of different models to improve overall prediction performance. In healthcare, ensemble learning has been increasingly utilized to enhance disease diagnosis, risk prediction, treatment response modelling, and various other healthcare applications. For example, in a study focusing on cardiovascular disease risk prediction, ensemble meta-learning using SVM was employed to improve the accuracy of risk prediction models (Punn, 2024). EL has been applied to Alzheimer's disease classification by integrating deep ensemble learning techniques with deep learning systems to enhance prediction accuracy (An et al., 2020). It has also been utilized for diagnosing chronic obstructive pulmonary disease (COPD), where bagging ensemble learning and artificial neural network classifiers improved detection accuracy (Siddiqui, 2024). In the area of healthcare claim fraud detection, ensemble-based algorithms have been used to predict social behavior with high accuracy in imbalanced data environments (Kaddi, 2023). Another application is the prediction of health trends on social media platforms, where ensemble techniques have demonstrated effectiveness in analyzing health-related data from social networks (Agarwal et al., 2019). Additionally, ensemble learning has been employed for high-dimensional imbalanced credit scoring datasets, with multiple optimized ensemble approaches proposed to develop reliable and accurate credit scoring models (Lenka et al., 2023). In conclusion, ensemble learning plays a crucial role in healthcare research by combining the strengths of multiple machine learning models to improve predictive accuracy, enhance disease diagnosis, and optimize treatment strategies. By leveraging the diversity of different models, ensemble learning techniques have shown promise in addressing complex healthcare challenges and improving decision-making processes.

Specifically, the ensemble methods combine multiple wear learners to form a strong, more accurate models. Each ensemble method utilizes a different strategy to aggregate weak learner for improved performance. In this study, several ensemble methods would be applied, such as Ensemble Boosted Trees, Ensemble Bagged Trees, Ensemble Subspace Discriminant, Ensemble Subspace KNN and Ensemble RUSBoosted Trees, detailed as follows:

(1) Ensemble boosted trees: Boosting combines weak learners iteratively, focusing on the errors of the previous iteration. Each subsequent tree is trained to correct the errors made by the preceding ones. Common boosting algorithms: AdaBoost, LogitBoost, GentleBoost.
(2) Ensemble bagged trees: Bagging (Bootstrap Aggregating) trains multiple trees on different bootstrapped samples of the training data, with predictions are being aggregated (majority voting for classification).
(3) Ensemble subspace discriminant: Trains multiple discriminant classifiers (e.g., linear discriminant analysis) on random subspaces of the feature space.
(4) Ensemble subspace KNN: Combines KNN classifiers trained on random subspaces of the feature space. Each subspace is a random subset of features.
(5) Ensemble RUSBoosted Trees: RUSBoost (Random Under-Sampling Boost) combines boosting with random under-sampling of the majority class in imbalanced datasets. Each iteration under-samples the majority class and trains a tree on the under-sampled data.

2.8 Neural Networks

NNs are computational models inspired by the human brain, consisting of interconnected artificial neurons arranged in layers that process input data and generate predictions (McCulloch and Pitts, 1943). Neural Networks are a class of machine learning algorithms inspired by the structure and function of the human brain. They consist of interconnected nodes, or neurons, organized in layers that process input data and generate output predictions. Tiwari, (2023) utilized the neural networks to enhance medical decision-making processes and improve patient outcomes. Sav et al. (2022) applied the neural networks to detect healthcare claim fraud, where they were used to predict social behavior accurately in an imbalanced data environment.

Furthermore, NNs have been employed in the development of an intelligent health monitoring system using IoT and advanced machine learning techniques to assist healthcare workers in providing appropriate interventions (Chandra et al., 2023). Moreover, Sav et al. (2022) adopted the NNs to predict the health trends on social media platforms, demonstrating their effectiveness in analysing health-related data from social networks and aiding in medical diagnosis and treatment. Haq et al. (2022) applied the NNs to classify brain tumors in IoT-enabled healthcare systems, showcasing their utility in medical image analysis and disease classification. Almutairi et al. (2022) utilized the neural networks to detect elderly behaviors, highlighting their role in monitoring and improving the well-being of elderly individuals. As mentioned above, the neural networks are capable of learning complex patterns from data and make informed decisions has made them valuable tools in advancing healthcare research and practice.

A comparison of the strengths and weaknesses of the reviewed classifiers is presented in Table 1. In this study, the three-axis signal, SSF, and the proposed GA-optimized EWMA features are respectively fed into these classifiers

Table 1. A comparison of several classifiers

classifier	model type	strengths	weaknesses
1. DT	non-linear, tree-based	* Easy to interpret and visualize * Easy to interpret and visualize	* Easy to overfitting * May create biased trees if some classes dominate
2. DA	linear or quadratic	Works well with normally distributed classes	Assumes normality and equal covariance
3. LR	linear	* Simple and interpretable * Works well with linearly separable data	* Limited to linear decision boundaries * May underperform with complex patterns
4. Naïve Bayes Classifiers	probabilistic, linear	* Performs well with high dimensional data * Handles irrelevant features effectively	Can perform poorly if feature independence is violated
5. SVMs	linear or non-linear kernels	* Effective in high dimensional spaces * Versatile through kernel trick * Robust against overfitting	* Can be computationally intensive * Less interpretable * Careful parameter tuning
6. KNN	instance-based, non-parametric	* No training phases * Adaptable to multi-class problems	Sensitive to irrelevant features and feature scaling
7. EL	combines multiple models (e.g., bagging, boosting)	* Improved accuracy * Reduces overfitting * Versatile and can handle various data types	* Can be complex to implement * Less interpretable * Higher computational cost
8. NNs	non-linear	* Flexible and powerful * Can model complex patterns	* Requires large amounts of data * Computationally intensive * Less interpretable (black box)

, and a thorough comparison is provided to demonstrate the efficiency of the proposed methodology.

3. MATERIALS AND METHODS

In this section, a GA-optimized EWMA feature engineering method will be presented in order to enhance the accuracy of HAR. Fig. 1 shows the flow chart of the proposed HAR method, with details provided as follows:

Step 1. Acquire data

The three-axial sensor data collected from 30 experimental subjects were recorded using a Galaxy S II cell phone's accelerometer. The acceleration will sample at 50 samples per second. Six human activities, including walking, walking upstirs, walking downstairs, witting, standing and lying down were used as classification labels. The recorded data is accessible from https://www.mathworks.com/matlabcentral/fileexchange/53001-code-for-webinar-signal-processing-and-machine-learning-techniques-for-sensor-data-analytics

Step 2. Statistical signal features

The three-axis sensor data was transformed into 66 statistical signal features, including the mean, RMSE, autocorrelation, peak analysis, and time-frequency analysis.

Step 3. EWMA-based statistical signal features

Given a set of EWMA weights for each statistical signal feature (denoted as *S*), where , then EWMA values at time *t* for each variable can be obtained by:

$$EWMA_t = \lambda_i S_t + (1-\lambda_i)EWMA_{t-1} = \left(\frac{\lambda_i}{1-(1-\lambda_i)B}\right) S_t \quad (1)$$

where B is the backward operator (i.e. $BS_t = S_{t-1}$). By applying EWMA to input features, we can smooth out short-term fluctuations and highlight long-term trends. This can improve the stability and robustness of the model, particularly in noisy datasets. Specifically, applying EWMA weights in a classification problem can make the model more responsive to recent changes in data, which is

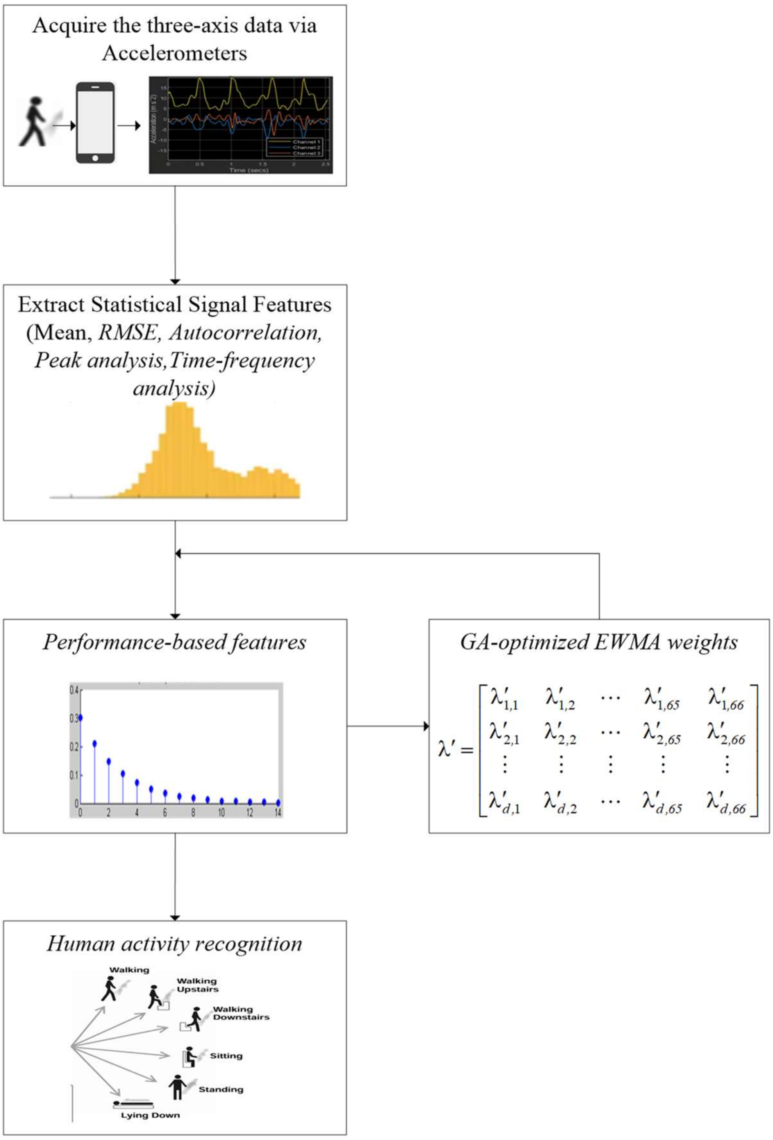

Fig. 1. The flow chart of proposed human activity recognition

beneficial in dynamic environments. However, it also requires careful tuning to avoid overfitting or loss of important historical information. In the next step, we will introduce how to determine the optimal EWMA weights for each statistical signal features. Another advantage of the use of EWMA-based statistical signal features is that it can conduct variable reduction once the   is set to be 0.

Step 4. Optimizing EWMA weights by using GA

GA is a powerful tool for solving complex optimization problems due to their global search capability, flexibility, robustness, and scalability. They are particularly advantageous in situations where the search space is large, the objective function is non-linear or noisy, and traditional optimization methods struggle to find optimal solutions. Therefore, the GA will be used to find the optimal EWMA weights. Fig. 2 shows the flowchart of GA implementation for searching the optimal EWMA weights

Detailed steps for GA implementation are:

(1) Initializing the search agents

By giving a population size d, we can generate a $d \times 66$ search agent matrix, with$0 \leq \lambda_i \leq 1$, which can be denoted as:

$$\lambda = \begin{bmatrix} \lambda_{1,1} & \lambda_{1,2} & \cdots & \lambda_{1,65} & \lambda_{1,66} \\ \lambda_{2,1} & \lambda_{2,2} & \cdots & \lambda_{2,65} & \lambda_{2,66} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \lambda_{d,1} & \lambda_{d,2} & \cdots & \lambda_{d,65} & \lambda_{d,66} \end{bmatrix} \tag{2}$$

(2) Evaluate the fitness function

The optimal EWMA weights for each statistical signal feature can be determined by maximizing the accuracy for each class, which can be expressed as:

Table 2 The transformed 66 statistical signal features.

statistics	feature name
mean	TotalAccXMean, TotalAccYMean, TotalAccZMean
RMSE	BodyAccXRMS, BodyAccYRMS, BodyAccZRMS
autocorrelation	BodyAccXCovZeroValue, BodyAccXCovFirstPos, BodyAccXCovFirstValue, BodyAccYCovZeroValue, BodyAccYCovFirstPos, BodyAccYCovFirstValue, BodyAccZCovZeroValue, BodyAccZCovFirstPos, BodyAccZCovFirstValue
peak analysis	BodyAccXSpectPos1, BodyAccXSpectPos2, BodyAccXSpectPos3, BodyAccXSpectPos4, BodyAccXSpectPos5, BodyAccXSpectPos6, BodyAccYSpectPos1, BodyAccYSpectPos2, BodyAccYSpectPos3, BodyAccYSpectPos4, BodyAccYSpectPos5, BodyAccYSpectPos6, BodyAccZSpectPos1, BodyAccZSpectPos2, BodyAccZSpectPos3, BodyAccZSpectPos4, BodyAccZSpectPos5, BodyAccZSpectPos6, BodyAccXSpectVal1, BodyAccXSpectVal2, BodyAccXSpectVal3, BodyAccXSpectVal4, BodyAccXSpectVal5, BodyAccXSpectVal6, BodyAccYSpectVal1, BodyAccYSpectVal2, BodyAccYSpectVal3, BodyAccYSpectVal4, BodyAccYSpectVal5, BodyAccYSpectVal6, BodyAccZSpectVal1, BodyAccZSpectVal2, BodyAccZSpectVal3, BodyAccZSpectVal4 , BodyAccZSpectVal5, BodyAccZSpectVal6
time-frequency analysis	BodyAccXPowerBand1, BodyAccXPowerBand2, BodyAccXPowerBand3, BodyAccXPowerBand4, BodyAccXPowerBand5, BodyAccYPowerBand1, BodyAccYPowerBand2, BodyAccYPowerBand3, BodyAccYPowerBand4, BodyAccYPowerBand5, BodyAccZPowerBand1, BodyAccZPowerBand2, BodyAccZPowerBand3, BodyAccZPowerBand4, BodyAccZPowerBand5

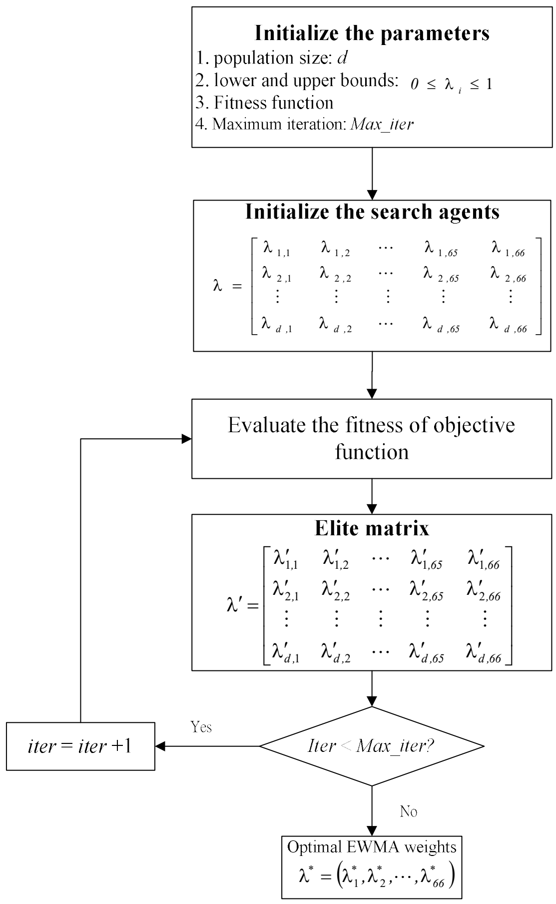

Fig. 2. GA implementation for searching EWMA weights

$$\max_{\lambda_i} \quad \text{Accuracy(Class 1)} + \text{Accuracy(Class 2)} + \cdots + \text{Accuracy(Class j)}$$
$$\text{s.t.} \quad 0 \le \lambda_i \le 1$$
$$i = 1,2,\cdots,66 \tag{3}$$

Where
$Accuracy(Class\ j) = \frac{TP_j + Sum\ of\ \mathrm{TN}_s\ for\ other\ classes}{Total\ number\ of\ instances}$,
TP is the number of instances where the model correctly predicted the positive class and TN is the number of instances where the model correctly predicted the negative class.

(3) Generate the elite matrix

A matrix that stores the best-performing individuals (elite individuals) from the current population. The goal of elitism is to preserve the best solutions found so far, ensuring that the Genetic Algorithm does not lose high-quality solutions during the evolution process. Without elitism, there's a risk that the crossover and mutation operations could degrade or lose the best solutions, especially if the population size is small or if the algorithm hasn't fully converged. The elite matrix can be expressed as

$$\lambda' = \begin{bmatrix} \lambda'_{1,1} & \lambda'_{1,2} & \cdots & \lambda'_{1,65} & \lambda'_{1,66} \\ \lambda'_{2,1} & \lambda'_{2,2} & \cdots & \lambda'_{2,65} & \lambda'_{2,66} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \lambda'_{d,1} & \lambda'_{d,2} & \cdots & \lambda'_{d,65} & \lambda'_{d,66} \end{bmatrix} \tag{4}$$

(4) Terminal criterion

In this study, the terminal criterion of a maximum number of generations is adopted, meaning the GA stops after reaching a predefined number of generations (iterations). The optimal EWMA weights for each feature are determined when the maximum number of generations is reached and are denoted as $\lambda^* = (\lambda_1^*, \lambda_2^*, \cdots, \lambda_{66}^*)$.

Step 5. Classifier comparison

The proposed GA- EWMA features will be used in various classifiers, including DT, DA, LR, Naïve Bayes classifiers, SVM, EL, and NNs. Table 3 lists the classifier types and their model methods. Therefore, there are total 30 classifiers will be implemented for a comparison.

Table 3. Classifier types and their model methods

classifier	model method
1. DT	fine tree
	medium tree
	coarse tree
2. DA	linear discriminant
	quadratic discriminant
3. LR	logistic regression
4. Naïve Bayes	Gaussian Naïve Bayes
classifiers	kernel Naïve Bayes
5. SVM	linear SVM
	quadratic SVM
	cubic SVM
	fine Gaussian SVM
	medium Gaussian SVM
	coarse Gaussian SVM
6. KNN	fine KNN
	medium KNN
	coarse KNN
	cosine KNN
	cubic KNN
	weighted KNN
7. EL	boosted trees
	bagged trees
	subspace discriminant
	subspace KNN
	Rusboosted trees
8. NNs	narrow NN
	medium NN
	wide NN
	bilayered NN
	trilayered NN

4. RESULTS AND DISCUSSION

This section will first introduce the data characteristics. In Case 1, the original three-axis data X, Y, and Z are used as inputs to the classifiers. Case 2 illustrates the use of SSF as inputs, while Case 3 demonstrates the use of proposed GA-optimized EWMA features.

4.1 Data resources

This study uses the experimental data of Davide Anguita et al. (2013) to collect information about human daily behavior by installing a Samsung Galaxy II smartphone on the waist of the human body to sense human body activities. 30 volunteers aged 19 to 48 years old were used to perform such a task, and were divided into six activity categories: standing, sitting, lying, walking, going downstairs and going upstairs. Each action was attempted at least twice and based on Table 4 shows the experimental activity procedure and duration. The sampling frequency is 50 HZ, corresponding to the activity category, and the three- axis data of X, Y, and Z in the accelerometer are recorded. The experimental design is divided into static and dynamic activities, totaling 192 s. Among them, the experimental procedure of static activity (A) is standing position (1), which refers to the first standing position 15 s, and so on, the static activity totals 90 s.

In the dynamic activity (B) experimental program, walking (1) refers to the first 15 s of walking, and so on, the total number of dynamic activities is 102 s. Table 5. defines the representative activities of each activity class in the following analysis. There are a total of 10,299 observations, with 70% of the observations used as the training dataset, while 30% used as the testing dataset. The execution environment is under Intel(R) Core (TM) i5-8400H CPU@ 2.81 Hz, NVIDGeForce GTX 1060 3GB and Sav et al. (2022) MATLAB 2021a is used for implementing the program.

Table 4. Experimental activity program

static activity (A)	time (s)	dynamic activity (B)	time (s)
start	0	walking (1)	15
standing position (1)	15	walking (2)	15
sitting position (1)	15	going downstairs (1)	12
standing position (2)	15	going upstairs (1)	12
lying position (1)	15	going downstairs (2)	12
sitting position (1)	15	going upstairs (2)	12
sying position (2)	15	going downstairs (3)	12
		going upstairs (3)	12
		stop	0
subtotal	90	subtotal	102
total 192 s			

Table 5. Representative activities of the confusion matrix diagram

dynamic activity (B)		static activity (A)	
activities	Class	activities	Class
walking	1	standing	4
going downstairs	2	sitting	5
going upstairs	3	lying	6

4.2 Case 1: Original data X, Y, Z as input variables

Table 6 shows the classification results when X, Y, and Z are used as input features. The results indicate that the lowest testing accuracy, 42.7%, is achieved with the cubic SVM classifier, while the coarse KNN approach yields the highest testing accuracy at 76.1%. In terms of computation time, the cubic SVM classifier spent 389,928 s (i.e., about 4.51 days) to train the model, while the quadratic discriminant classifier took only 3.52 s. Generally speaking, the coarse KNN classifier seems to be the better classifier when using original data as the input. From the confusion matrix diagram of coarse KNN in Fig. 3, it can be found that the average accuracy of the three static activities (i.e. Class 4–6) is 96.1%, which is compared to the average of 51.5% of the three dynamic activities (Class 1–3).

4.3 Case 2: 66 SSFs

In Case 2 of this study, the original data is transformed into 66 SSFs, with the classification results presented in Table 7. The results show a significant increase in accuracy compared to using the original variables as inputs. Table 7 indicates that bagged trees and medium Gaussian SVM are the top-performing classifiers when SSFs are used as input features. The training and testing accuracies for the bagged trees classifier are 94.5% and 87.4%, respectively, while for the medium Gaussian SVM classifier, they are 93.8% and 88.5%, respectively. Fig. 4 displays the confusion matrix for the bagged trees classifier. It shows that the average accuracy rate for dynamic activities has increased to 95.7% (compared to 51.5% in Case 1). This indicates that the use of SSFs has significantly improved the recognition accuracy of dynamic activities. Additionally, the computation time has also been significantly reduced compared to Case 1.

4.4 Case 3: GA-optimized EWMA features

In this Case, we use bagged trees as the classifier in order to determine the EWMA weights. The population size of 50, crossover rate 0.3, mutation rate 0.2 and maximum iteration 100 are used in the GA implementation. Fig. 5 shows the GA convergence plot for searching the EWMA weights. Table 8 shows the acquired GA-optimized EWMA weights for 66 SSFs. It shows that the number of SSFs has been reduced from 66 to 35. From Table 9, it shows that bagged trees has a training accuracy of 99.6% and testing accuracy of 95.2%. The training time in Case 1 is 1254.2 s, 105.01 s in Case 2, and only 77.56 s when using the GA-optimized EWMA features. Furthermore, the GA-optimized EWMA features were also applied to other classifiers, as shown in Table 9, where the cubic SVM demonstrated the best training time. Table 9 shows that using the GA-optimized EWMA features is capable of enhancing the recognition accuracy.

4.5 Discussion and Comparison

Fig. 6 displays the comparison results of training time between the three-axis method, SSF, and the proposed method when ensemble bagged trees is used as the classifier. The results indicate that the three-axis method requires the longest training time, while both SSF and the proposed method significantly reduce training time. Fig. 7 demonstrates the comparison results of recognition accuracy of the training and testing. Results shows that the test accuracy rate boosts to 87.4% from 74.6% when the statistical features are used. However, the SSF approach increases the number of inputs from 3 to 66. In contract, the proposed method not only enhance the accuracy both in training and testing, but also reduce the number of inputs to 35, leading to the training time takes only 19.3 s.

Table 6. Original data X, Y, Z accuracy rate of each classifier

classifier	model method	training accuracy (%)	testing accuracy (%)	training time (s)
DT	fine tree	71.4%	71.3%	44.25
	medium tree	67.7%	67.9%	40.34
	coarse tree	56.3%	56.3%	37.91
DA	linear discriminant	52.6%	52.6%	6.05
	quadratic discriminant	66.3%	66.2%	3.52
LR	logistic regression *applied to discrete data, this study adopts the verification of time series data, so it will not be collected if it cannot be verified.			
Naïve Bayes classifiers	Gaussian Naïve Bayes	63.3%	63.2%	9.3
	kernel Naïve Bayes	68.8%	68.8%	14754
SVM	linear SVM	48.4%	49.7%	340965
	quadratic SVM	48.1%	49%	343071
	cubic SVM	41%	42.7%	389928
	fine Gaussian SVM	75.7%	75.5%	160494
	medium Gaussian SVM	73.5%	73.5%	175052
	coarse Gaussian SVM	69.2%	69.1%	203506
KNN	fine KNN	71%	70.9%	20.46
	medium KNN	75.2%	75%	39.77
	coarse KNN	76.1%*	76.1%*	100.63
	cosine KNN	63.8%	64.1%	7052.9
	cubic KNN	75.1%	75%	99.86
	weighted KNN	73.8%	73.8%	51.66
EL	boosted trees	68.7%	68.8%	535.31
	bagged trees	74.5%	74.6%	1254.2
	subspace discriminant	53%	52.7%	157.07
	subspace KNN	64.9%	64.8%	440.87
	Rusboosted trees	67.9%	67.9%	773.56
NNs	narrow NN	70.9%	71%	3768
	medium NN	72.8%	72.1%	5098
	wide NN	73.8%	74.1%	9009.8
	bilayered NN	72.9%	72.3%	4795
	trilayered NN	72.3%	72.1%	6643

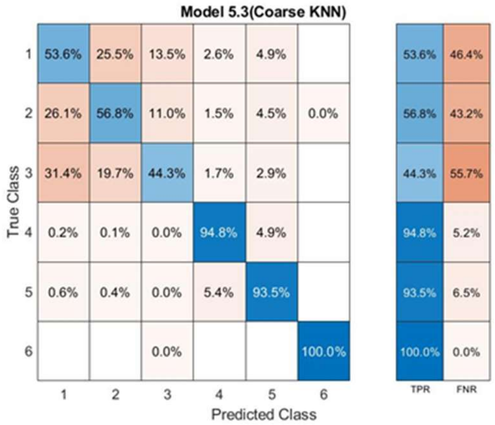

Fig. 3. Model 5.3 (coarse KNN) testing confusion matrix diagram

To further demonstrate the efficiency of the proposed method, Fig. 8 displays the comparison results of training time when cubic SVM is used as the classifier. It demonstrates that the three-axis method requires 4.51 days to train the cubic SVM model, making it time-inefficient. In contrast, both SSF and the proposed method are significantly more time-efficient than the three-axis method. Fig. 9 shows the recognition accuracy. It displays that the proposed method has superior training and testing accuracy compared to the three-axis and SSF methods. Furthermore, it is noted that the prediction time is less than 0.01 s when using the trained ensemble bagged tree and cubic SVM models, making the proposed method suitable for real-time HAR applications.

Table 7. Accuracy rate of each classifier under the statistical signal feature

classifier	model method	training accuracy (%)	testing accuracy (%)	training time (s)
DT	fine tree	91.8%	77.5%	13.99
	medium tree	87.9%	82.7%	10.28
	coarse tree	76.5%	69.6%	9.95
DA	linear discriminant	88.7%	86%	9.38
	quadratic discriminant	79.2%	74.8%	8.62
LR	logistic regression *applied to discrete data, this study adopts the verification of time series data, so it will not be collected if it cannot be verified.			
Naïve Bayes classifiers	Gaussian Naïve Bayes	72.3%	68.9%	9.08
	kernel Naïve Bayes	82.5%	80.7%	298.1
SVM	linear SVM	91.8%	87.5%	17.87
	quadratic SVM	93.5%	86.8%	20.54
	cubic SVM	92.9%	86.5%	34.89
	fine Gaussian SVM	69.3%	62.7%	67.82
	medium Gaussian SVM	93.8%	88.5%*	23.27
	coarse Gaussian SVM	89.9%	85.6%	23.06
KNN	fine KNN	85.9%	79%	62.97
	medium KNN	87%	80.7%	62.72
	coarse KNN	83%	76.9%	67.56
	cosine KNN	87.2%	82%	74.52
	cubic KNN	85.3%	84.4%	855.31
	weighted KNN	87.7%	81.3%	96.41
EL	boosted trees	90.7%	85.6%	147.84
	bagged trees	94.5%*	87.4%	105.01
	subspace discriminant	86.6%	83.9%	109.2
	subspace KNN	90.2%	84.7%	447.41
	Rusboosted trees	88.6%	82.8%	177.3
NNs	narrow NN	92.1%	86.6%	177
	medium NN	91.5%	86.6%	254.28
	wide NN	91.5%	85.9%	287.4
	bilayered NN	92%	87.4%	259.82
	trilayered NN	92.2%	86.1%	320.21

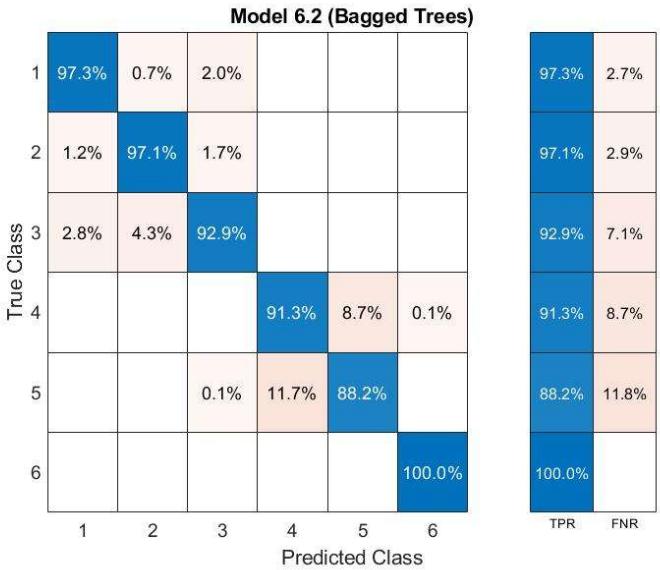

Fig. 4. Model 6.2 (bagged Trees) testing confusion matrix diagram

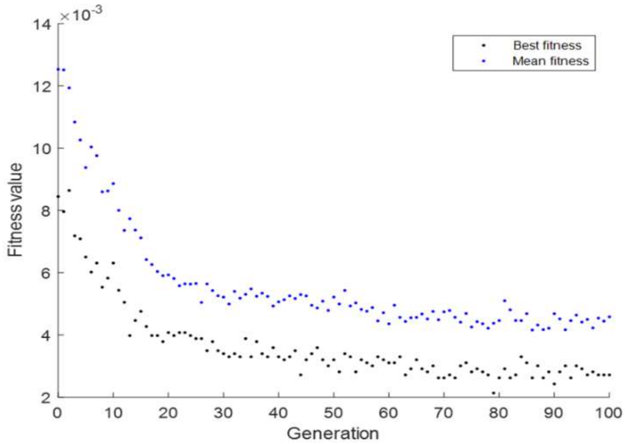

Fig. 5. Convergence plot

Table 8. GA-optimized EWMA weights

SSF No.	1	2	3	4	5	6	7	8	9	10	11
λ^*	0.04	0.89	0.70	0.00	0.00	0.46	0.97	1.00	0.95	0.24	0.00
SSF No.	12	13	14	15	16	17	18	19	20	21	22
λ^*	0.30	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.09	.001	0.20
SSF No.	23	24	25	26	27	28	29	30	31	32	33
λ^*	0.00	0.02	0.00	1.00	0.03	1.00	0.00	0.00	0.00	0.02	0.00
SSF No.	34	35	36	37	38	39	40	41	42	43	44
λ^*	0.99	0.00	1.00	0.04	0.00	0.00	0.38	0.06	0.00	0.03	0.00
SSF No.	45	46	47	48	49	50	51	52	53	54	55
λ^*	0.08	0.00	0.68	0.00	0.00	0.07	1.00	0.70	0.02	0.00	0.00
SSF No.	56	57	58	59	60	61	62	63	64	65	66
λ^*	0.00	0.00	0.00	0.03	0.00	0.00	0.11	0.39	0.92	0.02	0.00

Table 9. Accuracy rate of Performance-based features classifier

classifier	model method	training accuracy (%)	testing accuracy (%)	training time (s)
DT	fine tree	97.7%	89.4%	11.02
	medium tree	93%	90.6%	9.19
	coarse tree	77.2%	76.2%	8.93
DA	linear discriminant	87.3%	66.7%	6.27
	quadratic discriminant	75.2%	69.6%	3.52
LR	logistic regression *applied to discrete data, this study adopts the verification of time series data, so it will not be collected if it cannot be verified.			
Naïve Bayes classifiers	Gaussian Naïve Bayes		*unable to calculate	
	kernel Naïve Bayes	88.9%	86.4%	329.3
SVM	linear SVM	98.6%	94.1%	19.83
	quadratic SVM	99.6%	93.2%	19.65
	cubic SVM	99.8%*	92.8%	19.32*
	fine Gaussian SVM	95.4%	74.9%	65.49
	medium Gaussian SVM	98.9%	94.8%	20.86
	coarse Gaussian SVM	96.8%	91.7%	29.37
KNN	fine KNN	98.9%	88%	49.24
	medium KNN	97.3%	88.8%	50.56
	coarse KNN	92.2%	86.7%	54.11
	cosine KNN	97%	89.5%	60.04
	cubic KNN	96.3%	87.5%	563.27
	weighted KNN	98.5%	89.5%	81.83
EL	boosted trees	97.8%	94.6%	102.39
	bagged trees	99.6%	95.2%*	77.56
	subspace discriminant	92.7%	89%	77.28
	subspace KNN	99.6%	93%	367.51
	Rusboosted trees	93.6%	89.7%	122.12
NNs	narrow NN	99.1%	93.1%	99.02
	medium NN	99.3%	94.6%	112.46
	wide NN	99.6%	94.4%	126.16
	bilayered NN	99.2%	93.6%	133.58
	trilayered NN	99.1%	93.2%	148.99

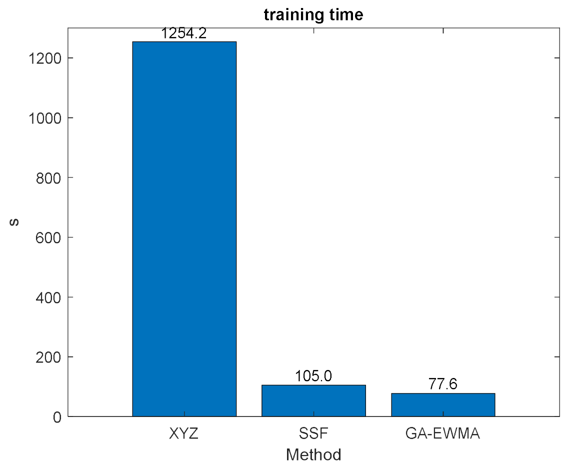

Fig. 6. The training time comparison under the implementation of ensemble bagged tree

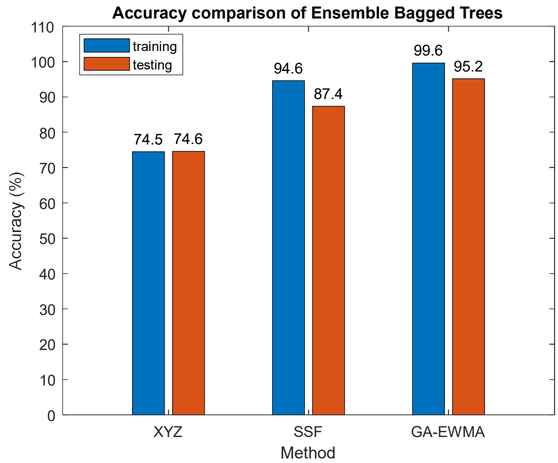

Fig. 7. Accuracy comparison under the implementation of ensemble bagged tree

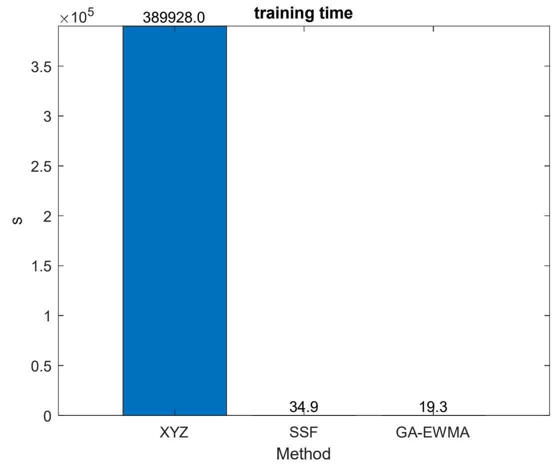

Fig. 8. The training time comparison under the implementation of cubic SVM

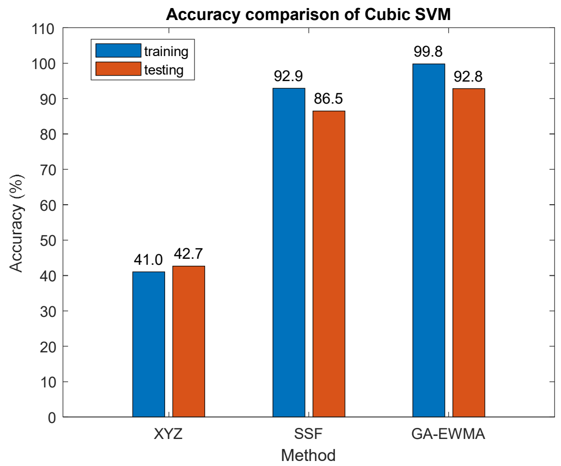

Fig. 9. Accuracy comparison under the implementation of cubic SVM

5. CONCLUSION

HAR is garnering attention across various fields, such as healthcare, fitness and sports, security and surveillance, occupational safety, smart environments, and more. This is largely attributed to the rapid development of mobile devices, which enable users to record human activity signals using accelerometers. In this study, we found that the recognition rates were poor when tri-axial activity signals collected from accelerometers were directly fed into classifiers, including DT, DA, LR, Naïve Bayes classifiers, SVM, EL, and NN. The recognition rates are significantly improved when the three-axis signals were transformed into SSF. Despite the improvement in accuracy, the increase in the number of input variables from 3 to 66 has burdened the computation time. Furthermore, a higher recognition rate is needed to have an effective decision making. This study innovatively uses multi-variable EWMA to calculate 66 feature variables, and uses GA to optimize the EWMA weight value of each feature. The performance based of GA-optimized EWMA features model can achieve efficiency with only 35 features. The classification accuracy of the Ensemble Bagged Tree classifier reaches 95.2%, with a prediction time of less than 0.01 s. This demonstrates that the GA-optimized EWMA features model proposed in this study can significantly enhance recognition accuracy and time efficiency in HAR. In future work, the proposed method can be integrated into wearable devices, such as smartwatches or bracelets, for applications in healthcare, health promotion, elderly monitoring, and more.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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