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Generalized and Improved Human Activity Recognition for Real-Time Wellness Monitoring

Qurban Memon*, Mohammed Al Ameri, Namya Musthafa

Department of Electrical Engineering, UAE University, Al Ain, UAE

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Abstract

Human activity categorization using smartphone data can be useful for physicians in real-time data monitoring in sports or lifestyle monitoring. The goal of this research is to develop a methodology that can identify strong machine-learning classifiers applied to various human activity datasets. The first step is pre-processing the data, followed by feature extraction, selection, and classification. Relying on a single dataset does not yield high confidence in the findings. Instead, examining multiple datasets is crucial for a comprehensive understanding, as it avoids the pitfalls of basing conclusions on one dataset alone. Multiple datasets and classifiers are applied in different experiments to achieve improved and generalized human activity recognition performance. Experimental results of the support vector machine (SVM) with its generalized performance of 99% encourage us to use the trained SVM-based model to monitor normal human activities inside the home, in the park, in the gym, etc. enhancing wellness monitoring.

Keywords: lifestyle, healthcare monitoring, human activity recognition, accelerometer data, machine learning

1. Introduction

Current-era smartphones already have a plethora of built-in sensors, but usually, they are connected to a specialized application for specific functionality. Each smartphone model includes its unique collection of mobile sensors, which are divided into three distinct groups: motion sensors, environment sensors, and location sensors. Sensors for tracking health conditions do not have their class. The rationale for this is that each group of sensors can be utilized for healthcare monitoring when coupled with smartphone gadgets, wearable technology, or applications. For example, an application involving motion sensors can call an emergency service if an individual remains motionless for roughly a minute after falling. Position sensors function whenever an individual uses a fingerprint to monitor heart rate. Involving environment sensors can help people address their health risks when they have been exposed to extreme conditions for an extended period, such as high radiation levels, high levels of humidity, or extreme temperatures.

Human activity recognition (HAR) and monitoring is an evolving field of data science. It has practical applications in the field of healthcare, particularly in tracking the elderly to ensure they do not end up doing things that could harm them. HAR allows for a wide range of application scenarios in ambient assisted living. Healthcare is one of the most visible applications of HAR, benefiting both elderly and disabled persons as well as healthy ones. The ubiquitous use of numerous sensors embedded into mobile devices makes daily human actions simpler and more common to analyze. The broad use of HAR improves people's safety and overall health. A more recent HAR methodology consists of a wearable device containing accelerometers, gyroscopes, magnetometers, and other sensors that can record actions during daily life, and a system that can identify these activities conducted by the individual.

* Corresponding author. E-mail address: qurban.memon@uaeu.ac.ae

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HAR approaches facilitate the monitoring of daily human activities such as eldercare, research, healthcare, sports, and smart homes. It is quite possible to monitor indicators such as eye health, heart rate, pulmonary and lung health, daily activity, ear health, and cognitive functions using various sensors deployed in a health monitoring system. Remote monitoring of everyday activities inside the home environment or parks may aid in tracking patient adherence to therapeutic procedures such as exercise monitoring to better estimate the number of calories utilized by the body over time.

Lifestyle monitoring (LM) is especially useful to support the assessment process after hospital discharge, during rehabilitation, and in the reablement period. It provides a far more accurate depiction of a person's daily routine when they live on their own than a talk with the accompanying person and family members who do not live with them. The data assists health and social care providers in making appropriate care and support decisions, and it may even offer reassurance to families and caregivers. The market share of wearable healthcare devices, based on the size and accelerating growth of the global market of wearable health monitoring devices, stood at 20.1 billion US$ in 2021 and is expected to grow to over 83.9 billion US$ by 2026 [1].

Because of the widespread use of devices such as smartphones and their ability to collect activity data, HAR provides a diverse set of applications. One of the goals of activity recognition is to provide details about a user's behavior so that computing systems can support them proactively. As a result of the growing usage of HAR in sports and health, numerous HAR models have been published in the literature. Current models, however, frequently overlook the successful extraction of geographical and temporal information from data on human activities. Understanding such activities allows for engagement with the subject via the application. Advances in artificial intelligence (AI) have substantially boosted the ability to extract relevant information for precise detection. The typical multi-class classification used in such recognition tasks necessitates the acquisition of training data for all activity types that may be encountered during the prediction stage.

Maintaining a healthy lifestyle is now nearly impossible with demanding job schedules. In these situations, deep learning and machine learning can help by assessing medical data to accomplish a variety of objectives, such as patient fatality control and preventive healthcare. The merging of cloud computing and cloud storage can be adopted to enable real-time cost savings on services. The research conducted by Sujith et al. [2] covers current developments and obstacles, in addition to providing a comprehensive evaluation of smart health monitoring. The objective of this research is to develop a protocol-based methodology that yields a strong classifier, providing improved and generalized human activity classification performance across multiple open-access datasets for real-time monitoring in sports or LM in general.

The remaining portions of this paper are structured as follows. Section 2 presents an overview of related research in the area of HAR and accelerometer data. In Section 3, a model is proposed that reads human activity data from multiple datasets to satisfy two objectives: (a) a publicly available dataset is chosen for human activity positions of the subject, performs time-frequency-based feature extraction, and selects a strong classifier for improved performance in the final activity recognition step, and (b) a second dataset is chosen involving increased human activities for validation and generalized performance. Section 4 presents experimental results from three separate classifiers using two datasets and compares them for optimal performance. In Section 5, results are discussed, followed by conclusions in Section 6.

2. Related Works

Changes in activity profiles are utilized to indicate a change in an individual's wellness state in LM, a crucial area of telecare study. According to a literature survey by Brownsell et al. [3], the majority of research activity is focused on technology development initiatives, particularly those related to motion tracking, followed by door and electrical appliance usage. Cardinaux et al. [4] suggest an LM technology simulator for generating daily activity data, which can then be utilized for LM system development and validation. They propose that everyday activities are influenced by various external factors that affect the desire to carry out the activities. Additionally, real research was used to populate the simulator settings, including hardware testing and data collection from senior citizens. The authors demonstrate experimental validation, showing that the intended features are reasonably represented by the simulator.

Rosaline et al. [5] propose a machine learning classifier using the public domain USC human activity dataset (USC-HAD) for real-life HAR using smartphone sensors and the OPPORTUNITY dataset. The confusion matrix measure scores were calculated to investigate the results of the proposed classifier, with an accuracy of 97.9%. An activity monitoring platform capable of acquiring data from four inertial sensors placed on the human body may also be used for real-time data display or on a server for long-term data analysis [6].

In similar research, Hassan et al. [7] present a smartphone inertial sensors-based approach for HAR based on features that are processed using kernel principal component analysis (PCA), linear discriminant analysis (LDA), and deep belief network (DBN), which are compared with support vector machine (SVM) and artificial neural network (ANN). A human physical activity recognition system based on data collected from smartphone sensors is also discussed in Voicu et al. [8], where physical activities such as walking, running, sitting, standing, ascending, and descending stairs are classified using two datasets with accuracies of 86.1% and 76.8%.

Accelerometers have also been utilized to evaluate physical activity energy expenditure, physical activity, sedentary time, and sleep-related behaviors. The choice of appropriate features is a crucial component of HAR since the performance of the activity recognition system relies heavily on features retrieved from the sensing device. For feature extraction in a HAR system, a CNN model trained on accelerometer data is recommended [9], where the authors assert that the model outperforms several previously used recognition methods that use the same dataset.

Another study by Ahmed et al. [10] employed sensor data from smartphones mounted on the subjects' waists for HAR tasks with high-dimensional feature vectors selected using a hybrid approach. The features, once selected, are sent to an SVM model. A benchmark dataset is then used to validate the model, resulting in a classification performance of 96.81% when using optimal features, and an improvement in performance of about 6% compared to using no feature selection.

A CNN-based deep learning method relies on local feature extraction for online human activity classification, as reported in the literature [11]. To enable continuous activity classification, the duration of the time series is limited to 1 second while studying the impact on recognition accuracy. Two widely known datasets, WISDM and UCI, each containing labeled data, were utilized to assess the accuracy [11]. The outcomes show cutting-edge performance with minimal computational expense and no human feature engineering. Recently, there has been a surge in research interest in behavioral pattern recognition.

However, a solid deep learning-based model cannot be constructed without sufficient data or if the physical activity that needs to be identified has changed. In such an application, the research study by Ahmed et al. [12] develops a generic deep-learning model that uses an input image along with heterogeneous acceleration sensor data. The residual neural network (ResNet10), bidirectional long short-term memory (BiLSTM), CNN, and convolutional block attention module (CBAM) models were all utilized to analyze accelerometer data. With accelerometer data and a skeleton image, the accuracy was 94.08%; with coordinates, accelerometer data, and a skeleton picture, it was 93.09%. The recommended model was reported to be robust during testing that included inversion and noise data, with a performance degradation of only about 1%.

In a related study by Li and Wang [13], a deep learning model was suggested to retrieve spatial features from multidimensional signals using a residual block, obtain the dependencies of feature sequences through BiLSTM, and then complete HAR using a Softmax layer. In addition to two publicly available datasets, a locally constructed dataset encompassing six typical activities was created for evaluation. The experimental findings demonstrate that the suggested model, when applied to the local dataset and two public datasets, achieves accuracy levels of 96.95%, 97.32%, and 97.15%, respectively.

To identify specific kinds of physical activities using accelerometer data from a user's cell phone, the two most typical phone placements (hand and pocket) have also been examined [14]. Human subjects were used to train and then test the system. With an accuracy rate of 91.15%, a set of classifiers was employed utilizing a variety of statistical features for identifying activities and determining how to integrate classifiers into an optimal set. Approaches to smartphone-based HAR are also reported in a review article by Straczkiewicz et al. [15], which focuses on extracting data related to smartphone location, number of sensors, and activity types, concluding that most research activities have been conducted in recent years. Much more needs to be done for actions related to anomaly detection and forecasting [16].

Machine learning is making strides beyond healthcare, transforming various industrial sectors, including manufacturing, maintenance, and predictive analytics. By integrating machine learning into industrial applications, systems are becoming more intelligent, efficient, and reliable. Innovations such as digital twin-driven assessments for real-time monitoring, physics-informed residual networks (PIResNets) for enhancing fault diagnostics, and advanced data-driven approaches like multi-scale fused features and graphic recurrent units (GRUs) for comprehensive bearing health analysis are expanding the possibilities in predictive maintenance and fault detection. Despite the challenges of data quality, model complexity, and computational demands, these evolving technologies have the potential to significantly advance industrial processes and outcomes.

Though the healthcare sector has emerged as a primary application, the models still need to improve accuracy and generalization. Most prior research has focused on either a single dataset or smaller datasets with limited human activity classes. Incorporating multiple datasets enhances the credibility of the outcomes and enables more unbiased and robust interpretations during data analysis. In essence, evaluating a classifier across multiple datasets allows for a better understanding of its strengths and weaknesses across different data distributions, leading to a more comprehensive evaluation of its performance. In Section 3 below, a model development methodology is adopted that uses various classifiers and datasets to generate an optimized model with generalized performance.

3. Proposed Approach

The essential physical activities need to be identified to monitor wellness for post-treatment rehabilitation or fitness [17]. The important activities include walking, running, walking upstairs, and walking downstairs, among others. The benefits of these activities are summarized in Table 1. These activities, once measured as a ratio to all other activities, can be reviewed by the concerned physician to suggest further procedures for improvement in specific or overall healthcare.

Table 1 Human activities and their importance to health

Activities	Healthcare indicator
Walking	cardiovascular fitness, strengthen bones, reduce excess body fat, boost muscle power and endurance, lower blood pressure, etc.
Running	helps improve blood pressure, HDL (good) cholesterol, and blood sugar sensitivity, lowers your resting heart rate, builds strong bones, strengthens muscles, etc.
Walking upstairs	enhances lung function, improves blood circulation, and reduces the risk of developing coronary heart disease, hypertension, diabetes, colon cancer, etc.
Walking downstairs	Increases muscle strength, tones muscles, and joints, improves balance and coordination, improves insulin sensitivity, and lipid profiles.

In this research, accelerometer data taken from a smartphone is utilized for human activity recording. It is assumed that the smartphone is worn by the subject during these activities. The methodology adopted with two datasets is shown in Fig. 1, and the concept is illustrated in Fig. 2. Fig. 2 shows human activity data accumulated, pre-processed, and classified intelligently. The first stage in the methodology is dataset pre-processing, followed by feature extraction and feature selection. A set of approaches to predict current activity compared to trained results is adopted. The classifiers are built through training as models and reused for new activity prediction. Below, the details of each sub-process are presented.

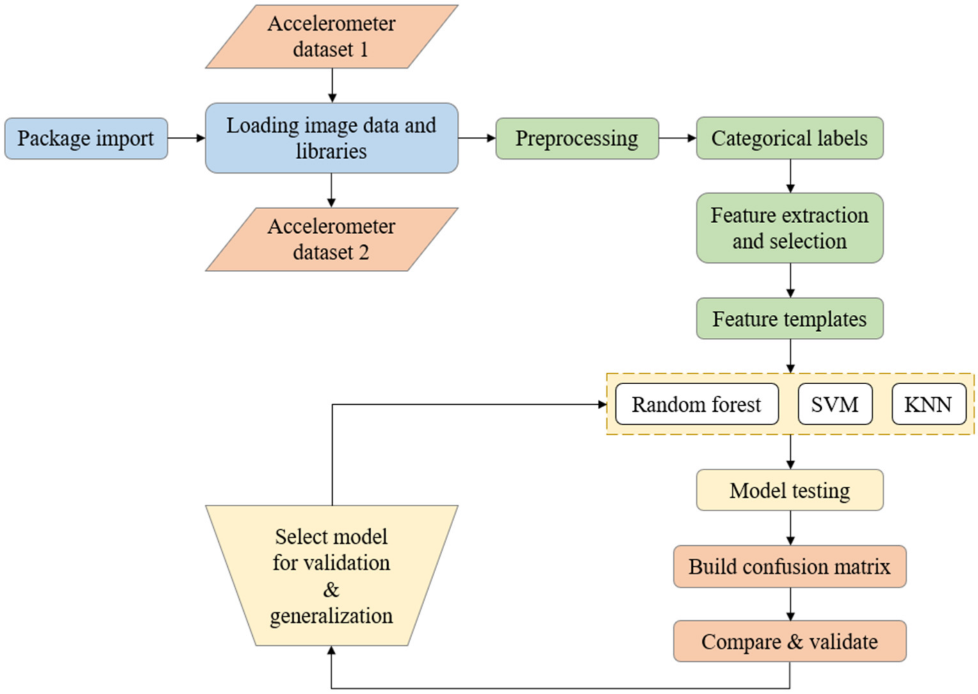

Fig. 1 Proposed methodology

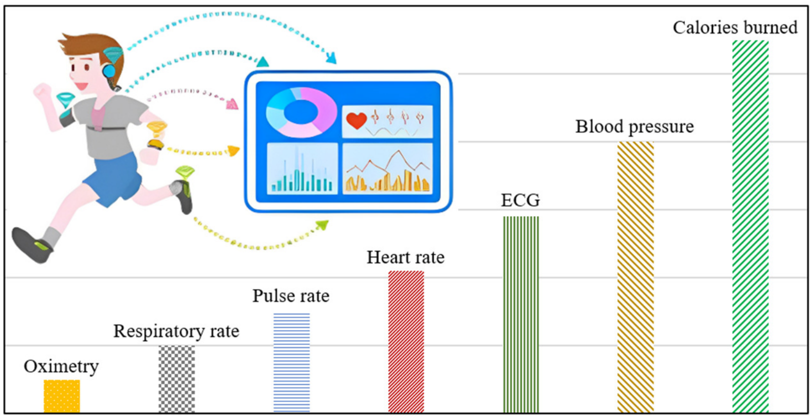

Fig. 2 Intelligent lifestyle monitoring concept

3.1. Preprocessing

Two data preprocessing steps, feature scaling, and labeling, were done before starting the training of feature vectors. Feature scaling prevented certain features from dominating the data analysis due to their variations in scale, thus ensuring that all features are treated equally in the analysis. Label encoding was implemented using LabelEncoder [18], which transformed categorized activity labels into numerical values to facilitate understanding and interpretation of the data.

3.2. Classifiers

k-nearest neighbor (KNN) is one of the simplest supervised learning algorithms [19], where each new sample in the training set is predicted using the KNN. Similarity measures include Euclidean norms and Manhattan distance. The parameter k is usually determined using a grid-style search, where the lowest loss rate is identified. The SVM classifier is a well-known supervised learning algorithm [20]. The approach involves using a set of support vector instances to determine an optimal separating plane with maximum margin. Variants of this approach include non-linear kernel functions and multiclass classification to address various problems. Examples of kernel functions include linear, polynomial, or Radial basis function (RBF) kernels, while multiclass classification is achieved by treating several binary classification problems, for example, using a one-against-all strategy.

(1) Polynomial kernel is expressed as:

$$K(x, y) = (\langle x, y \rangle)^d \tag{1}$$

where d can be 1, 2, 3, …, n.

(2) RBF kernel is expressed as:

$$K(x, y) = e^{-\frac{\|x-y\|^2}{2\sigma^2}} \tag{2}$$

where σ is the variance.

Random forest (RF) [21] is also a supervised machine learning algorithm that involves building multiple decision trees during training. To determine the final result, RF predicts through bagging or bootstrap aggregating algorithms applied to these decision trees. The main steps of RF are:

(1) Select the number of trees you want to create.

a. Choose random samples from the training set, and generate a decision tree for selected samples.
b. Continue

(2) To test the new sample, find the prediction of each decision tree, and assign the new sample to the class that wins the majority votes.

4. Experimental Results

This section presents experimental details of all steps mentioned in Fig. 1. First, the evaluation protocol is presented that discusses how each experiment is conducted and evaluated. Next, three experiments are discussed each detailing what data was used along with classifier(s). The testing results of each experiment are tabulated.

4.1. Evaluation protocol

To conduct a comprehensive investigation of the proposed approach, the following evaluation protocol was devised:

(1) Specify classifiers for training and testing of extracted features of the datasets

(2) For each model, do:

a. Train each classifier by optimizing its parameters
b. Apply the testing data on the optimized model, and tabulate the confusion matrix values
c. Record the accuracy for each classifier from the confusion matrix

(3) Compare results with other works.

This protocol is graphically illustrated in Fig. 3.

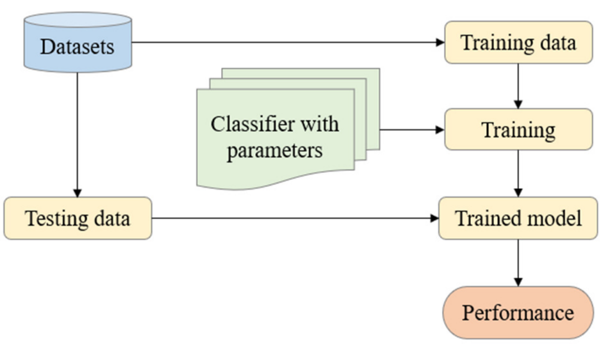

Fig. 3 Evaluation protocol

4.2. Results

After the evaluation protocol, three experiments were conducted to get HAR data. In the first experiment, the smartphone is attached to the waist of one person, and four different types of physical activity are monitored. The second experiment monitors the six daily activities from smartphone data attached to the waist of thirty individuals. In the third experiment, the results obtained are compared to recent research works found in the literature. Below, each experiment is discussed and corresponding results are plotted.

Experiment 1: For this experiment, the smartphone was attached to the waist of one subject during four different types of physical activity. The resulting dataset consists of 7776 x-direction accelerometer data values, with each containing 44 samples (forming a 44 × 7776 matrix) corresponding to four human activities: sitting, standing, walking, and running, labeled as 1, 2, 3, and 4 respectively [22]. The second stage involves feature extraction followed by feature selection, forming feature vectors for each signal instance. A high-pass filter is used to separate rapid variations from slower ones. To classify these features, a table is created with predictors and responses, size 7776 × 23, where 22 features are included and the last one represents activity ID.

Once dataset 1 is loaded, the code sets up two time-feature extractor objects. The first extracts the mean of signals, while the second extracts various features from filtered signals such as shape factor, peak value, root mean square, crest factor, impulse factor, and clearance factor. The code extracts parameters for frequency-based features including band power, half power bandwidth, mean frequency, peak location, and peak amplitude. The calculation of spectral peaks is further refined by setting the maximum number of peaks to 6, with a minimum distance of 0.25 Hz between each spectral peak. The code utilizes transformed array datastores to enhance parallelization for computing features across all signals, which read each matrix column and perform feature extraction. A pool of eight processes is created for parallel execution. The resulting features are concatenated into sequences of 22 features for each of the 7776 signal observations.

For feature classification, the dataset is split into training (75%) and testing (25%) parts ensuring similar activity label proportions. While many classifiers exist in the literature, this experimental study initially uses two well-known classifiers: the K-NN algorithm and SVM. For K-NN training, the parameter k is set to four (4) based on various trials, verified using the elbow method [23], as shown in Fig. 4. Euclidean distance measured the distance between input and class centroids, with training continued until no changes in the classification of training samples occurred. Once trained, the model is stored in a variable. An average testing (predicted) accuracy score of about 87% was achieved with K-NN (k = 4). These accuracy results in the form of a confusion matrix (false positive, false negative, true positive, and true negative) parameters are presented in Table 2. The last column in Table 2 shows that errors during K-NN classification are relatively higher during 'Sitting (20.4%)' and 'Standing (12.8%)', whereas these errors are down to 4.7% and 5.0% respectively when the SVM classifier was employed.

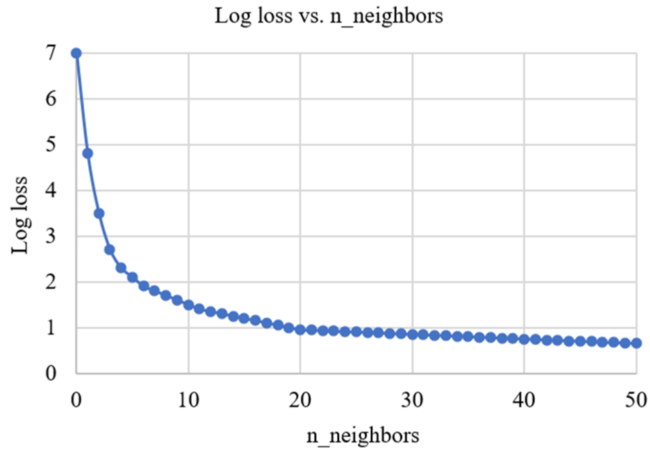

Fig. 4 Choosing the value of k for better performance

Table 2 Confusion matrix values for dataset 1

			True class				Accuracy	Error
	Running	KNN	487	58	3	0	88.9%	11.1%
		SVM	330	1	0	27	92.2%	7.8%
	Sitting	KNN	115	453	1	0	79.6%	20.4%
		SVM	0	507	23	2	95.3%	4.7%
	Standing	KNN	5	44	414	12	87.2%	12.8%
		SVM	0	28	537	0	95.0%	5.0%
	Walking	KNN	0	0	39	313	88.9%	11.1%
		SVM	14	0	2	473	96.7%	3.3%
	Accuracy	KNN	80.2%	81.6%	90.6%	96.3%	-	-
		SVM	95.9%	94.6%	95.6%	94.2%	-	-
Predicted class	Error	KNN	19.8%	18.4%	09.4%	3.7%	-	-
		SVM	4.1%	5.4%	4.4%	5.8%	-	-

For SVM-based classification, a multiclass SVM classifier [24] using a polynomial order of two is employed in one-on-one mode for training. Testing accuracy is evaluated using a confusion matrix with parameters. The overall classification accuracy using SVM on the test partition is 95%, compared to 87% with the K-NN classifier. Most errors were observed in misclassifying similar activities, such as standing as sitting and running as walking.

Thus, it is concluded from this experiment that the SVM using a multiclass SVM approach categorized the given data accurately, achieving approximately 95% accuracy. However, this dataset was generated using one subject wearing a smartphone during four (4) activity types. Results from a machine-based classifier using a single dataset can provide valuable insights, but they may be limited in scope and lack generalizability. While the model might perform well on that specific dataset, it may fail to capture the variations in different data sources. Using a variety of datasets helps mitigate the effects of bias or errors that could stem from a single source, as relying on just one viewpoint can skew the results.

Measuring performance across a diverse population makes the data more reliable and reflects the classifier's generalizability. This is essential because, in the real world, data varies and is rarely perfect. By learning from a broader range of examples, the model can capture more diverse patterns and reduce the risk of overfitting. The more data points considered, the closer the results will align with the true value. To generalize this accuracy, it seems necessary to involve multiple people wearing smartphones during an increased number of activity types. Additionally, another classifier was investigated as KNN performed poorly (with an average accuracy of 87%) during *Experiment 1*.

Experiment 2: The second dataset is obtained from accelerometer data recordings of smartphone devices [25] attached to the waist of thirty individuals aged 18-45, who performed six daily activities. The dataset comprises 7352 rows and 563 columns, with no missing values. The counts for each activity in the dataset are as follows: 1407 for Laying, 1286 for Sitting, 1374 for Standing, 1226 for Walking, 986 for Walking downstairs, and 1073 for Walking upstairs. The activities monitored are now six compared to four in *Experiment 1*. From recorded videos, labeling was performed to train the classifiers on this data. The labeled data was later converted into numerical values using LabelEncoder. The data was then low-pass filtered with a cutoff frequency of 0.25 Hz. The dataset was partitioned into 70% for training and 30% for testing purposes. Instead of K-NN, an RF classifier was employed to categorize the data in addition to SVM.

For the SVM model, the "RBF" kernel was found to perform better during the training phase with the C parameter set to 100. During testing, the SVM model achieved an accuracy score of approximately 99% on this dataset. As a secondary model, the RF model involved specifying crucial hyperparameters such as the number of trees (n_estimators), maximum tree depth (max_depth), and minimum samples per leaf (min_samples_leaf). The RF classifier performed multiple iterations across training data and achieved a maximum testing accuracy score of 98%. The confusion matrix results on the test data (from the second dataset) consisting of 1471 samples across six categories, for these classifiers are shown in Table 3.

The results shown in Table 3 suggest that 'Standing' and 'Walking upstairs' categories were classified 100% by both classifiers, 'Walking downstairs' and 'Walking' were classified 100% by SVM compared to RF with five and one misclassifications respectively, 'Sitting' activity was classified better by SVM (with five misclassifications) compared to RF (with twelve misclassifications), and 'Lying' was also classified better by SVM (with nine misclassifications) compared to RF (with twelve misclassifications).

Table 3 Confusion matrix values for dataset 2

			Predicted class						No. of testing samples
			Standing	Sitting	Lying	Walking	Walking upstairs	Walking downstairs	
True class	Standing	SVM	249	0	0	0	0	0	249
		RF	249	0	0	0	0	0	
	Sitting	SVM	0	272	5	0	0	0	277
		RF	0	265	12	0	0	0	
	Laying	SVM	0	9	284	0	0	0	293
		RF	0	12	281	0	0	0	
	Walking	SVM	0	0	0	251	0	0	251
		RF	0	0	0	246	1	4	
	Walking upstairs	SVM	0	0	0	0	186	0	186
		RF	0	0	0	0	186	0	
	Walking downstairs	SVM	0	0	0	0	0	215	215
		RF	0	0	0	0	1	214	
								Total	1471

Experiment 3: In this experiment, various approaches mentioned in recent literature involving different datasets are compared to the results achieved in *Experiment 2*. The resulting accuracy data are tabulated in Table 4. Based on the tabulated results, it is evident that the proposed approach employing the SVM classifier on the second dataset is optimal with 99% accuracy and is generalized as the dataset was generated by thirty individuals during six normal activities. Thus, it may be concluded that SVM may be efficiently applied across various emerging HAR datasets for wellness monitoring.

Table 4 Comparative results

Approach	Accuracy	Dataset	Generalized
HAR classification using random forest	90%	KU-HAR (Philip, et al., 2022) [27]	No
Ignatov, 2018 [11]	96.37%	UCI machine learning repository (Reyes-Ortiz et al., 2012) [25]	No
Kang, et al., 2021 [12]	96.81%	UCI machine learning repository (Reyes-Ortiz et al., 2012) [25]	No
Li and Wang, 2022 [13]	97.32%	WISDM dataset (Sikder and Nahid, 2021) [26]	No
The proposed approach	99%	UCI machine learning repository (Reyes-Ortiz et al., 2012) [25]	Yes

The results in *Experiments 2* and *Experiment 3* are the main drivers for the viability of this research. The improved classification performance of SVM and its generalized performance led us to use the trained SVM-based model to monitor normal human activities inside the home, in the park, gym, etc. for wellness monitoring.

5. Discussion

There are numerous mHealth apps, each intended to serve distinct healthcare needs. Health tracking applications, for example, allow individuals to monitor their sleep habits, physical activities, etc. These apps motivate people to stay active and live a healthier lifestyle. The use of established profiles may expand the mHealth ecosystem and provide end users with more options. The low adoption rate of current apps that utilize built-in sensors suggests a need for further research into integrating sensors for data collection in fitness and healthcare apps, which could enhance the overall customer experience [27]. Despite the potential benefits of mHealth apps, there are several obstacles to their deployment and development. Protecting privacy and security is a top priority. To safeguard private information, developers must employ strong encryption techniques and comply with regulations such as the Health Insurance Portability and Accountability Act (HIPAA). Customer experience and cross-platform interoperability pose additional challenges. mHealth app developers need to ensure that their apps function seamlessly across a variety of devices as the app industry continues to grow.

The reliability and expertise of application developers in sensor-based applications are crucial for the success of future healthcare solutions [28]. Integrating new sensors, such as those from the Internet of Things, could enhance the effectiveness of this approach by enabling the use of additional devices to further assess and develop practical, high-performance solutions for LM. Future research could advance activity recognition tasks by employing deep learning to automate the entire process for more accurate and faster predictions.

6. Conclusions

Smartphones provide real-time data that can be utilized for LM and developing healthcare applications. In this study, multiple open-access datasets from smartphone sensors were used to classify human activities using various models. A protocol-based methodology was adopted, involving multiple experiments to achieve generalized and improved performance. The machine learning approach, specifically the SVM, performed exceptionally well, with accuracy rates reaching 99%. This robust classification performance can be generalized, encouraging researchers in the medical field to develop applications for wellness monitoring among the elderly and adults during and after treatment procedures. Improving classification performance beyond 99% accuracy may not be a new direction of research. However, this accuracy needs to be robust across multiple datasets. A possible factor for improvement is the optimal extraction of features from human activities. Future research on wellness monitoring may involve deep learning-based techniques to optimally extract features for robustness, followed by a classification step.

Conflicts of Interest

The authors declare no conflict of interest.

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