Comparison of Machine Learning Algorithms for Human Activity Recognition

Hassan Ashraf[a], Olivier Brüls[b], Cédric Schwartz[c] and Mohamed Boutaayamou[d]
Laboratory of Movement Analysis (LAM-Motion Lab), University of Liège, Liège, Belgium

Keywords: Human Activity Recognition, Daily-Life Activity Classification, Machine Learning, Pattern Recognition, Wearable Sensors, Inertial Sensors, Accelerometer, Gyroscope, IMU Signals.

Abstract: Human activity recognition (HAR) is utilized to automatically identify the daily-life activities of people for the effective management of age-related health conditions. Classical machine learning (ML) algorithms are used to design HAR systems, in a subject-specific or population-based configuration depending on the application. In this study, the performance of 8 classical and ensemble-learning-based ML classifiers has been studied for both HAR configurations. Inertial measurement unit (IMU) signals from 10 healthy participants, corresponding to various static, dynamic, and transitional daily-life activities, were acquired. Random forest (RF), ensemble adaptive boosting (EAB), ensemble subspace (ES), decision tree (DT), k-nearest neighbors (KNN), linear discriminant analysis (LDA), support vector machine (SVM), and artificial neural network (ANN) were used to classify these activities. The performance of the classifiers was measured in terms of mean classification accuracy (MCA). The results showed that, for a subject-specific HAR system, ES (97.78%) has achieved the highest MCA followed by RF (96.61%) and SVM (96.11%) while outperforming the DT, KNN, and LDA (P-value < 0.05). For a population-based HAR system, SVM (95.18%) achieved the highest MCA, however, no significant difference has been observed among the MCA of all the investigated classifiers (P-value > 0.05). Also, the class-wise comparison reveals that SVM outperformed the other investigated classifiers in terms of MCAs for each of the distinct activities. Based on the HAR configuration incorporating diverse static, dynamic, and transitional daily-life activities, the findings may be used to develop a customized HAR system for the effective management of movement disorders.

1 INTRODUCTION

According to the International Diabetes Foundation (IDF), the global diabetes prevalence in adults aged 20 to 79 years old is expected to be 536.6 million in 2021, rising to 783.2 million in 2045 (Atlas, 2015). Similarly, more than 10 million people worldwide are living with Parkinson's disease (PD) and the incidence of PD increases with age (Tysnes & Storstein, 2017). Such an aging population needs care. Smart healthcare systems seem to be a possible answer to the rising aging population dilemma. They can provide smart health services to meet the needs of this rising population by monitoring and analysing any critical health state of the elderly in their daily activities. Smart healthcare systems not only allow older people to live autonomously, but they may also offer more sustainable healthcare solutions by reducing the strain placed on the entire health system by the aged and dependent persons.

Human activity recognition (HAR) is a prominent research topic that can give a solution to such a challenge by playing an important role in healthcare, particularly in medical diagnosis and fitness monitoring. Accurate assessment of physical activity is therefore critical in establishing intervention methods, as it provides rich contextual information from which more important information may be inferred. HAR may also be used for people with a mental ailment or disease, such as Parkinson's

[a] https://orcid.org/0000-0003-0519-0619
[b] https://orcid.org/0000-0003-2668-1353
[c] https://orcid.org/0000-0002-7307-7821
[d] https://orcid.org/0000-0001-9564-528X

Ashraf, H., Brüls, O., Schwartz, C. and Boutaayamou, M.
Comparison of Machine Learning Algorithms for Human Activity Recognition.
DOI: 10.5220/0011631500003414
In *Proceedings of the 16th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2023) - Volume 4: BIOSIGNALS*, pages 162-169
ISBN: 978-989-758-631-6; ISSN: 2184-4305

disease, to monitor their actions regularly and notice any abnormalities (Church, 2021).

Machine learning (ML) or pattern recognition methods are primarily used to process signals for the development of HAR applications. Irrespective of the chosen ML method, the data is processed in two stages, i.e., training the ML model on the pre-recorded dataset and then testing the trained model on unseen data. The HAR signal processing with ML methods involves data acquisition, signal pre-processing, feature extraction, and classification. Each of the subsequent steps of the signal processing pipeline is of crucial importance to capture the desired information and extract patterns. Along with different choices for each subsequent signal processing step, a HAR system can be designed in two configurations i.e., subject-specific and population-based, depending on the application. In subject-specific HAR systems the training and testing data is utilized from the same subject, whereas, in population-based HAR systems the model is trained on data acquired from multiple subjects (population) and tested on new subjects.

Among other parameters, the selection of the classifier is of utmost importance since its objective is to map extracted features into distinct classes. Various researchers have done tremendous work to identify the impact of each of the parameters on the performance of the HAR system. Ambati et al. 2020 conducted a comparative study for a smartphone-based HAR system to evaluate the performance of different ML classifiers including naïve Bayes (NB), logistic regression (LR), decision tree (DT), and random forest (RF) using 3 different HAR datasets (Ambati & El-Gayar, 2020). The study reported that RF performed better than the rest of the utilized ML algorithms, however, the study did not report the utilized HAR configuration. Similarly, another study also conducted a comparative analysis to evaluate the performance of different ML classifiers for mobile-based HAR applications to recognize 6 different daily life activities (Min et al, 2020).

For a subject-specific HAR system, the study reported that the RF algorithm outperforms the rest of the ML classifiers (Min et al., 2020). Another study compared LR, support vector machine (SVM), DT, and RF for a 6-class population-based HAR system and reported that SVM outperformed all the other ML classifiers by achieving a validation accuracy of 96.57% (Muralidharan et al., 2021). Logacjov et al. (2021) presented a body-worn sensors-based HAR dataset from 22 participants (Logacjov et al., 2021). For a population-based HAR system with leave-one-out validation the performance of k-nearest neighbors (KNN), SVM, RF, and XGBoost (XGB) was compared. The results demonstrated that SVM outperformed the rest of the algorithms with an F1 score of 0.81±0.18. Baldominos et al. (2019) performed a comparative analysis of ML techniques for a mobile phone-based HAR system (Baldominos et al., 2019). The data were recorded from 10 healthy participants for 13 daily life activities and the performance of ensemble trees (ET), NB, KNN, LR, artificial neural network (ANN), and RF was compared for a population-based HAR system. The results demonstrate that ET outperformed the rest of the ML algorithms by achieving an accuracy of 94.87%. Another study was conducted by Attal et al. (2015) from a dataset of 6 healthy subjects for 12 different HAR activities (Attal et al., 2015). For a subject-specific HAR system KNN, SVM, and RF classifiers were used to classify different HAR activities. The results report that KNN outperforms the rest of the algorithm with an accuracy of 96.53 ± 0.2. Vijayvargiya et al. (2021) compared the performance of KNN, LDA, bagging classifier (BagC), boosting classifier (BosC), DT, RF, and SVM for population-based HAR system by concluding that RF yields the best results with an accuracy of 92.71% (Vijayvargiya et al., 2021).

Table 1: Daily life activities performed by each participant.

ID	Activity type	Activity	Description
1	Dynamic	Walk normal (WN)	Walking and turning at normal speed on a flat surface.
2		Walk dual task (WD)	Walking and turning at normal speed while carrying a tray and having glasses.
3		Walk slow (WS)	Walking and turning at a slow speed on a flat surface.
4		Walk fast (WF)	Walking and turning at a fast speed on a flat surface.
5		Stairs descending (SD)	Descending the stairs.
6		Stairs ascending (SA)	Ascending the stairs.
7	Transitional	Walk and sit (WSit)	Walking towards the chair, sitting, and standing up.
8		Walk and lay down (WLay)	Walking towards the bed, laying down, and standing up.
9	Static	Sitting on a chair (Sit)	Sitting on a chair.
10		Laying on a bed (Lay)	Laying on a bed.

Although various researchers have done great work to identify the best ML algorithm for the development of HAR applications by conducting both subject-specific and population-based studies. However, there is no consensus about which ML algorithm is best suitable for both HAR configurations and there is a lack of simultaneous comparison of both configurations for the data recorded from the same population. For generalization, we hypothesize that it is important to compare different ML algorithms on the same population (subjects) for both HAR configurations due to the data-driven nature of the ML algorithms. Secondly, statistical significance and class-wise performance should also be taken into consideration while evaluating the performance of the algorithms. Finally, the performance of the ensemble learning-based ML classifiers should also be investigated along with classical ML classifiers.

Thus, this study aims to identify, among many available ML algorithms, which is best suited to HAR applications for both configurations (subject-specific and population-based). Furthermore, to statistically validate the results a one-way analysis of variance (ANOVA) test was also conducted.

2 METHODOLOGY

2.1 Dataset

The experiment was conducted on ten healthy subjects (one female and nine males; average age (years) = 26.6±1.7; average height (cm) = 174.0±5.9; average weight (kg) = 69.6±6.3) without having any gait or movement disorders. Before recording the data, the participants were informed about the experimental protocol and they were instructed to follow their natural pattern of daily-life activities. The experimental protocol consisted of ten different static, dynamic and transitional activities as described in table 1. All the participants completed the designed daily-life activities in a lab environment (Laboratory of Movement Analysis (LAM-Motion Lab), University of Liège, Liège, Belgium) by following a structured experimental protocol. For each daily-life activity, the subjects performed 5 repetitions.

An existing IMU-based hardware system was used to record the movement signals (Boutaayamou et al., 2019). Four customized wired-IMU sensors were placed on the left heel, right heel, left wrist, and lower back. To minimize the movement of IMU sensors all sensors were tightly attached to the body. Each IMU sensor (2 cm × 0.7 cm × 0.5 cm) with a sampling frequency of 200 Hz was equipped with a three-axis accelerometer (range: ±16 g) and a three-axis gyroscope (range: 2000 degrees/second). All the IMU sensors, through wires, were connected to an integrated system comprised of a system-integrated memory, a microcontroller, and a battery. Once the data is recorded, all the data were transferred to a computer for further processing and analysis. MATLAB 2022a has been used to process and generate the results.

2.2 Pre-Processing

Most of the spectral power of human body movements is concentrated between 0 to 20 Hz (Wohlfahrt, 2012). Furthermore, the signals recorded by accelerometers are a combination of acceleration due to the movement of the body, acceleration due to gravity, the noise which is intrinsic to the measurement system, and motion artifacts. Only the acceleration signals (body acceleration and gravity acceleration) are required for the analysis in most of the applications, whereas other components are regarded as unwanted noise (Awais, 2018). Depending on the application and types of noise embedded in the original signals various digital filters can be utilized to minimize the effects of unwanted noise. For HAR applications both acceleration signals are quite useful thus it is only desired to separate any spectral content beyond the spectral range of human body movements. In this study, a third-order Butterworth lowpass filter with a cut-off frequency of 20 Hz was applied to the acquired signals to remove the unwanted frequency components. Figure 1 depicts the raw and filtered signal both in the time and frequency domains. It can be observed that with the application of the applied digital filter the frequencies above 20 Hz have been discarded.

2.3 Segmentation/Windowing

The sensors attached to the body supply a continuous stream of signals acquired from the human body. To analyse and process them, these signals are segmented into segments of finite length. Primarily disjoint and overlap windowing/segmentation techniques are utilized to make segments of the signals under consideration. Before segmentation, it is important to consider the variable durations of different human body movements. For example, transitional activities (e.g., sit-to-stand) are completed in less time as compared to static (e.g., standing) or dynamic activities (e.g., walking). Intuitively, smaller segments or window sizes capture

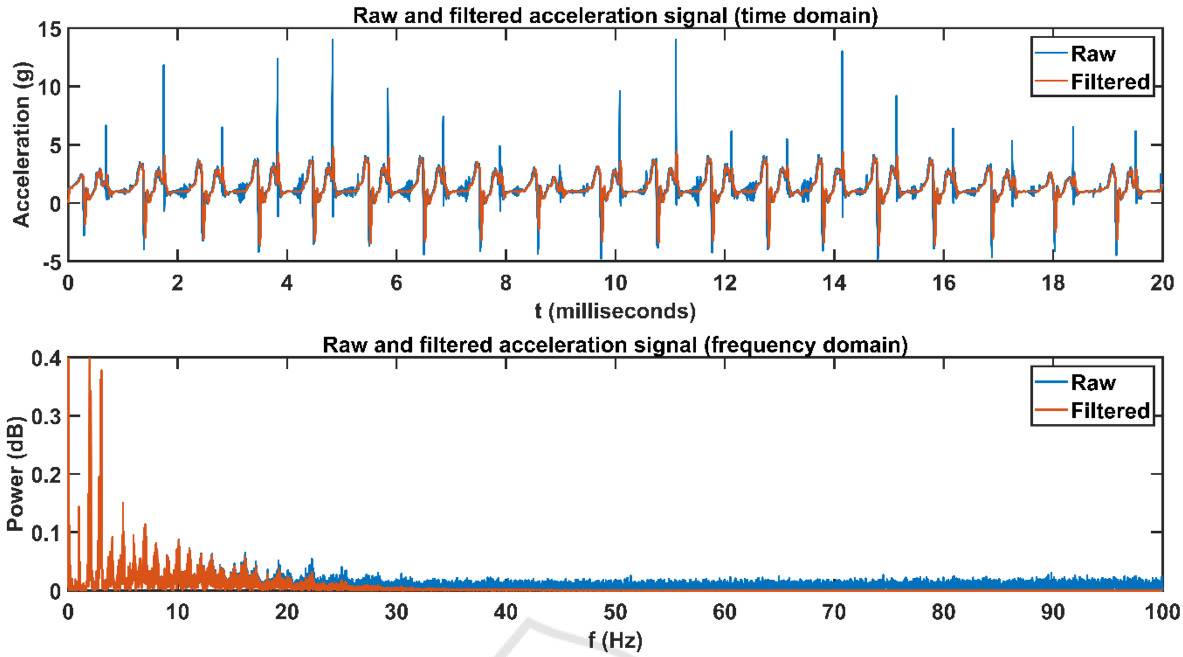

Figure 1: The raw and filtered acceleration signal in the time and frequency domain. The upper graph shows the acceleration signal in the time domain, the lower graph shows the frequency spectrum of the raw signal.

Table 2: ML classifiers and the training parameters.

Classifier	Training parameters
Random forest (RF)	Number of decision splits = 942 Number of learning cycles = 30
Ensemble adaptive boosting (EAB)	Number of decision splits = 20 Number of learning cycles = 30 Learning rate = 0.1
Ensemble subspace (ES)	Learner = Discriminant analysis Number of learning cycles = 30
Decision tree (DT)	Number of decision splits = 100
K-nearest neighbors (KNN)	Number of nearest neighbors = 1
Linear discriminant analysis (LDA)	Discriminant type = linear Amount of regularization = 0
Support vector machine (SVM)	Box constraint = 1 Kernel function = linear
Artificial neural networks (ANN)	Hidden layers = 18 Training function = scaled conjugate gradient

the underlying patterns of transitional activities while missing the information necessary to capture the patterns of dynamic and static activities. Similarly, longer window sizes provide better results for static and dynamic activities and perform poorly for transitional activities since the longer window sizes overlap the important information of transitional activities also these windows are very prone to noise. Furthermore, longer windows require more computational power as compared to smaller window sizes. Yamansavaşçılar & Güvensan (2016) suggested that, for HAR activities, a window size of more than 6 s is sufficient to capture the underlying patterns of the movements (Yamansavaşçılar & Güvensan, 2016). Thus, in this study, an overlap windowing technique with a window size of 6 s and an overlap size of 60% has been employed.

2.4 Feature Extraction

After the signals have been segmented, they must be transformed into feature space. The goal of the feature space is to minimize the dimensionality of the original data and extract the descriptive hidden underlying information of movement patterns, making it easier to map the complicated data into predetermined categories. The collected features should have enough data to train the machine learning algorithms. Various temporal, frequency, and time-frequency domain features have been reported to enhance the efficacy of a HAR system (Rosati et al., 2018). In this study, the investigated features are: mean, root mean square, autocorrelation features for all three axis components (height of the main peak; height and position of the second peak), spectral peak features (height and position of the first 6 peaks), spectral power features (total power in 3 adjacent and pre-defined frequency bands of 1.5, 5, and 10 Hz) and signal magnitude area.

2.5 Classification

The feature space is utilized as an input to the classifier after extracting relevant information from the segments. The classifier creates the final mappings from the characteristics associated with each class. To classify daily-life activities for various HAR applications, multiple ML classifiers such as NB, DT, RF, SVM, LDA, KNN, and ANN are often employed. The performance of several ML algorithms (classical and ensemble-learning-based) has been evaluated, as the goal of this work is to determine the most suited ML classifier for subject-specific and population-based HAR systems. Table 2 describes the explored ML algorithms as well as the training parameter choices.

In subject-specific HAR configuration, 70% of the data from each subject was randomly selected to train the classifier, and the remaining 30% of the data was utilized to assess the trained classifier's performance. A leave-one-out validation technique, on the other hand, has been used for a population-based HAR system. The data from nine participants were initially concatenated and fed into the classifier for training, then the data from the last subject was utilized to evaluate the developed ML model. The technique continued until all of the participants, one by one, were tested. To assess the performance of each classifier, the classification accuracy (CA) has been calculated based on the actual and predicted results. CA is a percentage that is calculated by dividing the proportion of accurate predictions by all possible predictions and multiplying the result by 100. To further validate the results, statistical analysis has been undertaken by using ANOVA with Tuckey's honest post-hoc test to reject the null hypothesis by considering a P-value of 0.05 significant.

3 RESULTS

3.1 Subject-Specific HAR System

Table 3 presents the CAs for all subjects corresponding to each investigated classifier. The cells with bold syntax represent the highest achieved testing accuracy for each subject. For all the subjects RF, EAB, ES, and SVM obtained more than 90% CA. The results indicate that ES achieved the highest accuracies for most of the subjects (nine subjects) followed by RF (one subject). Although ES has obtained the highest CAs for most of the subjects the RF, EAB, and SVM have also achieved comparable results.

Mean classification accuracy (MCA) was calculated by averaging the CA for all subjects corresponding to each investigated classifier. MCA for all subjects showed that ES has achieved the highest MCA of 97.78% followed by RF (96.61%) and SVM (96.11%). Furthermore, statistical analysis revealed that ES has outperformed the DT, KNN, and LDA (P-value < 0.05). However, no significant difference in MCA of ES, RF, EAB, SVM, and ANN has been observed (P-value > 0.05). It can be observed that DT, LDA, KNN, and ANN performed poorly for SD, SA, WSit, and WLay activities. Furthermore, although ES, RF, SVM, and EAB have no statistically significant difference in MCAs, however, still ES is the only classifier obtaining more than 90% accuracy for all the individual activities. Despite having no statistically significant difference in MCA of ES, RF, EAB, SVM, and ANN (P-value > 0.05), ES has resulted in higher CAs for all the classes.

3.2 Population-Based HAR System

In the population-based HAR system, the ML classifiers were trained on data combined from nine subjects and tested on the data from the remaining subject. Table 4 presents the CAs for the population-based HAR system corresponding to each testing subject. The highest CAs for individual testing subjects have been attained by SVM (three testing subjects), ES (three testing subjects), and RF (two testing subjects).

All the classifiers attained more than 90% accuracy corresponding to at least one of the investigated classifiers except one testing subject (TSID = 8). According to statistical analysis, SVM and DT obtained maximum and minimum MCAs of 95.18% and 86.33%, respectively. However, no

Table 3: CA (%) for all the subjects corresponding to each investigated ML classifier for a subject-specific HAR system. The first column represents the subject ID (SID). The cells highlighted in bold represent the classifier with the highest CA for each subject.

SID	RF	EAB	ES	DT	KNN	LDA	SVM	ANN
1	98,3	96,0	**98,7**	94,0	94,4	98,0	96,0	91,7
2	**97,9**	97,5	**97,9**	93,6	94,0	93,6	97,2	**97,9**
3	97,9	95,4	**98,7**	92,4	91,6	94,1	97,0	96,6
4	95,3	95,3	**97,2**	88,1	91,3	91,7	96,0	94,9
5	96,1	96,1	**97,2**	89,0	91,5	92,9	95,8	94,3
6	95,7	94,5	**97,9**	86,0	94,9	88,9	96,2	93,2
7	96,9	96,9	**97,3**	93,9	92,9	95,9	96,9	96,6
8	94,8	93,1	**97,0**	86,6	86,6	77,9	92,2	88,7
9	**99,3**	96,0	98,9	93,8	95,2	98,5	97,1	97,1
10	93,8	93,4	**97,1**	91,8	94,7	93,0	96,7	95,1
Mean ± Std	96,6 ± 1,7	95,4 ± 1,3	97,8 ± 0,7	90,9 ± 3,0	92,7 ± 2,5	92,5 ± 5,6	96,1 ± 1,4	94,6 ± 2,7

significant difference in the MCA of all the evaluated classifiers for the population-based HAR system was identified (P-value > 0.05). SVM and DT resulted in the best and worst class-wise performance results, respectively. All the investigated classifiers are performing poorly in at least one of the classes, except SVM. Regardless of the testing subject data or signal class, SVM was able to classify all classes with substantially greater accuracy.

4 DISCUSSION

The study aimed to investigate the performance of classical and ensemble learning based on different ML classifiers to design subject-specific and population-based HAR systems. Both HAR configurations were designed based on IMU data recorded from 10 healthy volunteers. The data was comprised of various static, dynamic and transitional daily-life activities. For the first time, we explored the efficacy of ensemble-learning-based ML classifiers for both HAR configurations and compared the performance with classical ML classifiers.

The findings for the subject-specific HAR system demonstrated that ES has obtained the highest MCA of 97.78% while outperforming the rest of investigated ML classifiers. Statistical investigation revealed no significant difference in the performance of ES, RF, EAB, SVM, and ANN (P-value > 0.05). Most of the literature, regarding the selection of a classifier for a subject-specific HAR system, suggests that RF, KNN, and SVM are the best suitable ML classifiers (Attal et al., 2015; Logacjov et al., 2021; Min et al, 2020; Muralidharan et al., 2021). Our findings are consistent with past research in this area, suggesting that RF delivers higher performance results. However, the results showed that ES outperforms RF in terms of MCA. ES has not only outperformed the other classifiers in terms of MCA but also, achieved higher classification rates in terms of class-wise MCA. The average class-wise CA for all the investigated classifiers showed that only ES has achieved more than 90% MCA for all the individual classes. Intuitively, it is difficult for any HAR system to differentiate among transitional activities since the underlying patterns of the movement signals are so similar. For example, the WSit class incorporates both walking and sitting, which is similar to the classes that require both walking and sitting. Because of this resemblance, it is difficult to distinguish transitory activities from the rest of the activities. Except for ES, all of the tested classifiers resulted in decreased MCA for transitional activities (SD, SA, WSit, and WLay). Based on these findings, it can be concluded that in a subject-specific HAR system, ES delivers the best classification results in a subject-specific HAR system.

SVM resulted in the highest MCA for a population-based HAR system with an overall MCA of 95.18%. Statistical analysis has revealed that there is no significant difference in MCAs of all the investigated classifiers (P-value < 0.05). Previous literature on population-based HAR systems also indicates that SVM and RF are the best ML classifiers in terms of MCA (Baldominos et al., 2019; Logacjovet al., 2021; Muralidharan et al., 2021; Vijayvargiya et al., 2021). However, overall MCA is not the only indicator of the performance measure since it does not provide any insight into class-wise performance. Although SVM, LDA, ES, and RF have comparable performance in terms of MCA, however, the class-wise performance of these classifiers is vastly different. From figure 3 it is evident that RF, ES, and LDA are performing very poorly in transitional and dynamic activities. Conversely, SVM

Table 4: CA (%) for all the subjects corresponding to each investigated ML classifier for a population-based HAR system. The first column represents the testing subject ID (TSID). The cells highlighted in bold represent the classifier with the highest CA for each subject.

TSID	RF	EAB	ES	DT	KNN	LDA	SVM	ANN
1	94,4	87,1	94,4	85,1	93,1	94,7	**99,0**	94,4
2	95,0	95,4	**95,7**	92,9	86,9	94,3	95,0	93,6
3	95,0	94,1	**98,7**	91,2	85,3	98,3	98,3	95,8
4	95,2	94,0	96,8	88,1	92,5	95,2	98,0	**98,8**
5	96,2	94,1	95,5	92,0	86,0	94,1	**97,2**	96,9
6	93,6	87,1	**94,0**	84,1	82,8	92,7	93,6	92,7
7	92,2	75,7	81,8	71,3	84,5	79,1	**95,3**	80,4
8	75,3	77,1	83,5	69,7	86,6	**89,2**	80,5	80,5
9	**98,2**	93,8	97,5	93,5	86,2	92,0	95,6	85,5
10	**100,0**	97,5	99,2	95,5	88,9	99,6	99,2	98,8
Mean ± Std	93,5 ± 6,4	89,6 ± 7,3	93,7 ± 5,8	86,3 ± 8,6	87,3 ± 3,1	92,9 ± 5,4	95,2 ± 5,2	91,7 ± 6,7

is obtaining consistent MCA for static, dynamic, and transitional activities. Except for SVM, all the other investigated classifiers yielded a high misclassification rate for at least one of the activities. For example, ANN and LDA resulted in high MCA for all the activities, however, both classifiers misclassified WN activity with WS and/or WF. From these findings, it can be concluded that for a population-based HAR system, SVM provides better classification results in terms of overall and class-wise MCA.

While comparing the two configurations, it was discovered that the performance of the ML classifiers varies dramatically. Figure 4 illustrates the MCA for all classifiers examined in both configurations. Switching from a subject-specific HAR system to a population-based HAR system reduces the MCA for all ML classifiers except LDA. Although it is a well-known fact that ML algorithms perform better when trained on big datasets, a drop in accuracy has been reported for a population-based HAR system. One possible reason for this phenomenon is the increased variance of the dataset owing to the inclusion of data from various subjects. Since every human has different movement patterns, it is challenging for the ML algorithm to capture the between-subject variation for any daily-life activity. Despite the higher between-subject variation, LDA and SVM performed consistently in terms of MCA for all subjects for both configurations. The difference between subject-specific and population-based HAR systems is quite small in both circumstances. Further research should be done to determine how the number of individuals affects the performance of a population-based HAR system.

Despite the results providing a basic understanding of the choice of ML classifier to design a HAR system with subject-specific and population-based configuration, the limitations of the study are: (1) the utilized dataset should be increased further by including more number of subjects, (2) number of daily-life activities, more specifically, complex daily-life activities should also be considered in future, (3) since the dataset has been recorded in a controlled environment thus the unstructured and uncontrolled daily-life activities may induce a higher variability in the results.

5 CONCLUSIONS

The study presented the comparison of classical and ensemble learning-based ML classifiers to design subject-specific and population-based HAR systems to classify diverse daily-life activities. The movement data were acquired using custom-designed IMU sensors from ten healthy participants for different static, dynamic and transitional activities. The results demonstrated that, for both subject-specific and population-based HAR systems, ES and SVM are the best ML classifiers in terms of overall MCA and class-wise performance. For the subject-specific HAR system, the results demonstrated that ES outperforms RF and all other investigated classifiers by obtaining higher overall and class-wise MCA. The ES and SVM-based proposed HAR systems can be used to recognize intricate daily-life activities for the development of a smart healthcare system.

REFERENCES

Atlas, D. (2015). International diabetes federation. IDF Diabetes Atlas, 7th edn. Brussels, Belgium: International Diabetes Federation, 33.

Ambati, L. S., & El-Gayar, O. (2020). A Comparative Study of Machine Learning Approaches for Human Activity Recognition.

Attal, F., Mohammed, S., Dedabrishvili, M., Chamroukhi, F., Oukhellou, L., & Amirat, Y. (2015). Physical human activity recognition using wearable sensors. Sensors, 15(12), 31314-31338.

Awais, M. (2018). Physical Activity Classification Meeting Daily Life Conditions for Older Subjects.

Baldominos, A., Cervantes, A., Saez, Y., & Isasi, P. (2019). A comparison of machine learning and deep learning techniques for activity recognition using mobile devices. Sensors, 19(3), 521.

Boutaayamou, M., Schwartz, C., Joris, L., Forthomme, B., Denoël, V., Croisier, J.-L., Verly, J., Garraux, G., & Bruls, O. (2019). Adaptive method for detecting zero-velocity regions to quantify stride-to-stride spatial gait parameters using inertial sensors. In Proceedings of the 12th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2019). doi:10.5220/0007576002290236.

Church, F. C. (2021). Treatment options for motor and non-motor symptoms of Parkinson's disease. Biomolecules, 11(4), 612.

Logacjov, A., Bach, K., Kongsvold, A., Bårdstu, H. B., & Mork, P. J. (2021). HARTH: A Human Activity Recognition Dataset for Machine Learning. Sensors, 21(23), 7853.

Min, Y., Htay, Y. Y., & Oo, K. K. (2020). Comparing the performance of machine learning algorithms for human activities recognition using the wisdm dataset. International Journal of Computer (IJC), 38(1), 61-72.

Muralidharan, K., Ramesh, A., Rithvik, G., Prem, S., Reghunaath, A. A., & Gopinath, M. P. (2021). 1D Convolution approach to human activity recognition using sensor data and comparison with machine learning algorithms. International Journal of Cognitive Computing in Engineering, 2, 130-143.

Rosati, S., Balestra, G., & Knaflitz, M. (2018). Comparison of different sets of features for human activity recognition by wearable sensors. Sensors, 18(12), 4189.

Tysnes, O. B., & Storstein, A. (2017). Epidemiology of Parkinson's disease. Journal of neural transmission, 124(8), 901-905.

Vijayvargiya, A., Kumari, N., Gupta, P., & Kumar, R. (2021, May). Implementation of machine learning algorithms for human activity recognition. In 2021 3rd International Conference on Signal Processing and Communication (ICPSC) (pp. 440-444). IEEE.

Wohlfahrt, P. (2012). Spectral Analysis of Accelerometric Data to Identify Human Movement Patterns. Bachelorarbeit. Institut für Physik, Martin-Luther-Universität Halle-Wittenberg.

Yamansavaşçılar, B., & Güvensan, M. A. (2016, March). Activity recognition on smartphones: Efficient sampling rates and window sizes. In 2016 IEEE international conference on pervasive computing and communication workshops (PerCom Workshops) (pp. 1-6). IEEE.