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Evaluation of Human Activity Recognition using Machine Learning Techniques

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***Abstract*— Human Activity Recognition (HAR) in healthcare smartphone applications has enabled people to monitor their daily routine activities including exercises to control diabetes, blood pressure, and heart disease. It is possible through a single gadget such as wearable smart bands or smartphones. However, the literature on reliability and accuracy of such apps is less. In this work, the analysis on the results of various classifiers for HAR using smartphone dataset is presented. The results suggest that Support Vector Machine (SVM) is good at correctly recognizing the human activities with high accuracy.**

Keywords*— *Human Activity Recognition, HAR, Smart Band, Smart Phones, Sensor Data, Machine Learning

I. Introduction

Activity recognition is a broad field and has a lot of ongoing research. Several methods of activity recognition in different datasets have been tested. Approaches such as vision system based (where the cameras are used to detect the activities), and sensor-based (where the sensors are used to detect the activities). This sensor-based recognition is divided into the wearable-sensors (sensor is attached to the subject to predict the activity), object-based sensors (sensors attached to the object) and the smart-gadget based activity recognition such as smartphone sensors. Camera based Human Activity Recognition systems are popular for various security applications, it poses numerous challenges related to privacy and space constraints in smart environments. If you have room to capture the movement of people who are not the object of interest. This violates your privacy and raises security concerns about collecting such videos. Object-based activity recognition has limited approach and every object needs an installation of sensors, which is costly approach and not possible to do the everywhere. Wearable-Sensor classified as the number of sensors attached to the subject which is also not for the general purpose and it can be suitable for special, medical and security purposes. Wearable-Sensor based smart gadgets are the most popular approach to everyone and easily available in fair prices and use of this approach is easy and reliable. We focus our research to recognize the activities using smartphone sensor data that is publicly available.

II. Literature Review

Personal Digital Assistants (PDAs) furnished with rich arrangements of sensors are investigated as elective stages for Human Activities [1], [2]. Several authors in [3], [4], [5], [6] consider solitary classifier way to deal with study movement acknowledgement utilizing cell phones. Authors in [7] proposed a framework that used the blend of two classifiers to perceive exercises. The framework design was profoundly prominent as sensor information was gathered using PDA gadget and later analyzed. In [8], authors create a portable and unobtrusive real-time platform using a single smartphone and a sensor device. Signals acquired from sensors were processed to extract time and frequency features.

Authors in [9], [10], [11], [12], [13] utilized smartphones and it's installed sensors to pick up the input from client body movement and distinguish different exercise patterns. This research is on-going efforts to optimize the performance of activity recognition using Machine Learning (ML) classifiers.

III. Experiments

The experimental work is in three folds. The first part involves the selection and analysis of available datasets. The second part involves pre-processing of the data. The third part involves the implementation of various ML classifiers. Later, the performance of each classifier is analyzed, and the results are discussed.

A. Dataset

Dataset under consideration has been downloaded from the UCI machine learning repository titled "A Public Domain Dataset for Human Activity Recognition using Smartphones" [18]. Datasets comprise of 10299 samples, where 7328 samples have been used for training purposes, while 2945 samples are used for testing purpose. This dataset consists of six activities such as *walking*, *walking upstairs*, *walking downstairs*, *lying*, *sitting*, and *standing*. Fig. *1* shows an example in which a human performs an activity and this is detected by a smartphone sensor in the form of 3-dimensional axes such as *x-axis*, *y-axis*, and *z-axis*.

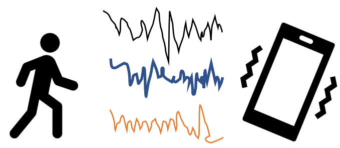

Fig. 1: Demonstration of Signal Pattern from Smartphone Sensor

The recorded data have certain noise, and to remove the noise, a pre-processing step is essential. The available dataset is already preprocessed data with 128 readings per window with 2.56 seconds overlap time. The frequency of 50 Hz and a sliding window filter has been used to remove the noise. The dataset was developed using 30 subjects who performed the six activities equally to avoid variance and biasness.

B. Machine Learning Classifier

Several ML approaches are available that claim to achieve robust results using the UCI ML Dataset. These approaches are tested, and results suggest that few are unable to achieve good results and the reason behind is dataset characteristics. To optimize, a pre-processing step is required. Fig. *2* show the process of recognizing the HAR.

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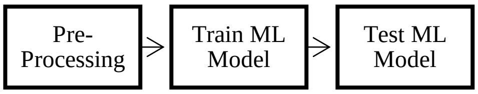

Fig. 2: Flow of ML Algorithm

After pre-processing the sensor data, ML algorithm is trained with certain optimized parameters. Once the training is successful, ML algorithm is tested to predict a given activity with new samples that are not part of the training set. Later, a confusion matrix or error matrix helps us to understand the prediction accuracy. This matrix includes parameters such as True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN). TP and TN that describes the condition that the model correctly recognized the activity. Whereas FP is the condition when there is no activity, and the model predicts an activity. Similarly, FN is the condition when there is an activity, and the model does not predict it.

IV. Results and Discussion

ML classifiers used for comparison are Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF), Decision Tree (DT), Extra Tree (ET), Gradient Boosting (GB), Bagging Classifier (BC). All mentioned classifiers are implemented using python 3.0 along with required libraries. The training and testing phase for each classifier take different amount of time.

- *Support Vector Machines (SVM)*: It is a supervised classification algorithm. SVM classifier executed in python programming language to evaluate the performance. The classifier provided the parametric values randomly to the kernel ('sigmoid and 'rbf') and set default value for gamma. The obtained result was good.

- *K-Nearest Neighbors (KNN):* KNN is a classification and regression machine learning algorithm. This algorithm executed in python by applying the available dataset. KNN works on the principle of a nearest outliers. KNN stores all the available data in training phase and classify new data point based on similarity.

- *Decision Tree (DT):* It is a decision-based classification approach in which incrementally tree like structure built. This classifier "sklearn.tree.DecisionTreeClassifier" executed in python platform. The parameter criterion set by default (gini) and fixed the splitter value "best".

- *Extra Tree (ET):* It is extremely randomized ensemble tree. It correlates the average of multiple decision trees. This classification algorithm executed and applied the "gini" as a model criterion, n-estimator value settled hundred. It reduces the overfitting problem by building multiple trees and replacement of observations.

- *Gradient Boosting (GB):* GB is gradually building an additive model; allows the optimization of arbitrary differentiable loss functions. In each phase, the n-classes regression trees are fitted to the negative gradient of the loss function for binomial or multinomial deviance.

- *Random Forest (RF):* A random forest is a meta estimator that matches a variety of decision tree classifiers on numerous sub-samples of the dataset and uses averaging to enhance the prognosticative accuracy and control over-fitting.

- *Bagging Classifiers (BC):* It is an ensemble classification technique in which individual predictive results aggregated to form a final prediction. This meta estimator used to reduce the variance of black box.

Performance of each classifier is compared in using metrics such as *accuracy*, *precision*, *recall*, and *f1-score*. Fig. *3*, Fig. *4*, Fig. *5* shows the comparison of performance for the activity of "Lying", "Sitting", and "Standing" using mentioned classifiers. The results suggest that almost all the classifiers perform very well in recognizing the "Lying" activity. The reason for this behavior is stative activity.

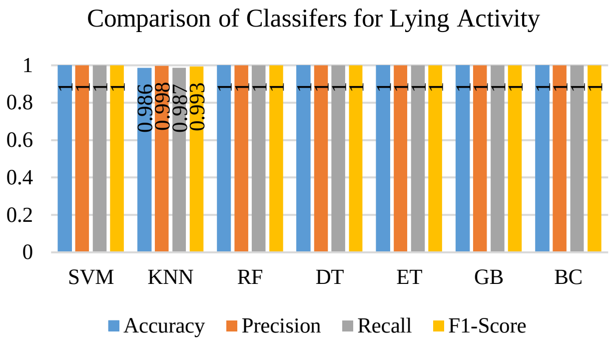

Fig. 3: Comparison of ML algorithms for Lying Activity

Whereas SVM is shown to perform relatively better for "Sitting" and "Standing" activity. The activity of "Walking" is classified in to "Walking", "Walking Downstairs", and "Walking Upstairs". This activity involves a lot of movement and its correct prediction and classification is very important. It needs to train the model accurately to strengthen the prediction of new unknown samples.

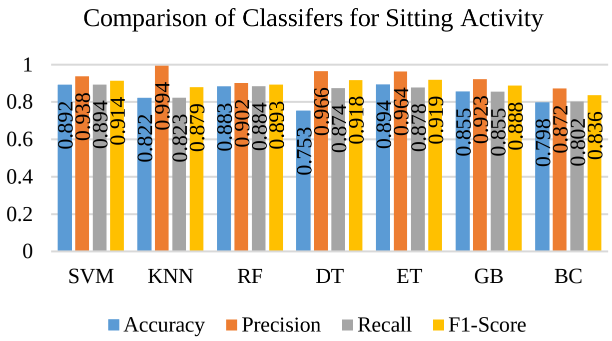

Fig. 4: Comparison of ML algorithms for Sitting Activity

Fig. *6* shows comparison of performance for the activity of "Walking" on straight surface using mentioned classifiers. Walking activity is a dynamic in nature, it produces a greater number of patterns as compare to stative nature activities. KNN and SVM give remarkable accuracy in this case. Score of recall relatively to other metrics is high. Variation of metrics score depends on the confusion matrix. These calculations are totally computer generated by classification report of classifiers.

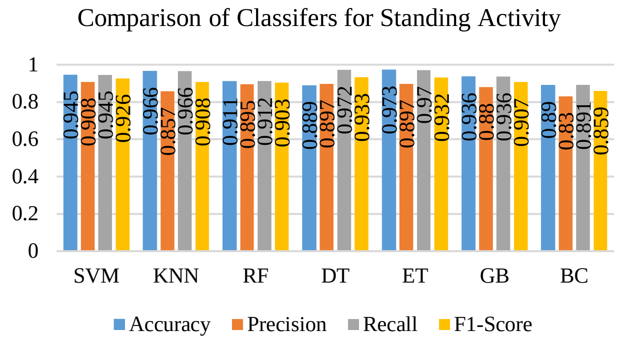

Fig. 5: Comparison of ML algorithms for Standing Activity

The "*precision*" parameter of recognizing the activity of walking is shown to vary for different classifiers. However, again we observe that the SVM performs relatively better.

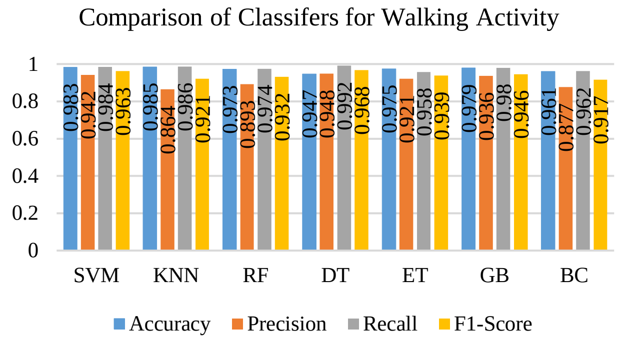

Fig. 6: Comparison of ML algorithms for Walking Activity

The activity of "Walking Downstairs" and "Walking Upstairs" show similar trend of variation as can be seen in Fig. 7 and Fig. *8*.

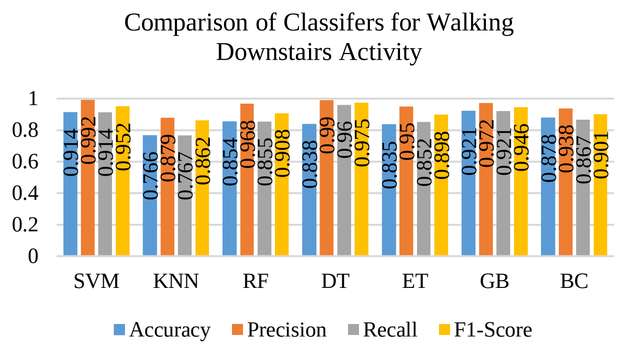

Fig. 7: Comparison of ML algorithms for Walking Downstairs Activity

The results suggest that accuracy metric of walking downstairs is less than walking activity metric because in this case pattern has more irregularity. GB and SVM have performed better than other classifiers for the walking downstairs activity.

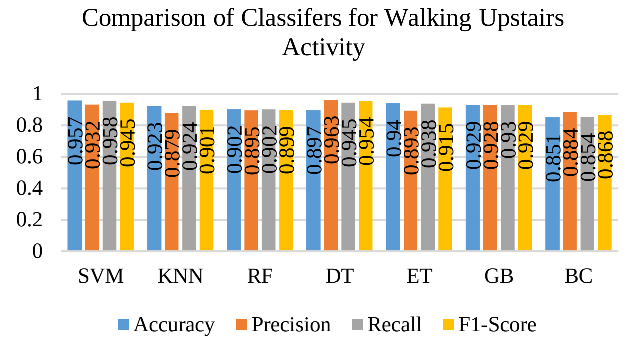

Fig. 8: Comparison of ML algorithms for Walking Upstairs Activity

Figure 8 shows that the SVM has highest accuracy for walking upstairs activity and BC accuracy came in the last. The comparison of accuracy, precision, recall, and f-1 score metrics for a single classifier shows that variation of metric values relative with each other.

V. CONCLUSION AND FUTURE WORK

An extensive implementation of various ML algorithms to correctly predict 6 Human Activities was conducted using benchmarked dataset from UCI repository. The results suggest that SVM perform better and has least FP and FN. However, the accuracy can be improved if the sensor data is properly pre-processed to remove any outliers or noise. This will improve training and enhance the performance. Moreover, the optimization of training parameters also helps in improving the performance. In future, we plan to test the performance of ML algorithms against real-time test subjects such as how would these algorithms perform and alert if the subjects are patients at the hospital.

REFERENCES

[1] I. M. Freeman, "Impact of Science on Society," Am. J. Phys., Feb. 1953, vol. 21, no. 2, pp. 148–148, doi: 10.1119/1.1933385.

[2] M. B. Abidine, L. Fergani, B. Fergani, and A. Fleury, "Improving Human Activity Recognition in Smart Homes," Int. J. E-Health Med. Commun., Jul. 2015, vol.6 ,no 3, pp. 19–37, doi: 10.4018/IJEHMC.2015070102.

[3] D. N. Tran and D. D. Phan, "Human Activities Recognition in Android Smartphone Using Support Vector Machine," in 2016 7th International Conference on Intelligent Systems, Modelling and Simulation (ISMS), Jan. 2016, pp. 64–68, doi: 10.1109/ISMS.2016.51.

[4] M. Shoaib, H. Scholten, and P. J. M. Havinga, "Towards Physical Activity Recognition Using Smartphone Sensors," in 2013 IEEE 10th International Conference on Ubiquitous Intelligence and Computing and 2013 IEEE 10th International Conference on Autonomic and Trusted Computing, Dec. 2013, pp. 80–87, doi: 10.1109/UIC-ATC.2013.43.

[5] N. Ahmad, L. Han, K. Iqbal, R. Ahmad, M. A. Abid, and N. Iqbal, "SARM: Salah Activities Recognition Model Based on Smartphone," Electronics, Aug. 2019, vol. 8, no. 8, p. 881, doi: 10.3390/electronics8080881.

[6] M. B. Abidine, N. Yala, B. Fergani, and L. Clavier, "Soft margin SVM modeling for handling imbalanced human activity datasets in multiple homes," in 2014 International Conference on Multimedia Computing and Systems (ICMCS), Apr. 2014, pp. 421–426, doi: 10.1109/ICMCS.2014.6911407.

[7] C. Zhu and W. Sheng, "Human daily activity recognition in robot-assisted living using multi-sensor fusion," in 2009 IEEE International Conference on Robotics and Automation, May 2009, pp.2154–2159, doi: 10.1109/ROBOT.2009.5152756.

[8] Ó. D. Lara, A. J. Pérez, M. A. Labrador, and J. D. Posada, “Centinela: A human activity recognition system based on acceleration and vital sign data,” Pervasive Mob. Comput., Oct. 2012, vol. 8, no. 5, pp. 717–729, doi: 10.1016/j.pmcj.2011.06.004.

[9] Y. Tian and W. Chen, “MEMS-based human activity recognition using smartphone,” in 2016 35th Chinese Control Conference (CCC), Jul. 2016, pp. 3984–3989, doi: 10.1109/ChiCC.2016.7553975.

[10] T. Meena and K. Sarawadekar, “Gender Recognition using in-built Inertial Sensors of Smartphone,” in 2020 IEEE REGION 10 CONFERENCE (TENCON), Nov. 2020, pp. 462–467, doi: 10.1109/TENCON50793.2020.9293797.

[11] A. Guo and J. Ma, “Context-Aware Scheduling in Personal Data Collection From Multiple Wearable Devices,” IEEE Access, 2017, vol. 5, pp. 2602–2614, doi: 10.1109/ACCESS.2017.2666419.

[12] Q. Guo, B. Liu, and C. W. Chen, “A two-layer and multi-strategy framework for human activity recognition using smartphone,” in 2016 IEEE International Conference on Communications (ICC), May 2016, pp. 1–6, doi: 10.1109/ICC.2016.7511487.

[13] Z. Chen, Q. Zhu, Y. C. Soh, and L. Zhang, “Robust Human Activity Recognition Using Smartphone Sensors via CT-PCA and Online SVM,” IEEE Trans. Ind. Informatics, Dec. 2017, vol. 13, no. 6, pp. 3070–3080, doi: 10.1109/TII.2017.2712746.

[14] S. Amir Shah, I. Ullah Khan Marwat, A. Ud Din, and A. Khan, “Impact of various factors on student’s attitude towards adoption of Learning Management System (LMS) in Pakistan,” J. Bus. Tour., 2017, vol. Special Is, pp. 113–127, [Online]. Available: https://www.awkum.edu.pk/jbt/downloads/Special Issue-ICCSS-Indonesia-November-2017/113 - 127.pdf.

[15] S. S. Binyamin, M. J. Rutter, and S. Smith, “Extending the Technology Acceptance Model to Understand Students’ use of Learning Management Systems in Saudi Higher Education.,” Int. J. Emerg. Technol. Learn., 2019, vol. 14, no. 3.

[16] O. Jimenez-del-Toro et al., “Chapter 10 - Analysis of Histopathology Images: From Traditional Machine Learning to Deep Learning,” in Biomedical Texture Analysis, A. Depeursinge, O. S. Al-Kadi, and J. R. Mitchell, Eds. Academic Press, 2017, pp. 281–314.

[17] Google, “Machine Learning Crash Course | Google Developers.” https://developers.google.com/machine-learning/crash-course/.

[18] D. Anguita, A. Ghio, L. Oneto, X. Parra and J. Reyes-Ortiz,."A Public Domain Dataset for Human Activity Recognition Using Smartphones." 21th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN 2013. Bruges, Belgium 24-26 April 2013..

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