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The Trade-off between Energy-Accuracy in the IoT-based Activity Monitoring System

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***Abstract*—Activity monitoring system is used in many fields such patient's activity monitoring system for self-quarantine in their home. The IoT- based activity monitoring system uses the limited resources (e.g., bandwidth, battery and memory) for monitoring the user's activity. The limited resources (such as battery) provide the limited lifetime battery in activity monitoring system. By resource efficiency, it will extend the battery lifetime. Resource efficiency is achieved by adaptively reporting user activity depending on the level of the user's activity emergency. But, when the user's activity reporting data is based on the emergency level, then it reduces the data detail and its activity recognition accuracy. So, we develop energy-savings techniques for user's activity reporting and analyze the effect of energy-savings techniques to the accuracy of activity recognition using different methods. The results show the energy-savings techniques can save battery life up to 8%, bandwidth up to 146,5 bytes/sec and memory up to 2,8% compared to non-energy saving technique. But the energy-saving techniques give less accuracy in the four different activity recognition methods up to 11% in average.**

Keywords*—*internet of things, energy-accuracy, activity recognition

I. Introduction

Nowadays, human activity can be monitored using Internet of Things in the long distances. A user can monitor other user's activity using Internet of Things in mobile devices. This activity monitoring system can be used in many fields, such as for infectious disease patient's activity monitoring system like now COVID-19 pandemic period [1]. To avoid someone who takes care of the patient, get contact with the infectious patient, they can use this activity monitoring system for monitoring the patient's activity.

The two most used methods in Human Activity Recognition (HAR) are video-based HAR and sensor-based HAR [2]. The use of video-based HAR has some issues those are privacy, pervasiveness, and high cost-time consuming. People are not comfortable being recorded all day (privacy) and the video based HAR makes it difficult to collect the image data from the target individually. Video-based HAR is also highly cost and time consuming to process the video data. To overcome those issues, there is another method in HAR namely sensor based HAR. It is HAR that collects the data from wearable sensors. One of the wearable sensors used to collect motion data from a human is Accelerometer [3].

The mobile device as the one of IoT hardware can be used to get raw data from user's activity using Accelerometer in it. There are some researchers who have concluded that the axis in Accelerometer provides the accuracy level in HAR. The research results that the same human activities could provide different accuracy level depending on which axis parameter measured [4][5].

For monitoring the user's activity, the mobile device uses its resources (e.g., battery, memory, and bandwidth) continuously even though the mobile device has limited resources [6]. Activity monitoring system that is used to monitor the other user's activity will give the accelerometer data continuously from the mobile device to the server. The more frequently data transfer, the more the battery level drain rapidly, the more memory, and consume the more bandwidth [7].

The system needs continuous data transfer to get the detail/continuous data for real- time activity recognition. For the usual continuously real-time activity monitoring system, it will get the raw data and transfer the data to the server in a certain period time [8]. If the activity monitoring system periodically transfers the amount of data to the server for activity recognition, it will run through more resources (e.g., battery, memory and bandwidth) that is a limited resources in mobile devices. Furthermore, there is a condition for the user that do not need to use the more resources in transferring the data in mobile devices continuously, like when the users doing the same activity in a certain period time and the mobile device continuing transfer the same data of the user's activity [9][10]. This condition can be beneficial to reduce the utilization of the limited resources in mobile devices by establishing more dynamic data transfer from mobile devices to the server. If there is no activity change in user's mobile device, then we do not need to transfer the raw data to the server and vice versa. If there is an activity change in the user's mobile device, the mobile device transfers the raw data to the server. With this dynamic data transfer, the battery can have more lifetime and other resources. Memory and bandwidth can have more free space to handle the more other data required.

In this paper, to determine the user's activity change, the system runs through the change prediction techniques. Change prediction techniques can be obtained by analysis of variances. Analysis of variances finds the similarity of two data groups. It will take the N previous raw data and the N current raw data, then the system will compare both data groups to predict the activity changes. If the previous N data group is like the current N data group, then there is no change activity occurs. If the previous N data group is not like the current N data group, then there is a change activity occurs. So, activity change prediction can be obtained by this analysis of variance. The activity change prediction is used to optimize the use of limited resources, and it needs to analyze its impact to the activity recognition accuracy.

If the activity monitoring system do not use the activity changes prediction, then the system will transfer the data periodically and the system will get the more detail data to get the detail information of user's activity. Otherwise, if the activity monitoring system uses the activity changes prediction, then the system will transfer the data dynamically, based on the presence of the user's activity changes. So, the system will get the aggregated data to be transferred to the server. Because of this condition, it needs to be evaluated and analyzed the energy-savings techniques impacts (activity change prediction) to the activity recognition accuracy. There are some test scenarios, the first test scenario is to observe the resource usage (e.g., battery, memory and bandwidth) compared both systems using energy-savings techniques and non-energy-savings techniques. The second test scenario is to observe accuracy, comparing both systems using energy-savings techniques and non-energy-savings techniques.

II. METHOD

The aim of this research is to analyze the trade-off between the energy-savings techniques and the activity recognition accuracy in an activity monitoring system. Mobile devices are used to get raw data and transfer it to the server for activity monitoring system even though it has limited resources (e.g., battery, memory and bandwidth) to overcome the process. Activity monitoring system repeats the process continuously to keep monitoring the user's activity. This process runs through the limited resources in mobile device although for the same user's activity that kept being transferred to the server in the certain period time. The limited resources can be optimized by transferring the user's raw data to the server simply when there is an activity change. This condition is used to reduce the limited resources utilization by predicting the user's change activity using analysis of variance.

The user's activity type that used in this research are "laying", "sitting", "standing", "walking" and "running". In activity change prediction, we do not recognize the type of activity. But we predict if the activity changes or not. So, the first is the mobile device get the raw accelerometer data and divided into two data groups. They are, N previous raw data and N current raw data. Then, find the similarity of the two data groups using analysis of variance. If both of data groups is similar, then it indicates that there is no activity change, and the N current data is not transferred to the server. If both of data groups is not similar, then it indicates that there is an activity change, and the N current data is transferred to the server.

Following the current data in the server, then the server recognizes the activity using the activity recognition method. The monitoring user can view the monitored user's activity from a website. In this research, we tested some activity recognition methods to compare the accuracy of each method. Here is the overview of the whole system can be seen in Figure 1 and Figure 2.

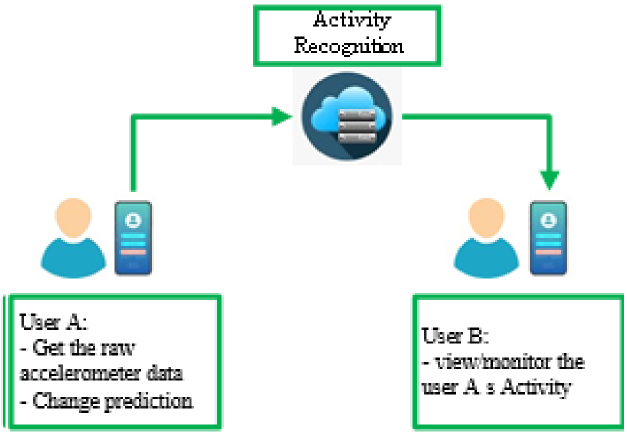

Fig. 1. Architecture system overview

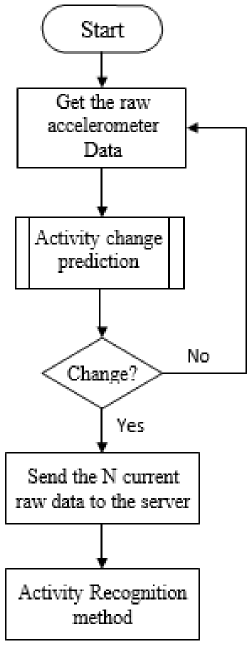

Fig. 2. Flowchart system overview

A. *Change Prediction Techniques*

Activity monitoring system sends raw data frequently to the server that runs through the limited resources in mobile device. This process sometimes runs through limited resources with the condition that mobile device sends the same user's activity in a certain period time. It throws away the limited resources used for transferring the same data for the user's activity.

For the same user's activity, we do not need to update frequently. The monitoring user is usually concerned with the monitored user's activity changes. This condition is utilized for optimizing the limited resources for transferring the raw data of the user's activity changes. The activity monitoring system only transfers the raw data to the server when there are a user's activity changes. The user's activity changes are predicted using change prediction techniques that are named by analysis of variance. It predicts the user's activity changes by assigning the similarity between two data groups that in this case, the previous N data and the current N data. Analysis of variance examines the similarity of data and the other in a group (within-class). Furthermore, it also examines the similarity of a data in a group and data in the other group (between-class). The following stages are the change prediction techniques using analysis of variance:

- Define the total number of the sample data (N), the total number of the population (k) and the number of the sample data for each population (n)
- Define the meaning of each population and the mean of all the mean of each population

$$\bar{\bar{x}} = \frac{\overline{x_1}+\overline{x_2}+\overline{x_3}+\cdots+\overline{x_k}}{k} \quad (1)$$

- Then, calculate the SSB (Sum of Square Between) and SSW (Sum of Square Within).

$$SSB = \sum_{j=1}^{k} n_j (x_j - \bar{\bar{x}})^2 \quad (2)$$

were,

k = the amount of *population*

j = j^{th} population

$\overline{x_j}$= j^{th} population *mean*

$\bar{\bar{x}}$= *mean* of *mean* from each *population*

$$SSW = \sum_{j=1}^{k} \sum_{i=1}^{n_j} (x_{ji} - \overline{x_j})^2 \quad (3)$$

Were,

k = the amount of population

j = j^{th} population

n_j = the amount of data in j^{th} population

i = i^{th} data of j^{th} pop ulation

x_{ji} = i^{th} data in j^{th} population

$\overline{x_j}$ = *mean* of j^{th} population

- Calculate MSB (*Mean of Square Between*) and MSW (*Mean of Square Within*)
- MSB is calculated by dividing SSB to degree of freedom.

$$MSB = \frac{SSB}{k-1} \quad (4)$$

Where, k = the amount of population

- MSW is calculated by dividing SSW to degree of freedom

$$MSW = SSW/(N-k) \quad (5)$$

Where,

N = the amount of sample data of the entire population

k = the amount of population

-
- Then, calculate F Ratio

$$F\ Ratio = \frac{MSB}{MSW} \quad (6)$$

- Then, find F table in F distribution table by intersecting the degree of freedom of MSB, k-1, in the horizontal way and degree of freedom of MSW, N-k, in the vertical way as shown as Figure 3. (Example, N=8 dan k=2).

	1	2	3
1	161	199	216
2	18.51	19.00	19.16
3	10.13	9.55	9.28
4	7.71	6.94	6.59
5	6.61	5.79	5.41
6	5.99	5.14	4.76
7	5.59	4.74	4.35
8	5.32	4.46	4.07
9	5.12	4.26	3.86

Fig. 3. F distribution table

- Then, the F ratio is examined. If F ratio > F table, then there is different population meaning (not similar). If F ratio <= F table, then there is no different population mean (similar)

B. Activity Recognition Method

The activity change prediction techniques are utilized to determine whether the raw data must be transferred or not. As the raw data transferred, then the server utilized the activity recognition method to determine the types of activity (e.g., "laying", "sitting", "standing", "walking", "running"). The activity recognition method assigns the user's activity information. In this paper, we tested some activity recognition methods (Naïve Bayes, KStar, KNN and TreeJ48) to analyse the impacts of the change prediction techniques to the activity recognition method accuracy in some different method.

III. Results and Discussion

The activity monitoring system is developed with the IoT-based (Internet of things) that utilizes the client-server architecture as shown as Figure 4. The utilized experimental

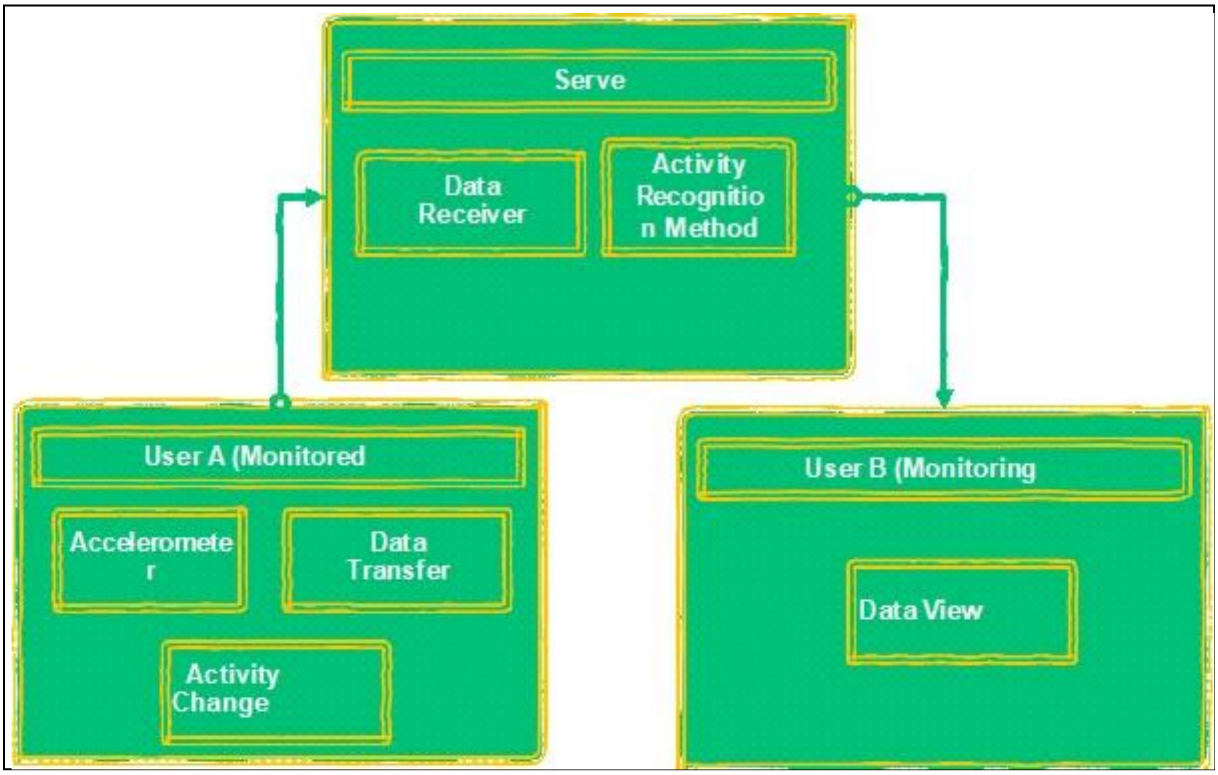

Fig. 4. experimental environment overview

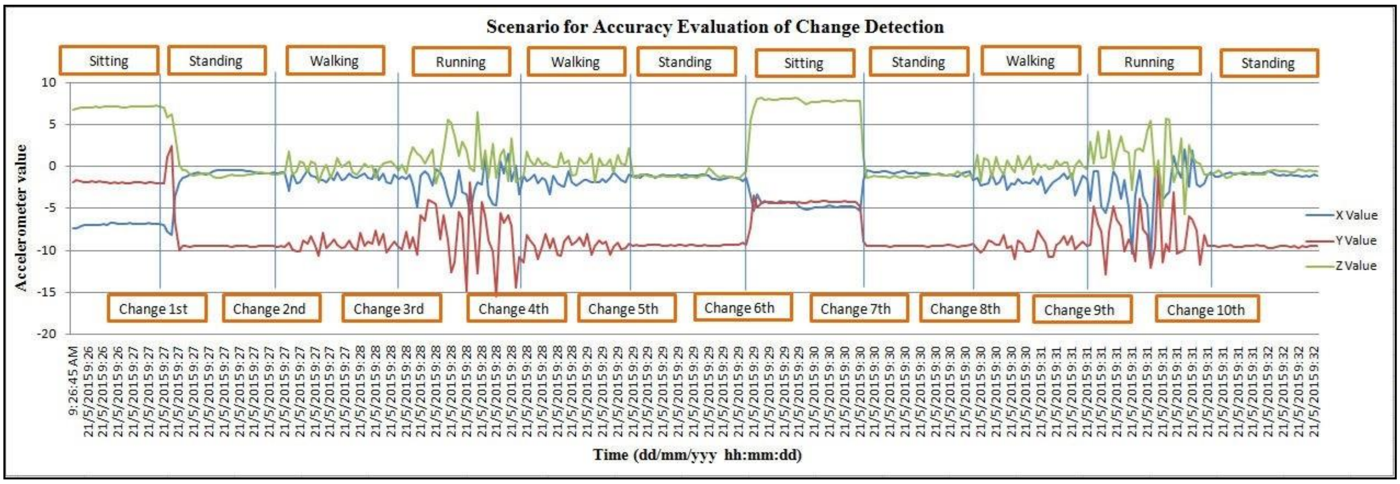

Fig. 5. experimental scenario for the evaluation

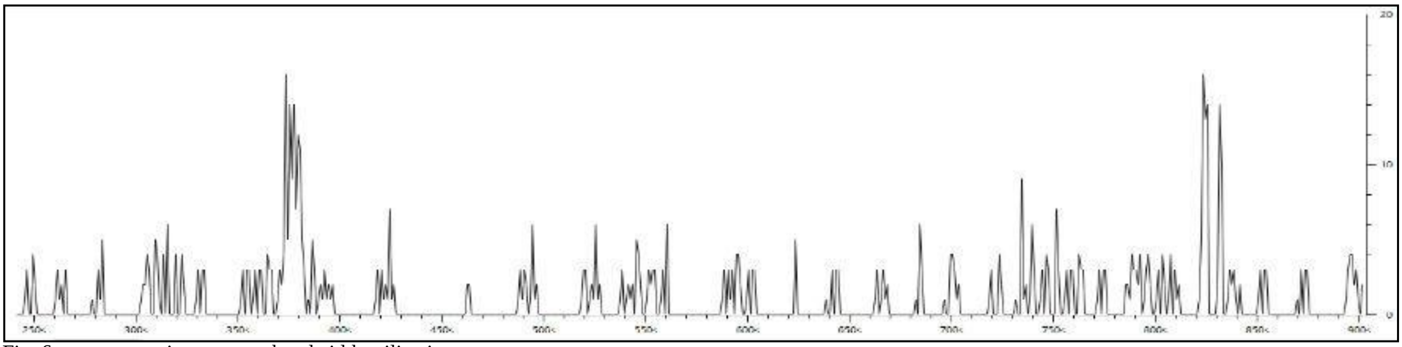

Fig. 6. energy-savings system bandwidth utilization

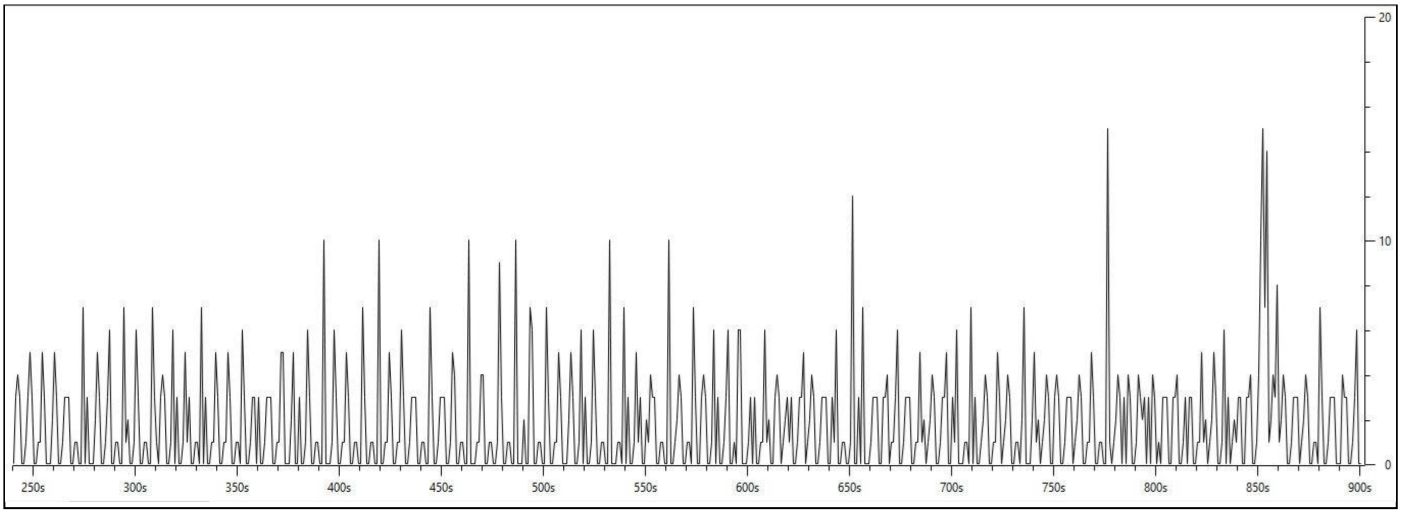

Fig. 7. non-energy-savings system bandwidth utilization

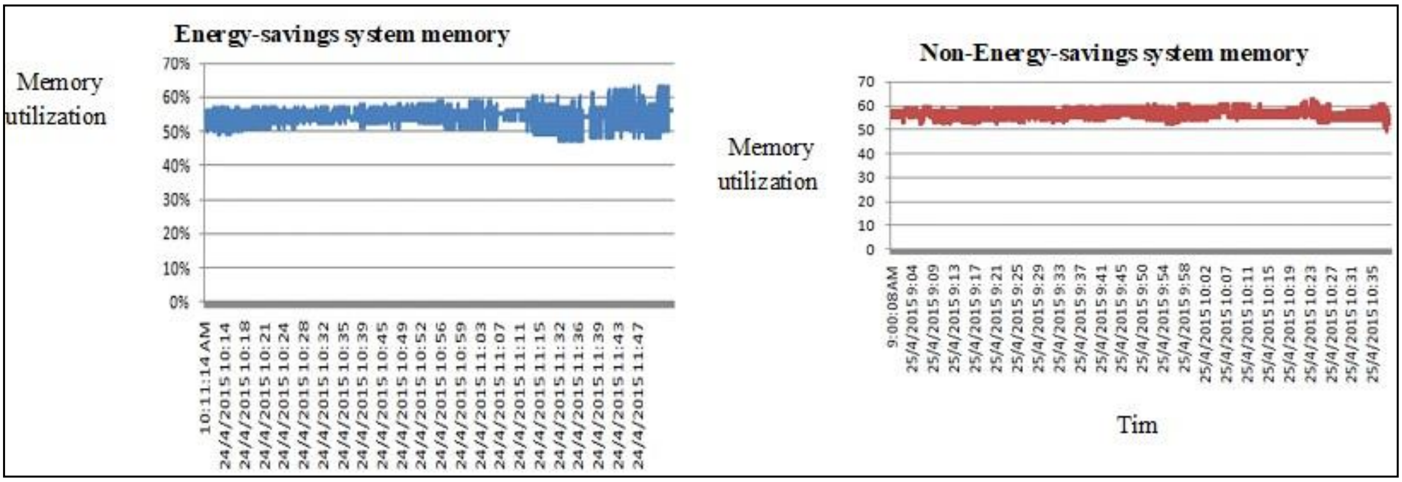

Fig. 8. energy-savings and non-energy-savings system memory utilization

environment consists of three main components, they are monitored user mobile device (user A), server and monitoring user mobile device (user B). User A has three embedded modules, namely accelerometer module, activity change module and data transfer module. Server has two embedded modules, namely data receiver module and activity recognition module. User B has one embedded module, namely data view module.

Activity monitoring system gets the user A's activity using accelerometer module to get the raw data (x, y, z) from the accelerometer sensor. Then the raw data, assigned as the input to the activity change prediction module and assign the prediction output, whether the user's activity changes or not. If the activity monitoring system assigns the output "no change", then user A mobile device does not transfer the raw data and keep acquiring the raw data from accelerometer module. If the activity monitoring system assigns the output "change", then user A mobile device activate the data transfer module to transfer the raw data accelerometer to the server. If the transferred raw data received by the data receiver module in the server, then the raw data are assigned as the activity recognition method input. Then, the activity recognition method assigns the result to the user B through data view module.

The evaluation is assigned to observe the activity change prediction impacts to the energy- savings of the limited resources in mobile devices. There are three parameters to be evaluated, namely battery utilization, memory utilization and bandwidth utilization utilization. Furthermore, the system evaluated for the energy-savings impacts to the activity recognition accuracy compared to four different methods, namely Naïve Bayes, KNN, KStar and TreeJ48.

The system (using energy-savings techniques) will be compared to the non-energy- savings techniques. The system runs through the same scenario as shown as Figure 5 with the ten activity changes. We tested the bandwidth utilization between the energy-saving techniques system and non-energy-savings techniques. The result as shown as Figure 6 and 7. From the experimental result of bandwidth utilization, the energy savings system bandwidth utilization about 62.6 bytes/sec, whereas the non-energy savings system bandwidth utilization about 209.1 bytes/sec.

The energy-savings system utilizes less bandwidth compared to the non-energy savings system. It assigns more space free up for other data needed.

From the experimental result of memory utilization, the energy savings system memory utilization about 54%, whereas the non-energy savings system bandwidth utilization about 56.8%. The energy savings system utilize less memory compared to the non-energy savings system. It assigns more space free up for other data needed.

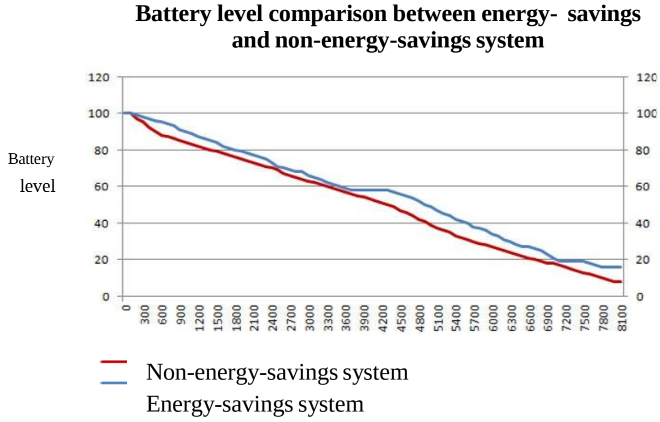

Fig. 9. Battery level derivation comparison between energy-savings and non-energy-savings system

From the experimental result of battery utilization, the energy savings system sustains the battery level derivation of about 84%, whereas the non- energy savings system sustains the battery level derivation of about 92%. The energy savings system uses less battery utilization compared to the non- energy savings system up to 8% in difference. It assigns the more lifetime battery.

From the experimental result of bandwidth, memory and battery utilization, the energy-savings techniques can use less resource utilization that the mobile devices have the limited resources. Consequently, it sustains the accuracy reduction.

The system tested for the activity recognition accuracy. It tested in the four different methods for comparisons, namely Naïve Bayes, KNN, Kstar and TreeJ48. The selected methods are the the most common method for activity recognition. The test was conducted comparing several methods by carrying out 4 activities (sitting, standing, walking and running) in a certain period. The experiment compared in different method of:

1. Naive Bayes provide the activity recognition accuracy of 82% in energy savings system and 89% in non-energy savings system. It makes 7% in accuracy difference. The experimental result is shown as Figure 10. The experimental results show that the energy- savings techniques reduce the activity recognition accuracy as much as 7% in average.

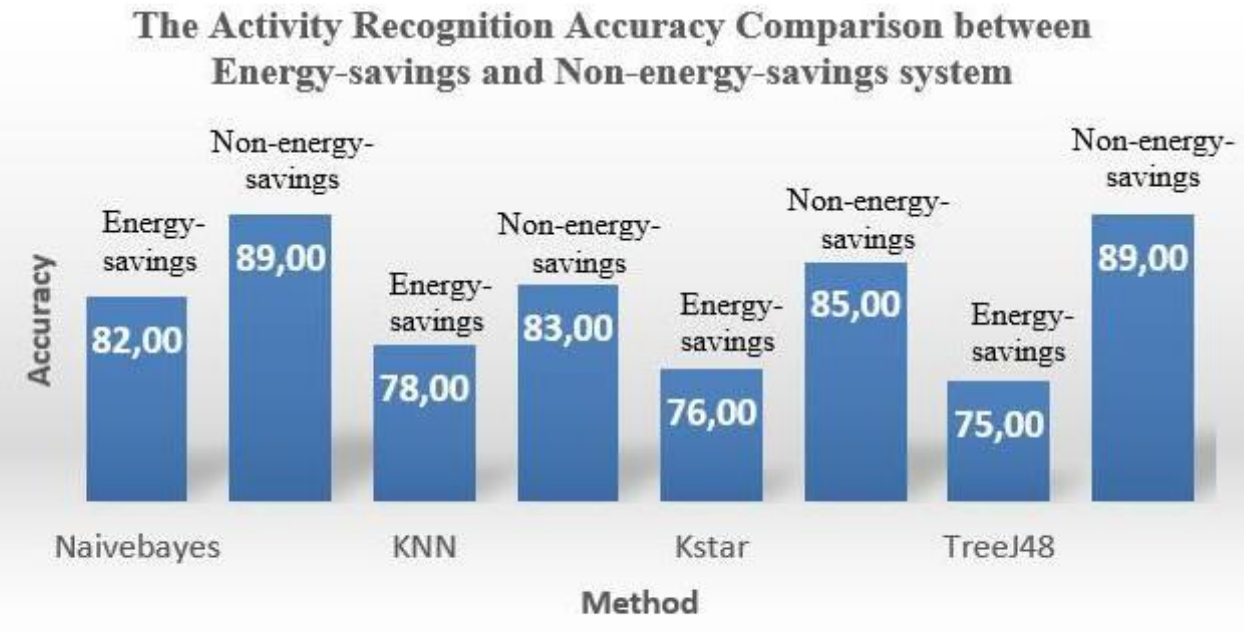

Fig. 10. The Activity Recognition Accuracy Comparison between Energy-savings and non-energy-savings system

2. KNN provide the activity recognition accuracy of 78% in energy savings system and 83% in non-energy savings system. It makes 5% in accuracy difference.

3. KStar provide the activity recognition accuracy of 76% in energy savings system and 85% in non-energy savings system. It makes 9% in accuracy difference.

4. TreeJ48 provide the activity recognition accuracy of 75% in energy savings system and 89% in non-energy savings system. It makes 14% in accuracy difference.

The experimental result as shown as Figure 10. The experimental result shows that the energy- savings techniques reduce the activity recognition accuracy as much as 8.75% in average of the four activity recognition methods.

IV. Conclusion

As the research experimental results, it can be concluded that energy-savings techniques in the activity monitoring system can save the limited resources in mobile device such as bandwidth, memory and battery lifetime. Consequently, the energy-savings techniques reduce the activity recognition accuracy method by as much as 8.75% in average compared to the non-energy-savings system.

References

[1] A. Gupta, K. Gupta, K. Gupta, and K. Gupta, “A Survey on Human Activity Recognition and Classification,” in 2020 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, Jul. 2020, pp. 0915– 0919.

[2] A. Das Antar, M. Ahmed, and M. A. R. Ahad, “Challenges in Sensor-based Human Activity Recognition and a Comparative Analysis of Benchmark Datasets: A Review,” in 2019 Joint 8th International Conference on Informatics, Electronics & Vision (ICIEV) and 2019 3rd International Conference on Imaging, Vision & Pattern Recognition (icIVPR), Spokane, WA, USA, May 2019, pp. 134–139.

[3] S. O. Slim, A. Atia, M. M.A., and M.-S. M.Mostafa, “Survey on Human Activity Recognition based on Acceleration Data,” Int. J. Adv. Comput. Sci. Appl., vol. 10, no. 3, 2019.

[4] A. R. Javed, M. U. Sarwar, S. Khan, C. Iwendi, M. Mittal, and N. Kumar, “Analyzing the Effectiveness and Contribution of Each Axis of Tri-Axial Accelerometer Sensor for Accurate Activity Recognition,” Sensors, vol. 20, no. 8, p. 2216, Apr. 2020.

[5] N. Ahmed, J. I. Rafiq, and M. R. Islam, “Enhanced Human Activity Recognition Based on Smartphone Sensor Data Using Hybrid Feature Selection Model,” Sensors, vol. 20, no. 1, p. 317, Jan. 2020.

[6] W. Jiang, P. Yin, and Y. Zou, "Human Activity Recognition Using Wearable Sensors by Deep Convolutional Neural Networks," IEEE Transactions on Industrial Informatics, vol. 15, no. 11, pp. 6513–6520, Nov. 2019.

[7] F. A. Gers, D. Eck, and J. Schmidhuber, "Applying LSTM to Time Series Predictable Through Time-Windowing Instead of Truncation," IEEE Transactions on Neural Networks and Learning Systems, vol. 30, no. 9, pp. 2756–2766, Sept. 2019.

[8] J. Ronao and S.-B. Cho, "Human Activity Recognition With Smartphone Sensors Using Deep Learning Neural Networks," Expert Systems with Applications, vol. 59, pp. 235–244, Oct. 2016.

[9] X. Chen, L. Zhang, and C. Xu, "Activity Recognition Using a Combination of Category Components and Local Models for Wearable Sensors," IEEE Access, vol. 7, pp. 112750–112761, 2019.

[10] M. Zeng, L. T. Nguyen, B. Yu, O. J. Mengshoel, J. Zhu, P. Wu, and J. Zhang, "Convolutional Neural Networks for Human Activity Recognition Using Mobile Sensors," in Proc. 6th International Conference on Mobile Computing, Applications and Services (MobiCASE), Austin, TX, 2014, pp. 197–205.

[11] Chaima Bouali, Olivier Habert, Abderrahim Tahiri, “Daily Activity Monitoring System designed for Elderly People using Hidden Markov Models based on Realworld Datasets” in 2023 International Journal of Intelligence Systems Technologies and Applications, Vol 21 No. 1.

[12] Preethi Palanisamy, Amudhavalli Padmanabhan, Asokan Ramasamy, Sakthivel Subramaniam. “Remote Patient Activity Monitoring System by Integrating IoT Sensors and Artificial Intelligence Techniques” in 2023 Journal of Sensors 25 June 2023.

[13] Martin Schiemer, Lei Fang, Simon Dobson Juan Ye, “Online Continual Learning for Human Activity Recognition,” Pervasive and Mobile Computing Elsevier, vol. 93, 2023.

[14] Md. Milon Islam, Sheikh Nooruddin Fakhri Karray, Ghulam Muhammad, “Human Activity Recognition Tools of Convolutional Neural Networks : A State of the Art Review, Datasets, Challenges and Future prospects” Elsevier : Computers in Biology and Medicine, vol. 149, no. 8, October. 2022.

[15] Fuqiang Gu, Mu-Huan Chung, Mark Chignell, Shahrokh Valaee, Baoding Zhou, Xue Liu, “A Survey on Deep Learning for Human Activity Recognition,” ACM Computing Surveys (CSUR), vol. 54 issues 8, p. 1-34, October. 2021.

[16] Anette Paulin Mercado Rueda, "Analysis of Variance: ANOVA," Chapter 31 Elsevier Handbook for Designing and Conducting Clinical and Translational Research, pp. 157-160. 2023.

[17] Nand kishor Kumar, "F-Test and Analysis of Variance (ANOVA) in Economics" Mikailalsys Journal of Mathematics and Statistics, vol. 2 issues 3, pp. 102-113, October. 2024.

[18] Nazanin sedaghati, Sondos ardebili and Ali Ghaffari, "Application of Human Activity/Recognition : A Review," Multimedia Tools and Application, January. 2025.

[19] Michail Kaseris, Ioannis Kostavelis and Sotiris Malassiotis, "A Comprehensive Survey on Deep Learning Methods in Human Activity Recognition" Machine Learning and Knowledge Extraction, April 2024.

[20] Ugonna Oleh, Roman Obermaisser and Abu Shad Ahammed, "A Reviewof Recent Techniques for Human Activity Recognition: Multimodality, Reinforcement Learning, and Language Models" Algorithms. September 2024, pp. 1-35.