Human Activity Recognition Using Machine Learning With Wearable Inertial Sensors

Nurul Husna Hanis Binti Kharullnizam
Faculty of Computing and Informatics
Universiti Malaysia Sabah
Kota Kinabalu, Malaysia
bi19110035@student.ums.edu.my

Assoc. Prof. Dr. Azali Saudi
Faculty of Computing and Informatics
Universiti Malaysia Sabah
Kota Kinabalu, Malaysia
azali@ums.edu.my

***Abstract*—Human Activity Recognition gives considerable research interests from every research field and human computer interaction for various application. Realizing wearable inertial sensors in human activity recognition can be beneficial for a user because it convenient. Machine learning also plays a vital role in recognizing human activity for example, in healthcare and sports areas. Nevertheless, there still has been no standard algorithm selection that can be employed for identifying human activity recognition. Recent studies have been unable to archive satisfy performance result using standalone classifier, and mechanism for recognizing human activity that can be utilized openly by people still unsexist. This research aims to analyze the performance using instance-based learning and ensemble learning to achieve significant result by training and testing using two different datasets. This study proposes a method for human activity recognition based on Support Vector Machine, k-Nearest Neighbor, Random Forest, Extreme Gradient Boosting (XGBoost), Categorical boosting (CatBoost), Extremely Randomized Trees (ExtraTrees), and Light Gradient Boosting Machine (LightGBM). The methodology employed in this study consisted of obtaining data from WISDM and Xsens datasets. To improve the performance, ensemble method has been proposed by combining several single classifiers; five experiments were carried out during the implementation. The results show that ensemble stacking using a combination of SVM, KNN, Random Forest, and ExtraTrees outperforms other methods; the accuracy of 75.48% in the WISDM and 90.74% in the Xsens dataset which higher than these classifiers in a single method.**

Keywords—Machine learning, Wearable inertial sensors, Ensemble stacking, Human activity recognition

I. Introduction

Human activity recognition (HAR) has been a popular research topic in recent years, impacting fields as diverse as health care and sports. Activity recognition seeks to perceive human activity by observing movements and environments [1]. Furthermore, activity recognition plays a significant role in defining the capacity to recognize some actions based on information obtained from a variety of sensors. Recognition can be carried out such as, by utilizing data collected from wearable inertial sensors such as accelerometers due to convenient, low cost, and intrusiveness. Wearable inertial sensors are increasingly being adopted for intelligent daily activity monitoring in a variety of application. The useable of wearable inertial sensors in human activity recognition provides inspiration for this study.

Wearable technology is highly appealing in a variety of applications as a result of the rapid development of wearable sensors that can respond swiftly to accelerations of body motions and reliably capture quantitative measurements [2]. However, most researchers have published on the sensor and investigated detecting human activity, but most of the data is inaccurate. More additional sensors are being added to open new possibilities for tracking more details of human activity [3]. Moreover, the number of sensors utilized also influence on data collecting since many sensors can generate a large volume of data dependent on each location [4]. Prior research has established that it is preferable to gather their own dataset to avoid any unnecessary justifications.

Past studies have proposed various machine learning techniques included Support Vector Machine, k-Nearest Neighbor, Random Forest, Artificial Neural Networks, Naïve Bayes, Decision Tree, and more to capture movement identification; however, achieving high recognition accuracy with standalone classifiers remains challenging [5]. The research gap and challenges are that different classification techniques require different time complexities and precisions [6]. To fill the gaps and challenge for achieving high accuracy with low computation cost is a key challenge in human activity recognition. Next, when there is a lack of training data, classification models such as decision trees and neural networks can cause overfitting while SVM can cause the underfitting [6]. Indeed, implementation of algorithms carried out must be compatible with the data.

In addition, ensemble learning has been introduced to overcome this issue by combining several techniques to complete the learning tasks. The ensemble learning frequently results in generalized performance is much better than a single learner [5]. XGBoost has been proposed as an ensemble learning continuation from decision tree and some research has shown high results in a variety of applications such as online text classification and behavior prediction [5]. This method provides numerous benefits including high efficiency and cheap computing cost, parallelization support, resilience to overfitting, and many more. Furthermore, there are cases where multiple ML models are used in combination for HAR. Although combining multiple ML models is expected to improve classification accuracy, combining them requires additional training such as stacking which typically increases computational cost [7].

This paper presents the machine learning approach for recognizing human activity by implementing selected algorithms such as SVM, kNN, Random Forest, XGBoost, LightGBM, ExtraTrees and CatBoost tested in two different datasets (WISDM and Xsens). The contribution of this paper are as follows:

1. Collection of new HAR datasets employing wearable inertial sensors (Xsens DOT), as there is presently no public dataset using these sensors.
2. Applying new algorithms to increase the resilience and accuracy of human activity identification regions (LightGBM, ExtraTrees, and CatBoost).

II. LITERATURE REVIEW

This paper with goals in discovering human activity recognition performance based on few aspects which are the machine learning used, number, types, and location of sensors by the study itself. Apart from that, the datasets utilized are critical since the data must persist with the recognition area.

The current work shown that HAR based on sensor data is extremely difficult, especially given the variety of machine learning algorithms available [3]. Leonardis *et al* [8] stated there are several algorithmic techniques for activity recognition that may be used, depending on the kind and amount of examined actions, the ultimate application, available computer capacity, and processing time. Meanwhile, Cheng *et al* [9] said there is a lot of researchers have suggested various classifier methods for activity recognition, such as neural network-based classification, pattern matching-based classification, fixed threshold classification, and so on. However, the computability of the embedded system limits the ability to implement such a complex algorithm in wearable technology.

Besides, SVM technique would focus on finding a faster way to determine the ideal parameters rather than requiring cross validation, which is time demanding [9]. Zhang, Zhao & Li, [10] stated that SVM excels at tackling machine learning challenges involving tiny samples. SVM is extremely sensitive to missing values, for example in computing the distance between two locations, which significantly affects resilience. Not only SVM, both RF and GBDT group together several weak learners in ensemble learning. RF has embraced the bagging concept because of each learner's independence, RF may analyze data in parallel. GBDT employs a boosting strategy based on mistake rate. Because the weak classifiers are interdependent, GBDT cannot analyze data in parallel and is vulnerable to outliers.

Moreover, Wu *et al* [11] defines the XGBoost algorithm outperforms as standalone classifiers in terms of recognition rate and KNN can produces a great accuracy, but it is computationally demanding and uses a lot of memory. To overcome this issue Zhang *et al* [10] has suggested using ensemble learning, which combines numerous learners to complete learning tasks, has played an important role in HAR. XGBoost has recently been presented as an innovative ensemble learning strategy in boosting ensemble learning classifiers, and it can obtain great results in many applications. Ambati & El-Gayar [12] mentioned if an application is more concerned with accuracy and has a limited budget, XGBoost would be an excellent choice with some run time trade-offs as compared to Random Forest.

Boosting is a popular ensemble learner in which decision trees are generated successively so that each successive tree minimizes the classification errors of the prior tree Adaptive Bootstrapping (AdaBoost) algorithm is one of the most used methods of enhancing machine learning and employed a sequential sequence of classifiers with the goal of constructing a strong classifier from weaker ones [13]. In addition, stacking also is the other good ensemble method which has two training stages, the training data is divided and distributed to classifiers in the first phase, and a classifier in the second phase is trained utilizing the output of the first phase classifiers as created new features.

With the growing number of wearable smart devices HAR has attracted several sorts of study, including sensors and cell phones [14]. Wearable sensors are incorporated in the gadgets that people wear such as accelerometers, gyroscopes, and magnetometers are the common sensors. In the early stages of HAR, most studies employ wearable sensors implanted in various regions of the human body, resulting in difficult data gathering and an additional expense for hardware [5]. Cell phones are a particularly important tool for activity monitoring in smart homes due to their capacity to handle sensors such as accelerometers and gyroscopes, as well as their wireless connection capabilities [15]. In general, specific sensors are inserted in various locations such as the arms, calves, chest, and waist to achieve optimal classification performance.

Mehta *et al* [4] have found that the best place to wear the accelerometer is inside the trousers pocket. Instead, other studies suggest that the accelerometer should be placed in a bag carried by the user: on the belt, or on the dominant wrist [16]. In the end, the optimal position to place an accelerometer depends on the application and type of activities to be recognized. For instance, an accelerometer on wrist may not be appropriate to recognize ambulation activities, since accidental arm movements could generate incorrect predictions. Badawi *et al* [17] revealed that the thigh is the optimal sensor location for the accelerometer, while the x-axis and y-axis are the best sensor positions for the gyroscope, respectively.

III. DATASET

This study decided using two different datasets from public datasets and own dataset. WISDM dataset was selected as the public dataset while Xsens DOT sensor as wearable inertial sensors used to collect the experimental dataset.

A. *WIDSM Dataset*

The dataset was released by Fordham University's Wireless Sensor Data Mining Lab. This dataset contains 6 attributes such as users, activity, timestamp, x-acceleration, y-acceleration, and z-acceleration. The total of 36 volunteers performed six activities:

- Walking
- Sitting
- Jogging
- Downstairs
- Upstairs
- Standing

The data was captured using smartphone consist of an acceleration sensor located at their front pants leg pocket when doing the activities. Total numbers of recorded data splits into 70% and 30% for training and testing set.

WISDM dataset using Android-based cell phones and data was collected directly from the files stored on the smartphone using a USB connection [18]. The accelerometer detects gravity's acceleration, which is approximately 9.8 m/s2 [18].

B. *Experimental Dataset*

To capture the motion of the human body in this experiment need at least 4 wearable inertial sensors attached to the right arm, left arm, right leg, and left leg shows in Figure 1 and 2. The activities chosen are same as WISDM dataset and collected by 6 subjects which the location of this experiment conducted at University Malaysia Sabah.

Furthermore, this dataset contains 16 attributes such as count, subject, activities, sample time, righand_X, righand_Y, righand_Z, lefhand_X, lefhand_Y, lefhand_Z, righleg_X, righleg_Y, righleg_Z, leftleg_X, leftleg_Y, and leftleg_Z. Each activity is repeated 3 times to receive the significant data and splits into training and testing set which 70% and 30% each.

Fig. 1. Xsens DOT sensors set.

Fig. 2. Xsens DOT attached.

IV. PROPOSED MODEL

There are five stages of proposed approach as follow: (i) data collection, (ii) data pre-processing, (iii) feature extraction, (iv) implementation of machine learning, and (v) evaluation metrics.

A. *Data Collection*

The accelerometer sensor data used from WISDM and Xsens Dataset. For WISDM dataset, the raw data file was downloaded from Wireless Sensor Data Mining (WISDM). For Xsens dataset, the raw data are collected by conducting an experiment.

B. *Data Pre-processing*

The acquired data must be done the pre-processing to be ready for the training and testing phase, required to balance and normalize the raw data. These characteristics must be informative in terms of the raw data qualities and supplied into a classification algorithm to identify the activity as near to the actual executed action as feasible.

C. *Feature Extraction*

Through the data pre-processing, extracting relevant information from a dataset and representing it in a simplified form that can be used as input for machine learning algorithms. Time domain features are a form of feature that may be retrieved from sensor data for human activity detection in machine learning.

The characteristics are based on the temporal characteristics of the sensor data and information about the signal's time-varying nature. The feature that has been extracted are distance, mean, and variance. These features are often employed in activity recognition because they are straightforward to compute, interpret, and have been shown to be useful.

D. *Implementation of Machine Learning*

The machine learning algorithms used in this paper includes SVM, KNN, Random Forest, XGBoost, LightGBM, ExtraTrees, and CatBoost. Prior studies mentioned that ensemble classifier performed better than single learner. Then, ensemble stacking is deployed by combining the numerous machine learning models in order to improve the ensemble overall performance.

The experiments are conducted by combining standalone together to perform the ensemble stacking. The base models employed referred as weak learners since their accuracy is often lower. In previous research only one paper conducted stacking in their studies [13] and proven ensemble stacking can archive higher than 90% of accuracy.

In an ensemble stacking experiment, selected classifiers are trained, and their predictions are combined to generate a final prediction. Base classifiers are selected standalone classifiers. The ensemble classifier is taught by training the basic classifiers on the same training data and then feeding their predictions into a meta-classifier, which makes the final prediction.

Logistic regression works as final estimator since is a popular approach for use as the final estimator (meta-model) in a stacking classifier. This strategy can frequently result in better performance than employing a single classifier alone. The figure 3 shows flow of stacking algorithm.

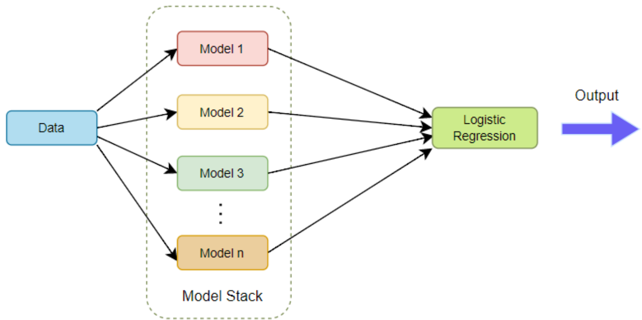

Fig. 3. Stacking Classifier flow.

E. Evaluation Metrics

The evaluation to evaluate the performance of each algorithm and define the accuracy, precision, recall and f1-score. In this paper, the confusion matrix was used as performance metrics based on True Positive, False Positive, False Negative and True Negative. The accuracy is calculated as shown in equation (1), precision in equation (2), recall in equation (3) and F1-score in equation (4).

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \times 100\% \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} = \frac{2 \times TP}{2 \times TP + FP + FN} \quad (4)$$

V. RESULT AND DISCUSSION

In this section, the detailed explanation is presented as follows: (i) performance of standalone classifier using WISDM and Xsens datasets, (ii) performance of ensemble classifier using WISDM and Xsens datasets, and (iii) comparison with other works.

A. Performance of Standalone Classifier

In WISDM dataset, RF outperformed than others standalone method which the accuracy is 74.15%. Followed by XGBoost, SVM and kNN which the accuracy values were 73.23%, 72.86% and 72.29%. Moreover, performance evaluation of new standalone classifier described LightGBM was the most performed rather than the two methods which the accuracy archived 75.18%. ExtraTrees and Catboost are next, with accuracy of 74.06% and 69.75%, respectively. Table 9 describe the summary of evaluation on standalone methods.

TABLE 9. Performance of Standalone Classifier for WISDM Dataset

Methods	Accuracy (%)	Precision	Recall	F1-Score
SVM	72.86%	0.7289	0.7286	0.7250
kNN	72.29%	0.7251	0.7223	0.7232
RF	74.15%	0.7453	0.7415	0.7402
XGBoost	73.23%	0.7371	0.7325	0.7321
LightGBM	**75.18%**	**0.7546**	**0.7561**	**0.7514**
ExtraTrees	74.06%	0.7412	0.7406	0.7395
CatBoost	69.75%	0.6927	0.6975	0.6924

In Xsens dataset, RF also performed better than others standalone methods the accuracy is 85.46%. Followed by kNN, XGBoost and SVM which the accuracy values were 84.62%, 82.96%, and 73.15%. Besides, performance evaluation of new standalone classifier shows ExtraTrees was the most performed rather than LightGBM and CatBoost which the accuracy was 91.11%. LightGBM performance was not that far than ExtraTrees and it consider higher because it can reach 90.56% of accuracy. Table 10 describe the summary of evaluation on standalone methods.

TABLE 10. Performance of Standalone Classifier for Xsens Dataset

Methods	Accuracy (%)	Precision	Recall	F1-Score
SVM	73.15%	0.7539	0.7315	0.6990
kNN	84.62%	0.8486	0.8463	0.8445
RF	85.46%	0.8567	0.8546	0.8547
XGBoost	82.96%	0.8312	0.8296	0.8299
LightGBM	90.56%	0.9059	0.9056	0.9054
ExtraTrees	**91.11%**	**0.9126**	**0.9111**	**0.9113**
CatBoost	75.28%	0.7521	0.7528	0.7511

B. Ensemble Classifier

In WISDM dataset, Stacking_4 (combination of svm, kNN, RF and ExtraTrees) becomes the most outperformed ensemble stacking which achieved the highest accuracy is 75.48%, followed by Stacking_3, Stacking_2, Stacking_5 and Stacking_1. Table 11 shows the summary of evaluation of ensemble stacking.

TABLE 11. Performance of Ensemble Classifier for WISDM Dataset

Methods	Accuracy (%)	Precision	Recall	F1-Score
Stacking 1	74.76%	0.7525	0.7479	0.7486
Stacking 2	74.87%	0.7531	0.7487	0.7493
Stacking 3	75.12%	0.7558	07517	0.7522
Stacking 4	**75.48%**	**0.7571**	**0.7537**	**0.7538**
Stacking 5	74.81%	0.7527	0.7476	0.7485

In Xsens dataset, the most performed ensemble method was Stacking_4 (combination of svm, kNN, RF and ExtraTrees) the accuracy is 90.74%. Followed by Stacking_3, Stacking_2, Stacking_5, and Stacking_1. Aside from that, the accuracy of Stacking_3 and Stacking_2 is not that far from Stacking_4, the percentage different is minimal and both of them archived 90% of accuracy which same as Stacking_4. Table 12 presented the summary of evaluation on experiments of ensemble stacking.

TABLE 12. Performance of Ensemble Classifier for Xsens Dataset

Methods	Accuracy (%)	Precision	Recall	F1-Score
Stacking 1	89.35%	0.8989	0.8972	0.8977
Stacking 2	90.19%	0.8995	0.8982	0.8985
Stacking 3	90.65%	0.9058	0.9046	0.9048
Stacking 4	**90.74%**	**0.9101**	**0.9083**	**0.9087**
Stacking 5	89.54%	0.8965	0.8944	0.8950

C. Comparison with other works

The comparison of dataset approach in human activity recognition was summarize in Table 13, [19] used WISDM dataset to measure Random Forest classifier showed 90.69% of accuracy. Meanwhile, [20] also used the same classifier but tested with kNN method achieved 78.40%. The results showed greater than this paper performed which these classifiers only reached 74.15% for Random Forest and 72.29% for kNN. The result may vary because of several reasons such as the pre-processing data and validation method. This study may lead to lack of processed data because only conducted normalization and standardization for raw data.

Furthermore, [13] performed experimental dataset tested with SVM and stacking classifier. It achieved 99.40% for SVM and 98.10% for stacking. Implemented ensemble stacking in this paper only reached 75.48% for WISDM dataset and 90.74% for Xsens dataset (combination of SVM, kNN, Random Forest and ExtraTrees), but it still lower than past study achieved. The parameter, classifiers and different dataset used could be the reasons why the classifier does not perform well. Wearable sensors used in each dataset also different types and locations applied.

Other than that, the main contribution in this paper which using new methods or rarely used methods (these methods were famous at another field and implemented in HAR field) which are LightGBM, ExtraTrees, and CatBoost. All of this classifier was the continuation of decision tree classifier same goes to XGBoost which it was a popular method in boosting [11] using experimental dataset reached 94.80% of accuracy. Lastly, the authors [21] and [22] using same UCI-HAR dataset performed with ExtraTrees achieved 96.68%, and LightGBM reached 93.16% of accuracy. ARAS dataset was used by [23] implemented CatBoost and archived 69% of accuracy.

Based on the prior results, all the classifiers used performed well in Xsens dataset. Most of the result can up to 90% which is contributing to this research field since the selected classifier is rarely used. The reasons why WISDM dataset only reached 70% is the amount of data was huge (up to 300,000 raw data). The difference of amount is large between these two datasets that may lead to different result performance. The chosen dataset also being the reason if the classifier can perform well or not based on the parameter used since the data was not pre-processed well. However, some of classifier showed the greatest results such as CatBoost achieved 75.28% in standalone and 89.54% in ensemble stacking. Moreover, ExtraTrees and LightGBM reached 91.11% and 90.56% in standalone model, and 90.65% and 90.74% in ensemble stacking.

TABLE 13. Comparison with other works

Author	**Dataset Used**	**Model**	**Accuracy (%)**
Nayak *et al* [19]	WISDM	RF	90.69%
Mohsen *et al* [20]	WISDM	kNN	78.40%
Bulbul et al [13]	Experimental	SVM	99.40%
		Stacking	98.10%
Wu *et al* [11]	Experimental	XGBoost	94.80%
Minarno *et al* [21]	UCI-HAR	ExtraTrees	96.68%
Shao *et al* [22]	UCI-HAR	LightGBM	93.16%
Ardebili *et al* [23]	ARAS	CatBoost	69.00%

VI. Conclusion

In conclusion, the work presented in this paper was successful in its goal of analyzing performance using instance-based learning and ensemble learning to achieve significant results by training and testing using two different datasets. In this work, the use of novel ensemble techniques has a considerable positive influence, with the combination of ExtraTrees providing the greatest performance among other classifiers and achieving up to 90% accuracy.

However, the limitation of this paper is only used four sensors from Xsens DOT sensors. Using huge or a smaller number of sensors could affect the accuracy of the sensors itself since the previous study advice using smaller number of sensors. In the next research suggested to use more or less than this paper occupied and try to put at different places of body.

Lastly, this paper only utilized six volunteers to collect data; the future study may include a big number of volunteers, resulting in a great amount of data. Aside from that, the activity can be changed because this study focused on comparing the performance of classifiers using different datasets by utilizing the same activity as the public dataset.

References

[1] Polu, S. K., & Polu, S. K. (2018). Human activity recognition on smartphones using machine learning algorithms. International Journal for Innovative Research in Science & Technology, 5(6), 31-37.

[2] Filippeschi, A., Schmitz, N., Miezal, M., Bleser, G., Ruffaldi, E., & Stricker, D. (2017). Survey of Motion Tracking Methods Based on Inertial Sensors: A Focus on Upper Limb Human Motion. *Sensors*, *17*(6), 1257. https://doi.org/10.3390/s17061257

[3] Subasi, A., Khateeb, K., Brahimi, T., & Sarirete, A. (2020). Human activity recognition using machine learning methods in a smart healthcare environment. Innovation In Health Informatics, 123-144. doi: 10.1016/b978- 0-12-819043-2.00005-8

[4] Mehta, S. K. Vaddadi, V. Sharma and P. Kala, "A Phase-wise Analysis of Machine Learning based Human Activity Recognition using Inertial Sensors," 2020 IEEE 17th India Council International Conference (INDICON), 2020, pp. 1-7, doi: 10.1109/INDICON49873.2020.9342466.

[5] W. Zhang, X. Zhao and Z. Li, "A Comprehensive Study of Smartphone-Based Indoor Activity Recognition via Xgboost," in *IEEE Access*, vol. 7, pp. 80027-80042, 2019, doi: 10.1109/ACCESS.2019.2922974.

[6] Jobanputra, Charmi; Bavishi, Jatna; Doshi, Nishant (2019). *Human Activity Recognition: A Survey. Procedia Computer Science, 155(), 698–703.* doi:10.1016/j.procs.2019.08.100

[7] Koichi Shimoda;Akihito Taya;Yoshito Tobe; (2021). Combining Public Machine Learning Models by Using Word Embedding for Human Activity Recognition . 2021 IEEE International Conference on Pervasive Computing and Communications Workshops and other Affiliated Events (PerCom Workshops), (), – . doi:10.1109/percomworkshops51409.2021.943

[8] De Leonardis et al., "Human Activity Recognition by Wearable Sensors : Comparison of different classifiers for real-time applications," 2018 IEEE International Symposium on Medical Measurements and Applications (MeMeA), 2018, pp. 1- 6, doi: 10.1109/MeMeA.2018.8438750

[9] Cheng, Y. Guan, Kecheng Zhu and Yiyang Li, "Recognition of human activities using machine learning methods with wearable sensors," 2017 IEEE 7th Annual Computing and Communication Workshop and Conference (CCWC), 2017, pp. 1-7, doi: 10.1109/CCWC.2017.7868369.

[10] Y. Zhang, X. Zhao and Z. Li, "Facilitated and Enhanced Human Activity Recognition via Semi-supervised LightGBM," 2020 IEEE Globecom Workshops (GC Wkshps, 2020, pp. 1-6, doi: 10.1109/GCWkshps50303.2020.9367452.

[11] Wu, Yuchuan; Qi, Shengfeng; Hu, Feng; Ma, Shuangbao; Mao, Wen; Li, Wei (2019). Recognizing activities of the elderly using wearable sensors: a comparison of ensemble algorithms based on boosting. Sensor Review, 39(6), 743–751. doi:10.1108/sr-11-2018-0309

[12] Ambati, L. S., & El-Gayar, O. (2021). Human activity recognition: a comparison of machine learning approaches. Journal of the Midwest Association for Information Systems (JMWAIS), 2021(1), 49.

[13] Bulbul, Erhan; Cetin, Aydin; Dogru, Ibrahim Alper (2018). [IEEE 2018 2nd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT) - Ankara (2018.10.19-2018.10.21)] 2018 2nd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT) - Human Activity Recognition Using Smartphones. , (), 1–6. doi:10.1109/ISMSIT.2018.8567275

[14] Ferrari, D. Micucci, M. Mobilio and P. Napoletano, "On the Personalization of Classification Models for Human Activity Recognition," in IEEE Access, vol. 8, pp. 32066-32079, 2020, doi: 10.1109/ACCESS.2020.2973425.

[15] Reza Akhavian, Amir H. Behzadan (2018). Coupling human activity recognition and wearable sensors for data-driven construction simulation. Journal of Information Technology in Construction (ITcon), Vol. 23, pg. 1-15, http://www.itcon.org/2018/1

[16] Kyritsis, M. Deriaz and D. Konstantas, "Considerations for the Design of an Activity Recognition System Using Inertial Sensors," 2018 IEEE 20th International Conference on e-Health Networking, Applications and Services (Healthcom), 2018, pp. 1-8, doi: 10.1109/HealthCom.2018.8531145

[17] Badawi, A. Al-Kabbany and H. Shaban, "Multimodal Human Activity Recognition From Wearable Inertial Sensors Using Machine Learning," 2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES), 2018, pp. 402- 407, doi: 10.1109/IECBES.2018.8626737.

[18] Dua, N., Singh, S.N. & Semwal, V.B. Multi-input CNN-GRU based human activity recognition using wearable sensors. Computing 103, 1461–1478 (2021). https://doi.org/10.1007/s00607-021-00928-8

[19] Nayak, S., Panigrahi, C., Pati, B., Nanda, S., & Hsieh, M. (2022). Comparative analysis of HAR datasets using classification algorithms. Computer Science And Information Systems, 19(1), 47-63. doi: 10.2298/csis201221043n

[20] Mohsen, Saeed & Elkaseer, Ahmed & Scholz, Steffen. (2021). Human Activity Recognition Using K-Nearest Neighbor Machine Learning Algorithm. 10.1007/978-981-16-6128-0_29.

[21] Minarno, Agus Eko; Kusuma, Wahyu Andhyka; Wibowo, Hardianto; Akbi, Denar Regata; Jawas, Naser (2020). [IEEE 2020 8th International Conference on Information and Communication Technology (ICoICT) - Yogyakarta, Indonesia (2020.6.24-2020.6.26)] 2020 8th International Conference on Information and Communication Technology (ICoICT) - Single Triaxial Accelerometer Gyroscope Classification for Human Activity Recognition. , (), 1– 5. doi:10.1109/ICoICT49345.2020.916632

[22] Z. Shao, J. Guo, Y. Zhang, R. Zhu and L. Wang, "LightBGM for Human Activity Recognition Using Wearable Sensors," 2021 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS), 2021, pp. 668-671, doi: 10.1109/ICITBS53129.2021.00169

[23] Ardebili, E. S., Eken, S., & Küçük, K. (2020). Activity Recognition for Ambient Sensing Data and Rule Based Anomaly Detection. The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 44, 379- 382.