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Human Activity Recognition using Extremely Fast Decision Tree Classifier

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Abstract: Human activity recognition (HAR) is a subfield of artificial intelligence that focuses on identifying and understanding human actions and movements using various sensors and data analysis techniques. It's like deciphering the language of our physical movements. These systems are so demanding these days as they have a wide range of applications in various fields including: healthcare, fitness and sports, smart homes & buildings, security and surveillance and human-computer interaction. As HAR technology continues to evolve, it's becoming increasingly accurate and sophisticated, opening up even more possibilities for the future. In this paper, we have explored diverse methods to assess the influence of chosen classifiers on training and testing procedures. To evaluate the model, we have used the data from the popularly known PAMAP2 dataset and five different classification techniques have been used. The Extremely Fast Decision Tree (EFDT) emerged as the fastest performing algorithm in attaining 99.6% accuracy in minimum execution time i.e. 20 minutes.

Keywords: *Decision Tree, HAR, K Nearest Neighbour, Logistic regression, Naïve Baye's, PAMAP2*

1. Introduction

Human Activity Recognition (HAR) is a technology that bridges the gap between sensor technology and artificial intelligence, enabling the development of sophisticated monitoring solutions that enhance our daily lives. The core process of Human Activity Recognition (HAR) involves four key steps: 1) data acquisition from sensors, 2) feature extraction from the raw sensor data, 3) model training using machine learning algorithms, and 4) prediction of user activities based on new unseen data [1].

While all the steps in the Human Activity Recognition (HAR) process are crucial, selecting a proper classifier for training and prediction studies is of great importance. Enhancing context recognition accuracy and reducing response time are key research objectives in Human Activity Recognition (HAR) [2-5]. Although various classification algorithms have shown promising results in HAR applications, a comprehensive evaluation of their relative performance efficiency has been discussed. This paper provides a comparative analysis of various machine learning (ML) models for Human Activity Recognition (HAR) by evaluating their performance on a benchmark dataset using accuracy and execution time as the primary metrics [6-8].

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The rest of the paper is structured as follows: section 2 delves into the intricacies of the HAR process, providing a comprehensive overview of the various steps involved in transforming raw sensor data into meaningful insights about human activities, section 3 discusses about the different classifiers used in HAR. Experimental results and evaluation done on PAMAP2 dataset using various classification models has been shown in section 4 and section 5 concludes the paper by summarizing the key findings and highlighting promising directions for future research in the domain of HAR. In addition to the aforementioned structural elements, the paper is enriched with illustrative figures and tables that effectively communicate the concepts and findings [9-12].

1.1. Process of HAR system

HAR is a process that encompasses four main steps, as depicted in Figure 1. The main role of HAR lies in the data collection phase, where raw sensor data is meticulously gathered from various sources mounted on user body parts [13-18]. These sensors could include various motion sensors like accelerometers, gyroscopes, magnetometers, and proximity sensors, as well as health sensors and finger temperature sensors. In the second step of HAR, features are selected from the raw data. The raw information is processed to extract various time and frequency domain features. Feature extraction is the most important step as it aims to reduce the complexity of the original information while preserving key information and potentially revealing new insights. Training the model is the third most important step in which various classifiers are applied on the labelled dataset. Various supervised learning algorithms that are applied in this step includes Decision Tree (DT), Random Forest Classifier (RFC) & Naive Bays (NB), etc. The last step is the prediction phase in which testing of the dataset is done for categorizing various activities such as sitting, walking, jogging, lying, etc. as multiple classes [19-25].

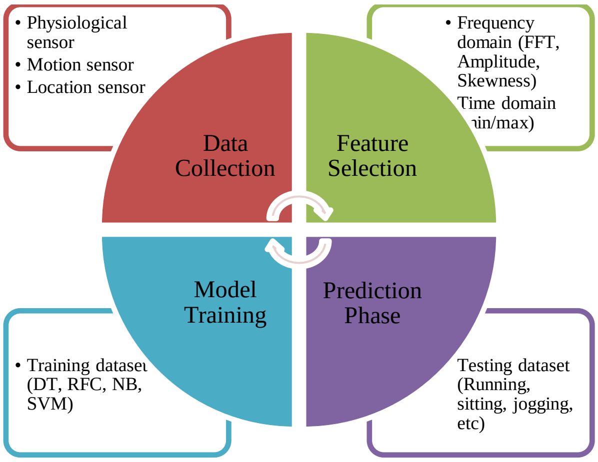

Fig. 1 The four main steps in a HAR process

2. Existing Background

The data gathered from dissimilar sensors deployed in cloud or from the wearable sensors are hoarded in the form of datasets. This dataset is trained by different ML techniques that will predicts the behaviour of individuals, the purpose of these is sending early warnings to and assessing the risk of deteriorating health of the people under observation. To design a ML application, activity recognition consists of two classes, that is training class & testing class. Training class has a data set obtained from a set of different people performing different daily living activities. This time series classification task is divided into 'n' number of time series window functions for applying feature extraction to filter out the relevant data from the available raw dataset. After that, a ML technique is required to establish a model for the extracted features. Similarly, the testing class contains the data collected from the window functions to extract different features and that feature set is analysed in the ML model will further generate labels for all the predicted activities [26-30].

2.1. Logistic Regression (LR)

Logistic regression is a fundamental algorithm in machine learning, widely used for classification tasks**.** Unlike linear regression, which predicts continuous values, it predicts the probability of an event belonging to a specific category**.** This method is used to assess discrete qualities for example binary qualities like 0/1, yes/no, valid/misleading, true/false. In the presence of certain free variables set [31-33].

2.2. Decision Tree (DT)

This is the most popularly used supervised learning algorithm. Apparently, it works for dependent variables. In this technique, the data is split into two homogeneous sets and further the decision will be made based on that. The choice of features and thresholds will have a significant impact on the accuracy of the decision tree. Overfitting can be a problem with decision trees, so it is important to use techniques such as validation sets to prevent the model from memorizing the training data. More complex decision tree algorithms, such as random forests, can be used to improve accuracy and robustness [34-36].

2.3. Random Forest (RF)

In this classifier instead of building one decision tree, the random forest builds many individual decision trees**.** Each tree analyses a subset of the training data and a randomly chosen subset of features. This diversity prevents any single tree from overfitting to the specific details of the training data. Each tree makes its own prediction for a new data point. The final decision of the RF model is determined by the majority votes as compared to the other individual trees. The class with the most votes wins [37].

2.4. Naive Baye's (NB)

This classification method is based on Baye's theorem and is easy to implement for large size datasets. This classifier presumes that availability of a particular feature in a particular class is correlated with any of the other available feature. Such as, some fruit may be a mango if it is yellow & oval in shape. Although these features are dependent upon each other, a naive Bayes classifier would correlate all of these features to wisely contribute to the result that this fruit is a mango [38].

2.5. K-nearest neighbor (KNN)

This technique is used in classification and regression. It works on the principle of collecting and storing all currently available subjects and then classifies a new subject by the majority voting of its k neighbours. It is the simplest algorithm. The subject being allotted to a class is most common amongst its K nearest neighbours measured by a distance function. The distance functions for continuous functions are Euclidean and for categorical variables is Hamming distance. A case has assigned to a class of its nearest neighbour when k = 1. Sometimes while performing kNN modelling, assuming the value of k turns out to be a challenging problem [38].

3. Implementation of decision tree (DT) classifier

A DT is a powerful algorithm for behavioral analysis based on sensor data. It is used to build a model that learns patterns and makes decisions based on input features from sensors. Here's a simple outline of how a decision tree algorithm can be used for sensor-based activity recognition:

1. Data Collection: In the first step, Collection of labelled sensor data is done for different activities. For example, for recognizing activities like walking, running, or sitting, data is collected from sensors such as accelerometer, gyroscope and magnetometer. Each data sample should include the sensor readings as features and the corresponding labelled activity.
2. Data Pre-processing: In the second step, cleaning of data is done by handling missing values and outliers. To ensure that features are on a similar scale, Normalization of the sensor readings is done by using simple inputers.
3. Feature Extraction: In the third step, identification of relevant features takes place from the sensor data. Depending on the type of sensors used, features could include mean, standard deviation, frequency domain features, etc. Features that capture the distinctive patterns for each activity are extracted.

4. Split Data: In the fourth step, data is divided into two sets. The testing set is used to evaluate its performance and the training set is used to train the decision tree.
5. Train Decision Tree: In the fifth step, training dataset is used to build the decision tree model. The decision tree will learn the relationships between the input features (sensor readings) and the target variable (activity labels).
6. Fine-Tuning (Optional): In the sixth step, to optimize the performance, tuning of hyperparameters, such as tree depth, minimum samples per leaf, etc. is done.
7. Evaluate Model: In the seventh step, for evaluating the performance of the DT model, testing dataset is used. Accuracy, precision, recall, and F1 score are considered as Common metrics.
8. Prediction: Once the decision tree is trained and evaluated, this model can be used to predict activities for new, unseen sensor data.

The implementation of decision tree algorithm is shown in Figure 2.:

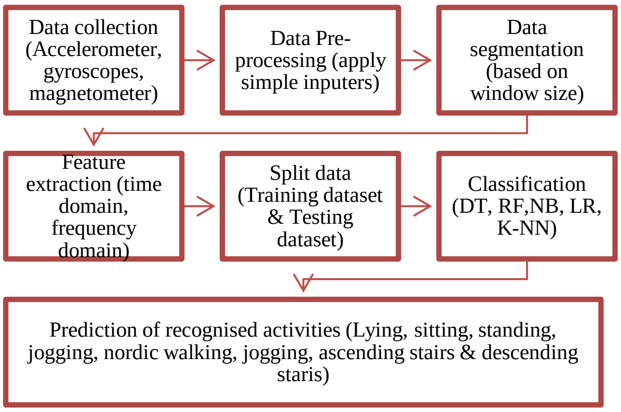

Fig. 2. Step-by-step implementation of DT classifier on PAMAP2 dataset.

4. Results & Discussion

The stepwise implementation of various classification models on PAMAP2 dataset are listed below:

- **Data Pre-processing:** Pre-process the raw sensor data to ensure that it is in a required format for input. Normalize the sensor data to a common range or apply other normalization techniques. Segment the time-series sensor data into smaller windows or frames, each representing a specific duration of activity.
- **Dataset Creation:** Label the segmented windows or frames with corresponding activity labels. Divide the dataset into training, validation, and testing sets.
- **Training:** Start the model with random weights. Train the model on the training dataset using techniques like stochastic gradient descent (SGD). During training, pass the segmented sensor data through the model and optimize the model's parameters to minimize the classification error using a suitable loss function (e.g., cross-entropy). Monitor the training process using the validation dataset and adjust hyperparameters if needed.
- **Evaluation:** Analyze the performance of the trained model using the testing dataset. Calculate the metrics to measure the model's effectiveness in recognizing human activities.

Evaluation metrics of various algorithms for multiclass classification is shown with the help of tables and confusion matrices. Table 1-5 gives the classification report of 13 different activities by using five different classifiers such as logistic regression, bayes naïve, decision tree, random forest and kNN. Confusion matrix is also shown for all the five models in figure3-7 respectively.

Our analysis focuses on climbing stairs activities because they posed the greatest recognition challenge. Confusion matrices reveal frequent misclassifications between climbing up and down. For the logistic regression and bayes naive model (Table 1 & 4), mis-predicting "downstairs" during ascents is most common (107 errors, 19.6% accuracy drop). Though "walking" surpasses "upstairs" as the top misclassification for descents (99 vs. 92 errors), this simply reflects its higher overall occurrence in our data. Similarities in acceleration patterns between walking and stair activities (Figures 3,4,5,6,7) likely contribute to the confusion. Table (2 & 3) shows the improved decision tree and random forest confusion matrix (other algorithms omitted for brevity). While stair recognition remains challenging, this approach yields significant improvements.

Table 1. Classification report of various activities performed by using Logistic regression

	Precision	Recall	F1 Score	Support
Ascending stairs	0.59	0.32	0.42	11756
Cycling	0.87	0.89	0.88	16344
Descending Stairs	0.52	0.24	0.33	10511
Ironing	0.75	0.82	0.78	23819
Lying	0.97	0.94	0.96	19270
Nordic walking	0.63	0.33	0.44	18784
Rope jumping	0.61	0.41	0.49	4957
Running	0.68	0.41	0.49	9701
Sitting	0.79	0.78	0.79	18428
Standing	0.66	0.75	0.7	19020
Transient	0.57	0.72	0.64	93026
Vacuum cleaning	0.72	0.63	0.67	17437
Walking	0.63	0.6	0.61	24200
accuracy			0.67	287253
Macro avg.	0.69	0.6	0.63	287253
Weighted avg.	0.67	0.67	0.66	287253

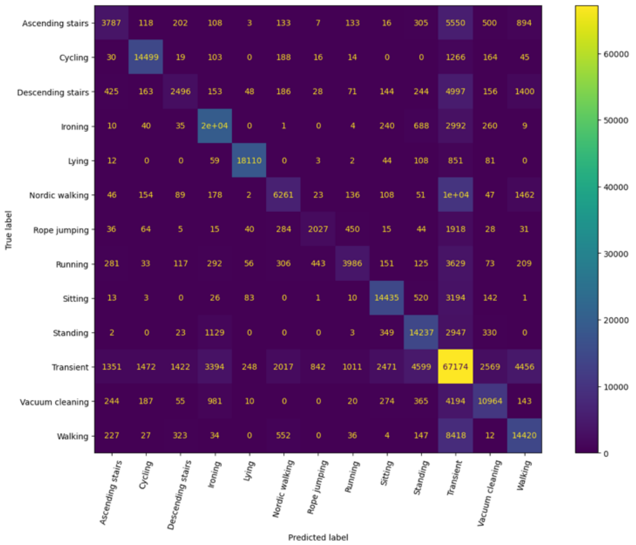

Fig. 3. Confusion Matrix for Logistic regression

Table 2. Classification report of various activities performed by using Decision Tree

	Precision	Recall	F1 Score	Support
Ascending stairs	0.98	0.98	0.98	11756
Cycling	0.99	0.99	0.99	16344
Descending Stairs	0.98	0.97	0.97	10511
Ironing	1	1	1	23819
Lying	1	1	1	19270
Nordic walking	0.99	0.99	0.99	18784
Rope jumping	0.99	0.98	0.98	4957
Running	0.99	0.98	0.98	9701
Sitting	1	1	1	18428
Standing	1	1	1	19020
Transient	0.99	0.99	0.99	93026
Vaccuum cleaning	0.99	0.99	0.99	17437
Walking	0.99	0.99	0.99	24200
accuracy			0.99	287253
Macro avg.	0.99	0.99	0.99	287253
Weighted avg.	0.99	0.99	0.99	287253

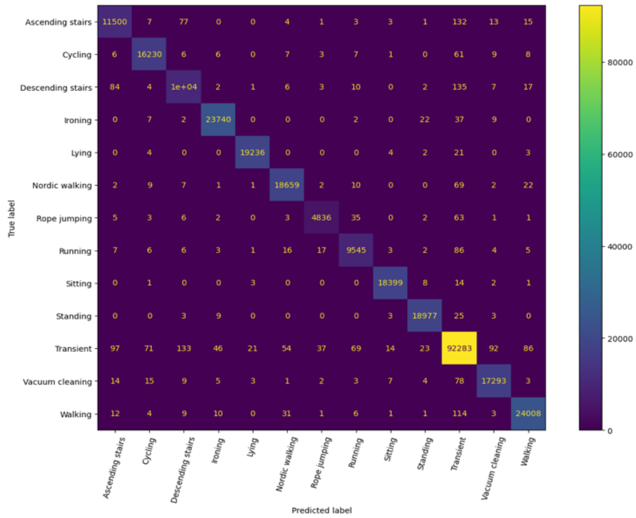

Fig. 4 Confusion Matrix for Decision Tree classifier

Table 3. Classification report of various activities performed by using Random forest classifier

	Precision	Recall	F1 Score	Support
Ascending stairs	0.96	0.96	0.96	11638
Cycling	0.95	0.95	0.95	16535
Descending Stairs	0.93	0.93	0.93	10595
Ironing	0.94	0.94	0.94	23875
Lying	0.97	0.97	0.97	19294
Nordic walking	0.94	0.94	0.94	18748
Rope jumping	0.97	0.97	0.97	4847
Running	0.96	0.96	0.96	9640
Sitting	0.98	0.98	0.98	18531
Standing	0.96	0.96	0.96	19084
Transient	0.96	0.96	0.96	92948
Vacuum cleaning	0.94	0.94	0.94	17651
Walking	0.96	0.96	0.96	23875
accuracy			0.96	287253
Macro avg.	0.96	0.96	0.96	287253
Weighted avg.	0.96	0.96	0.96	287253

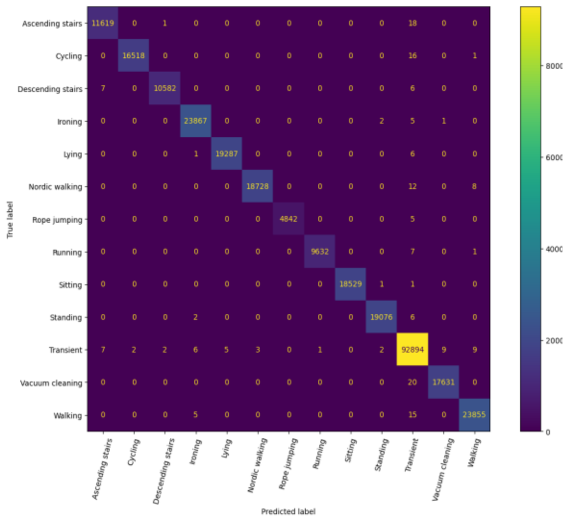

Fig. 5. Confusion Matrix for Random Forest classifier

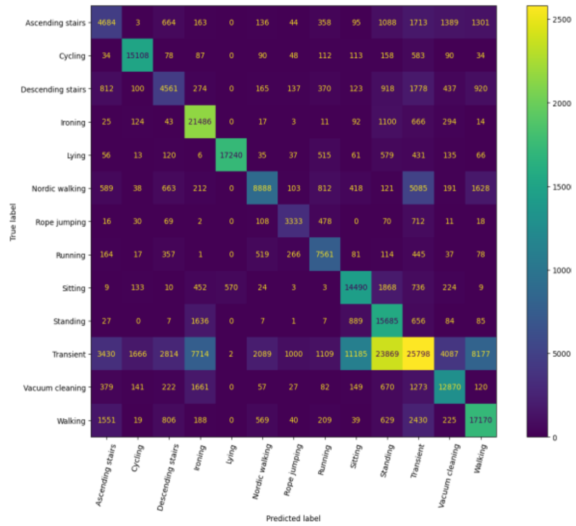

Fig. 6. Confusion Matrix for Gaussian Naïve Baye's classifier

Table 4. Classification report of various activities performed by using Gaussian Naïve Baye's

	Precision	Recall	F1 Score	Support
Ascending stairs	0.4	0.4	0.4	11638
Cycling	0.87	0.91	0.89	16535
Descending Stairs	0.44	0.43	0.43	10595
Ironing	0.63	0.9	0.74	23875
Lying	0.97	0.89	0.93	19294
Nordic walking	0.7	0.47	0.57	18748
Rope jumping	0.66	0.69	0.67	4847
Running	0.65	0.78	0.71	9640
Sitting	0.52	0.78	0.63	18531
Standing	0.33	0.82	0.48	19084
Transient	0.61	0.28	0.38	92940
Vacuum cleaning	0.64	0.73	0.68	17651
walking	0.58	0.72	0.64	23875
accuracy			0.59	287253
Macro avg.	0.62	0.68	0.63	287253
Weighted avg.	0.62	0.59	0.57	287253

Table 5. Classification report of various activities performed by using KNN

	Precision	Recall	F1 Score	Support
Ascending stairs	0.97	0.99	0.98	11638
Cycling	1	1	1	16535
Descending Stairs	0.97	0.98	0.98	10595
Ironing	1	1	1	23875
Lying	1	1	1	19294
Nordic walking	0.99	0.99	0.99	18748
Rope jumping	0.99	0.99	0.99	4847
Running	1	0.99	1	9640
Sitting	1	1	1	18531
Standing	1	1	1	19084
Transient	0.99	0.98	0.99	92940
Vacuum cleaning	1	0.99	1	17651
walking	0.97	0.99	0.98	23875
accuracy			0.99	287253
Macro avg.	0.99	0.99	0.99	287253
Weighted avg.	0.99	0.99	0.99	287253

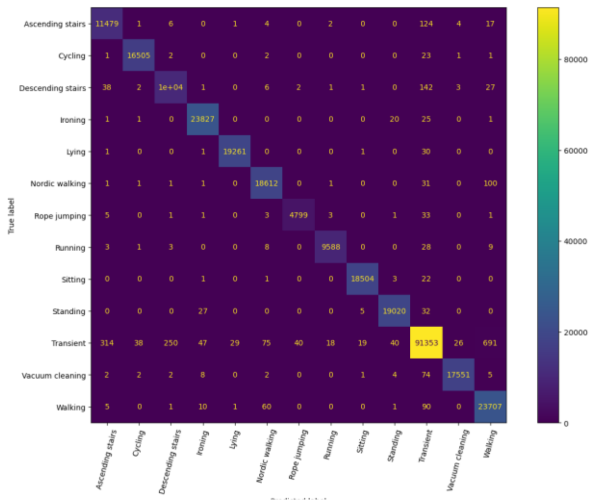

Fig. 7. Confusion Matrix for KNN classifier

The combined record of evaluation metrics such as F1 score, recall score, precision score and accuracy of various classifiers for multiclass classification has shown below in Figure 8. From the analysis, it can be predicted that DT algorithm gives the best results.

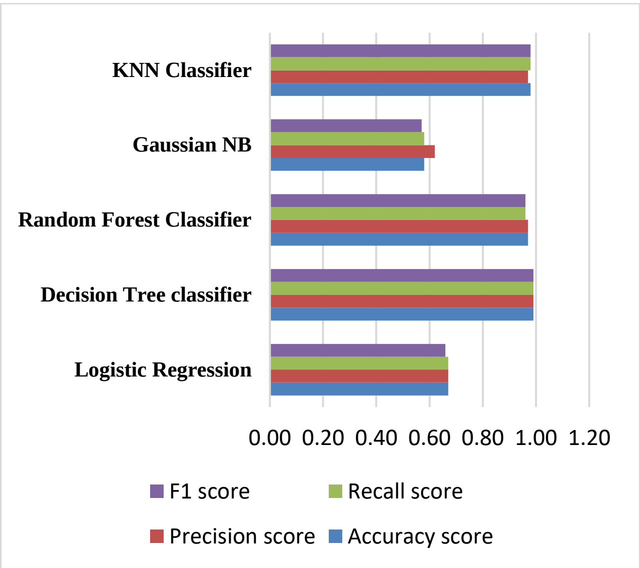

Fig. 8. Evaluation Metrics of various classifiers for multiclass classification

The below listed Table 6 shows the percentage of accuracies achieved from 13 activities by using five different machine learning algorithms. The results show that decision tree classifier attains maximum accuracy in minimum training time.

Table 6. Accuracies of activity recognition

Activities	Percentage of records correctly predicted by classifiers				
	Logistic regression	Decision Tree	Random Forest	Naïve Baye's	K-NN
Ascending stairs	0.59	0.98	0.96	0.4	0.97
Cycling	0.87	0.99	0.95	0.87	1
Descending Stairs	0.52	0.98	0.93	0.44	0.97
Ironing	0.75	1	0.94	0.63	1
Lying	0.97	1	0.97	0.97	1
Nordic walking	0.63	0.99	0.94	0.7	0.99
Rope jumping	0.61	0.99	0.97	0.66	0.99
Running	0.68	0.99	0.96	0.65	1
Sitting	0.79	1	0.98	0.52	1
Standing	0.66	1	0.96	0.33	1
Transient	0.57	0.99	0.96	0.61	0.99
Vacuum cleaning	0.72	0.99	0.94	0.64	1
walking	0.63	0.99	0.96	0.58	0.97

The graph shown in Figure 9, summarizes the performance of five learning algorithms in recognizing 13 different activities. Each cell displays the predicted accuracy for a specific activity-algorithm combination. In this graph 'indigo blue' color is used for LR, 'orange' for DT, 'grey' for RF, 'yellow' for NB and 'blue' for K-NN.

The Figures 10 & 11 show the training time taken by classifiers for recognising activities of daily living by using PAMAP2 dataset. The results show that decision tree algorithm attains maximum accuracy 99.6% in minimum training time i.e., 20 minutes. While random forest took 33 minutes in attaining 97% accuracy, logistic regression gives 67% accuracy in 8 minutes, gaussian bayes naïve gives 58% accuracy in 38 minutes and the maximum time was taken by kNN classifier and it attains 98% accuracy.

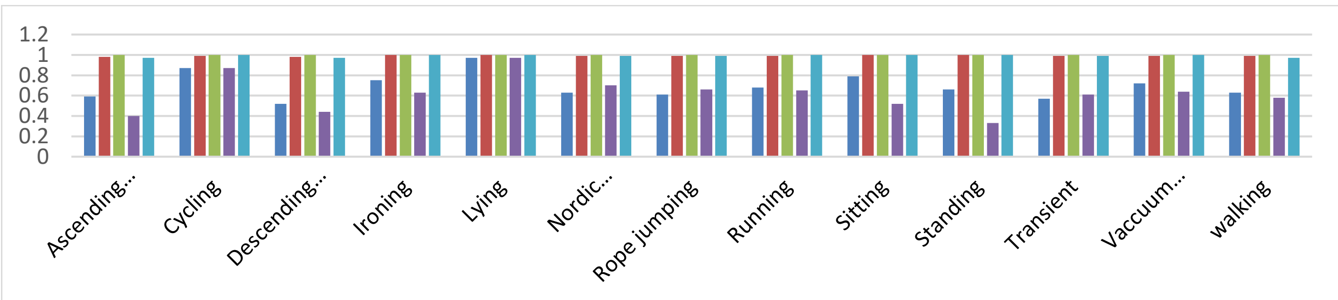

Fig. 9. Accuracies of activities

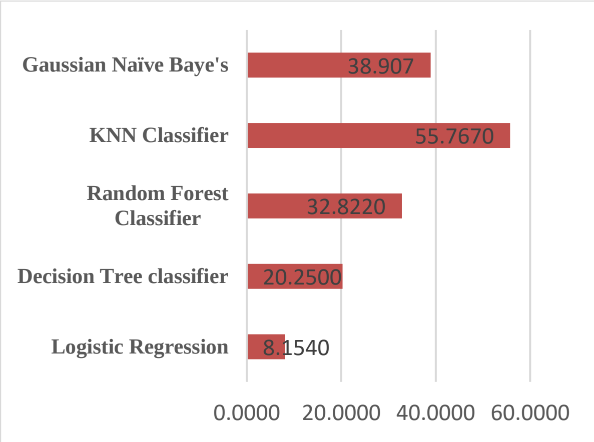

Fig. 10. Training time taken by multiple classifiers

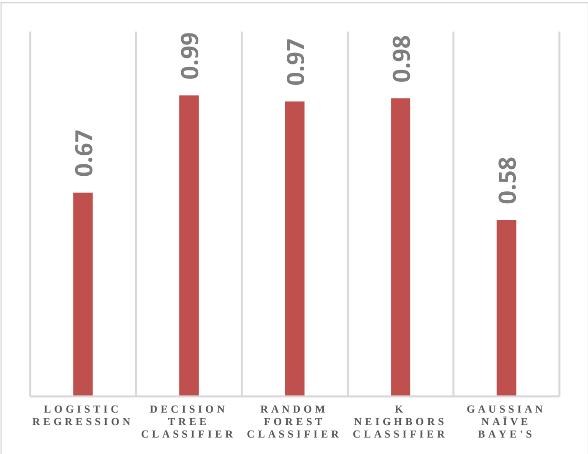

Fig 11. Comparison chart of accuracies achieved by multiple classifier

5. Conclusion

We evaluated the performance of extremely fast decision tree algorithm on the publicly available PAMAP2 dataset. Using four different classifiers, our method achieved better results in minimum training time than existing benchmark schemes across all metrics: training time, testing time, precision, recall, F-score, and accuracy. This suggests its effectiveness in handling wearable sensor-based HAR data.

In conclusion, the highly efficient decision tree classifier achieves a remarkable 99.6% accuracy with minimal execution time, highlighting its suitability for real-time applications in the HAR domain. Additionally, our analysis emphasizes the potential of combining handcrafted features with deep learning models for further performance optimization.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] Oresti Banos, Rafael Garcia, Juan A Holgado-Terriza, Miguel Damas, Hector Pomares, Ignacio Rojas, Alejandro Saez, and Claudia Villalonga., " mhealthdroid: a novel framework for agile development of mobile health applications", *in International Workshop on Ambient Assisted Living, Springer*, 91–98, 2014.

[2] Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra, and Jorge L Reyes-Ortiz., "Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine", *International workshop on ambient assisted living, Springer*, 216–223, 2012.

[3] Media Anugerah Ayu, Siti Aisyah Ismail, Ahmad Faridi Abdul Matin, and Teddy Mantoro.' "A comparison study of classifier algorithms for mobile-phone's accelerometer-based activity recognition" *Procedia Engineering*, (41), 224–229, 2012.

[4] Nahla Barakat and Andrew P Bradley., "Rule extraction from support vector machines: a review", *Springer Neurocomputing*, 74(1-3),178–190, 2010.

[5] Cagatay Catal, Selin Tufekci, Elif Pirmit, and Guner Kocabag., "On the use of ensemble of classifiers for accelerometer-based activity recognition", *Elsevier, Applied Soft Computing*, (37), 1018–1022, 2015.

[6] Zhenghua Chen, Chaoyang Jiang, and Lihua Xie. , "A novel ensemble elm for human activity recognition using smartphone sensors", *IEEE Transactions on Industrial Informatics*, (15)5, 2691-2699, 2019.

[7] Jennifer R Kwapisz, Gary M Weiss, and Samuel A Moore., "Activity recognition using cell phone accelerometers", *ACM SigKDD Explorations Newsletter*, 12(2), 74– 82, 2011.

[8] Oscar D Lara, Miguel A Labrador, et al. , "A survey on human activity recognition using wearable sensors", *IEEE Communications Surveys and Tutorials*, 15(3), 1192–1209, 2013.

[9] Jian Sun, Yongling Fu, Shengguang Li, Jie He, Cheng Xu, and Lin Tan., "Sequential human activity recognition based on deep convolutional network and extreme learning machine using wearable sensors", *Hindawi Journal of Sensors*, (2018), 1-10, 2018.

[10] Jindong Wang, Yiqiang Chen, Shuji Hao, Xiaohui Peng, and Lisha Hu., "Deep learning for sensor-based activity recognition: A survey.", *Elsevier Journal, Pattern Recognition Letters*, (119), 3-11, 2019.

[11] O. D. Lara and M. A. Labrador, "A Survey on Human Activity Recognition using Wearable Sensors," in *IEEE Communications Surveys & Tutorials*, (15)3, 1192-1209, 2013.

[12] De-La-Hoz-Franco, E., Ariza-Colpas, P., Quero, J. M., & Espinilla, M., "Sensor-based datasets for human activity recognition - A systematic review of literature", *IEEE Access, (6), 59192-59210, 2018.*

[13] Wang, Y., Cang, S., & Yu, H. "A survey on wearable sensor modality centred human activity recognition in health care", *Elsevier- Expert Systems with Applications*, (137), 167-190, 2019.

[14] Münzner, S., Schmidt, P., Reiss, A., Hanselmann, M., Stiefelhagen, R., & Dürichen, R. (2017), "CNN-based sensor fusion techniques for multimodal human activity recognition", *ACM Proceedings - International Symposium on Wearable Computers, 158-165, 2017.*

[15] C. A. Ronao, S.B. Cho, "Human activity recognition with smartphone sensors using deep learning neural networks", *Elsevier- Expert Systems with Applications*, (59), 235-244, 2016.

[16] D. Castro, W. Coral, C. Rodriguez, J. Cabra & J. Colorado, "Wearable-based human activity recognition using an IoT

Approach", *Journal of Sensor and Actuator Networks*, (6)4, 40-62, 2017.

[17] M. Janidarmian, A. Roshan Fekr, K. Radecka, and Z. Zilic, "A Comprehensive Analysis on Wearable Acceleration Sensors in Human Activity Recognition", Journal of *Sensors*, (17)3, 529, 2017.

[18] A. Jain and V. Kanhangad, "Human Activity Classification in Smartphones Using Accelerometer and Gyroscope Sensors", *IEEE Sensors Journal*, (18)3, 1169-1177, 2018.

[19] O. S. Eyobu and D. Han, "Feature Representation and Data Augmentation for Human Activity Classification Based on Wearable IMU Sensor Data Using a Deep LSTM Neural Network", *Journal of Sensors*, (18)9, 2892, 2018.

[20] F. Cruciani, I. Cleland, C. Nugent, P. McCullagh, K. Synnes, "Automatic Annotation for Human Activity Recognition in Free Living Using a Smartphone", *Journal of Sensors*, (18)7, 2203, 2018.

[21] Kowshik S, Anurag A, Nikhil Kumar Reddy Obili, "Human Activity Recognition based on Phone Sensors", *International Research Journal of Engineering and Technology*, (7)7, 4897- 4900, 2020.

[22] Demrozi, F., Pravadelli, G., Bihorac, A., & Rashidi, P. "Human Activity Recognition Using Inertial, Physiological and Environmental Sensors: A Comprehensive Survey", *IEEE Access*, (8),

[23] W. Sousa Lima E. Souto K. El-Khatib R. Jalali and J. Gama, "Human activity recognition using inertial sensors in a smartphone: An overview", *Journal of Sensors*, (19)14, 3213, 2019.

[24] N. Neverova C. Wolf G. Lacey L. Fridman D. Chandra B. Barbello, "Learning human identity from motion patterns", *IEEE Access* (4), 1810-1820, 2016.

[25] S. Ramasamy Ramamurthy and N. Roy, "Recent trends in machine learning for human activity recognition—A survey", *Wiley Interdiscipl. Rev. Data Mining Knowedge. Discovery* 8(4), 1254, 2018.

[26] M. Z. Uddin M. M. Hassan A. Alsanad and C. Savaglio, "A body sensor data fusion and deep recurrent neural network-based behavior recognition approach for robust healthcare", Inf. Fusion (55), 105-115, 2020.

[27] L. Liu Y. Peng M. Liu and Z. Huang, "Sensor-based human activity recognition system with a multilayered model using time series shapelets, Knowledge Based System", (90), 138-152, 2015.

[28] Pareek, P., & Thakkar, A, "A survey on video-based Human Action Recognition: recent updates, datasets, challenges, and applications", *Artificial Intelligence Review*, (54), 2259–2322, 2021.

[29] Zhang, H., Xiao, Z., Wang, J., Li, F., & Szczerbicki, E., "A Novel IoT-Perceptive Human Activity Recognition (HAR) Approach Using Multihead Convolutional Attention", *IEEE Internet of Things Journal*, (7)2, 1072-1080, 2020.

[30] Minh Dang, L., Min, K., Wang, H., Jalil Piran, M., Hee Lee, C., & Moon, H., "Sensor-based and vision-based human activity recognition: A comprehensive survey", Journal of *Pattern Recognition*, (108), 107561, 2020.

[31] Bhat, G., Tran, N., Shill, H., & Ogras, U. Y., "w-HAR: An activity recognition dataset and framework using low-power wearable devices", *Journal of Sensors*, (20)18, 2020.

[32] Qi, H., Wang, Y., Bi, J., Cao, H., & Xu, S., "Research on har-based floor positioning", *ISPRS International Journal of Geo-Information*, (10)7, 1-19, 2021.

[33] Ugulino, W., Cardador, D., Vega, K., Velloso, E., Milidiú, R., & Fuks, H., "Wearable computing: Accelerometers' data classification of body postures and movements", *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics).*, (7589), 52-61, 2012.

[34] Reyes-Ortiz, J. L., Ghio, A., Anguita, D., Parra, X., Cabestany, J., & Catalá, A., "Human activity and motion disorder recognition: Towards smarter interactive cognitive environments", *European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning*, (14)2, 22-29, 2013.

[35] Jalal, A., Kamal, S., & Kim, D., "A depth video sensor-based life-logging human activity recognition system for elderly care in smart indoor environments", *Journal of Sensors, 14*(7), 11735-11759, 2014.

[36] Fareed, U. (2015). "Smartphone sensor fusion-based activity recognition system for elderly healthcare", MobileHealth 2015 - Proceedings of the 2015 Workshop on Pervasive Wireless Healthcare, Co-Located with MobiHoc 2015.

[37] González, S., Sedano, J., Villar, J. R., Corchado, E., Herrero, Á., & Baruque, B., "Features and models for human activity recognition", *Journal of Neurocomputing*, (167), 52-60, 2015.

[38] Capela, N. A., Lemaire, E. D., & Baddour, N. "Feature selection for wearable smartphone-based human activity recognition with able bodied, elderly, and stroke patients". *Journal of PLoS ONE*, (10)4, 1-18, 2015.