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TELEWORKING MONITORING SYSTEM USING NILM AND K-NN ALGORITHMS: A STRATEGY FOR SUSTAINABLE SMART CITIES

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ABSTRACT: Working from home or teleworking has become a common practice for most office employees during certain special situations such as pandemic. One of the challenges faced by employers, however, is monitoring workers who are working from home. Webcam, live video feed, or mobile phone tracking deemed to be intrusive. Therefore, in this work, a non-intrusive monitoring approach is used to effectively help employers to keep track of teleworking employees through specific electrical appliances operating condition while maintaining users' privacies. This strategy uses non-intrusive load monitoring (NILM) approach to recognize four electrical appliances' switching events used during teleworking measured from a single power point. Together with an event classification method known as K-Nearest Neighbor (k-NN) algorithm, the teleworking event and duration can be identified. The results were presented using classification metrics that consist of confusion matrix and accuracy score. An accuracy of up to 62% has been achieved for the classifier. It is observed that the similarity of appliances' power usage affects the model accuracy and confusion matrix is constructed to help identify the number of events that are correctly classified as well as wrongly classified. Results from NILM and k-NN strategy can be implemented in the smart city towards sustainability to create a sustainable and employees well-being. It is also useful for an organization to evaluate an employee's performance who opt for teleworking.

ABSTRAK: Bekerja dari rumah telah menjadi amalan biasa bagi kebanyakan pekerja-pekerja pejabat semasa situasi khas tertentu seperti wabak penyakit. Salah satu cabaran yang dihadapi oleh para majikan, adalah memantau para pekerja yang bekerja dari rumah. Kamera web, suapan video langsung atau penjejakan telefon mudah alih adalah dianggap mengganggu privasi. Oleh itu, dalam kajian ini, pendekatan pemantauan tidak mengganggu privasi digunakan untuk membantu para majikan dengan berkesan menjejak para pekerja yang bekerja dari rumah melalui keadaan operasi peralatan-peralatan elektrik tertentu sambil mengekalkan privasi pengguna. Strategi ini menggunakan pendekatan pemantauan beban elektrik tanpa gangguan (NILM) untuk mengenali empat situasi pensuisan peralatan-peralatan elektrik yang digunakan semasa bekerja dari rumah diukur dari satu titik kuasa. Bersama-sama dengan kaedah-kaedah pengkelasan situation yang dikenali sebagai algoritma K-Nearest Neighbor (k-NN), acara bekerja dari rumah dan tempoh boleh dikenal pasti. Keputusan telah dibentangkan menggunakan metrik klasifikasi yang terdiri daripada matriks kekeliruan dan skor ketepatan. Ketepatan sehingga 62% telah dicapai untuk pengkelasan. Adalah diperhatikan bahawa persamaan penggunaan kuasa peralatan-peralatan elektrik mempengaruhi ketepatan model dan matriks kekeliruan dibina untuk membantu mengenal pasti bilangan peristiwa yang dikelaskan dengan betul serta dikelaskan secara salah. Hasil daripada strategi NILM dan k-NN boleh dilaksanakan di bandar pintar ke arah kemampanan untuk mewujudkan kesejahteraan para pekerja dan mampan. Ia juga berguna untuk organisasi menilai prestasi para pekerja yang memilih untuk bekerja dari rumah.

KEYWORDS: *Non-Intrusive Load Monitoring (NILM), K-Nearest Neighbors (k-NN), Teleworking, Sustainability, Smart Cities.*

1. INTRODUCTION

Smart cities are one of the solutions for countries to achieve sustainability [1]. Therefore, to build a smart city, sustainability through improving energy efficiency is an important element. A review paper of research works on energy efficiency summarizes improving, monitoring, and reducing energy consumption on buildings can achieve sustainability [2]. In the area of improving energy efficiency, the main solution is to be able to identify faults in the electrical load and systems. Various researchers have proposed non-intrusive fault monitoring in detecting possible faults through analyzing electrical signals measured at the utilities and systems level [3 and 4]. Next, to reduce energy consumption, energy usage behavior is an important factor. A survey done by researchers on a group of secondary school students in Gombak, Malaysia analyzes that energy efficiency knowledge is crucial to their energy consumption behavior [5].

In monitoring energy consumption, many researchers have worked on non-intrusive monitoring. Energy management and monitoring is an integral part of building a sustainable city [6]. Researchers work on a model-agnostic hybrid federated learning framework to work together to train non-intrusive electrical load monitoring as a city-wide approach for sustainable city application [7]. Researchers have also utilized deep transfer learning and deep domain adaptation of energy systems to perform energy prediction based on the data of human mobility for smart city applications [8].

The Non-Intrusive Load Monitoring (NILM) is a technique used to separate individual appliances based on their power consumption while respecting the consumers' privacy and this technique are often used as an alternative for the users to pursue energy efficiency [9]. One of the major advantages of this method is the non-intrusive nature as it does not require sensors to be mounted on directly onto each appliance to monitor its energy consumption. Although the method of using sensors ensures a high accuracy of energy consumption measurements, this method is costly because several sensors need to be installed and monitored for load identification [10]. Meanwhile, the NILM approach obtained the data to be analyzed and disaggregated to recognize daily electrical appliances consumption from a single point measurement. Based on the studies made in [11], the general framework of a NILM system consists of data acquisition, event detection and load identification.

Data acquisition is a process of acquiring data before further processed with the algorithms in event detection, load identification and anomaly detection in the non-intrusive load monitoring (NILM) system. The data is collected using the NILM technique as such the data will be collected from a single point measurement in the building without invading the consumer's privacies. Devices such as smart meters, current transformer or specific hardware

are used to measure the voltage drop over the device and the current that flows through the device that will be used for the NILM algorithms.

To perform the segregation of the power consumption of appliances, it is important to obtain and understand the features of the appliances. These features can represent various types of appliance data such as ON/OFF trends, voltage and current, power consumption (real, reactive, and apparent) and its temporal variations [12]. It is easy to segregate two devices with very different power profiles. However, if several appliances have approximately similar power profiles, then segregation becomes a difficult task. Moreover, devices that consume very low power are also a problem for classification since such low-level power can often be regarded as noise. One of the ways to tackle this is to detect the events of the appliances [13].

Based on the study in [10], the machine learning algorithms used for load classification in NILM can be classified into two which are supervised and unsupervised. Supervised techniques create databases information to design the classifier by using offline training. Some of the commonly supervised techniques are Support Vector Machines (SVM) [14], k-Nearest Neighbors (K-NN) [15,16], Naïve Bayes [15, 17], Conventional Neural Networks [18] and many more. In contrast, the unsupervised techniques do not require any training prior to load classification which will reduce human involvement in building database information. Despite the important advantage mentioned, unsupervised techniques are more costly, and the accuracy of load disaggregation is relatively low.

Based on a study made in [9, 20] states that NILM algorithm can efficiently recognize various types of human activity in a household through the information on the appliances' power consumption used inside the household at a particular time. To recognize the activity, the training datasets of daily routine obtained in the early stages of NILM system are fed into the NILM algorithm. K-NN has been used in various research for appliance disaggregation and it has been proven to be effective at classification [15].

Working from home (WFH) or teleworking is a common practice that has been introduced during the COVID-19 pandemic where there is no physical contact with the other colleagues [19]. Many workers are coming back to the office as the pandemic finally recedes but there are also companies that have a regular option to work from home. Due to that, teleworking during pandemic has also seen an increase in the use of technologies for employees' monitoring purposes. The existing hardware and software monitoring solutions such as webcam, live video feeds, mobile phone tracking, keyboard strokes, sensors, mouse movement, etc. deemed to be intrusive [11,14]. Therefore, a non-intrusive approach is more efficient for employers to keep track of employees' working attendance by monitoring the employees from their daily electrical appliances' consumption data. Researchers have proposed to utilize non-intrusive load monitoring to determine an electrical appliance's anomaly [21]. Previous work has initially been done to monitor electrical appliances for energy consumption [22].

In this paper, the novelty of our work is utilizing selected electrical appliance's anomaly and energy consumption and integrating the concept of NILM with K-NN to facilitate employers to implement an effective time and attendance system for teleworking activities. The paper is organized as follows: in section "Methodology", discussion of the methodology used in this project. In section "Results and Analysis", the results of the classification algorithm implementation are discussed. Finally, conclusions are drawn in "Conclusion" section.

Vol. 1, No. 2, 2023
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2. METHODOLOGY

As depicted in Fig. 1, the main components of the NILM system consist of four types of electrical appliances namely laptop charger, kettle, fan, and mobile charger. The electrical appliances are linked to the 4-gang multi plug extension, that serves as single point entry of NILM system. To acquire data on power consumption from a single point, a current transformer will be clamped onto the extension's live wire. The current transformer sensor is connected to Arduino Uno for data collection through AC measurement circuit. The NILM algorithm will be developed to disaggregate the power usage of each appliance through a single point measurement of its signal load. The disaggregated data then will be further processed to classify the working events as 'Late' or 'On Time' based on the time the employee clocks in.

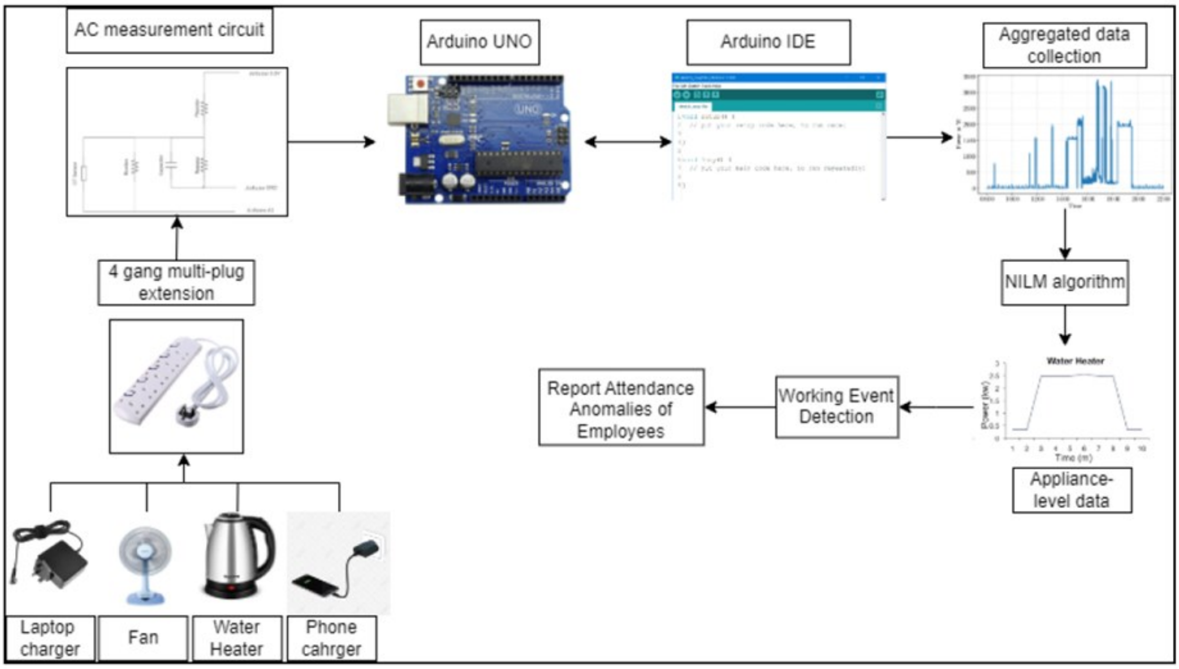

Fig. 1. The overall system for Teleworking using NILM and KNN Algorithm.

2.1. Data Collection of Teleworking Power Consumption

The experiment is conducted using four electrical appliances: phone charger (P), laptop charger (L), fan (F), and water heater (WH) which are the common appliances in any home. All the appliances will be plugged into a 4 gang multi-plug extension before being connected to the current transformer and AC current measurement circuit. The dataset provides appliance-level power consumptions along with aggregated power consumption. Since this project has four electrical appliances, there are sixteen probabilities of usage. The data on power consumption of all sixteen events will be acquired and stored in a CSV file. A fundamental part of NILM is detecting events accurately. Existing threshold-based event detection techniques rely heavily on the threshold that is selected manually. They are not expected to perform well on appliances that have similar power ranges. In this section, we propose event-based detection techniques that overcome all these challenges and accurately detect events of the appliances.

A total of 400 data are collected, labels with high accuracy each event of the aggregated signal with appliance mode transition as depicted in Table 1. The dataset obtained is properly

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labelled to events of the aggregated power signal. The datasets then will be uploaded into Jupyter Notebook to undergo code construction for the training and testing of the algorithm utilized in this work was conducted in Python language while using *sklearn* module for machine learning.

Table 1: Probability of Events for Monitoring Appliances

Events	State			
	Water Heater	Laptop Charger	Fan	Phone charger
1	OFF	OFF	OFF	OFF
2	OFF	OFF	OFF	ON
3	OFF	OFF	ON	OFF
4	OFF	OFF	ON	ON
5	OFF	ON	OFF	OFF
6	OFF	ON	OFF	ON
7	OFF	ON	ON	OFF
8	OFF	ON	ON	ON
9	ON	OFF	OFF	OFF
10	ON	OFF	OFF	ON
11	ON	ON	ON	OFF
12	ON	ON	ON	ON
13	ON	OFF	OFF	OFF
14	ON	OFF	OFF	ON
15	ON	ON	ON	OFF
16	ON	ON	ON	ON

2.2 Classifying Teleworking Event using KNN

Once the probability of events during teleworking has been identified (Table 1), the data will be classified using KNN algorithm. It identifies the classes of appliances from the extracted features and event detection results. In this work, the k-NN will find the data nearest neighbours' distance by utilizing the Euclidean distance calculation. K-nearest neighbour algorithm measures the distance between the test data and training data. For any test data, the attributes of the test data are compared with the previously trained data using distance measurement method. The k-NN algorithm is chosen as the classifier because this work only utilizes one feature to classify the appliance which is the power feature.

In the k-NN classifier, the number of nearest neighbours, k is varied, and the prediction accuracy for different k values is recorded. The highest percentage prediction accuracy with the corresponding training data set size, k value, is analysed. It is calculated by the square root of the sum of the squared differences of the values of horizontal axis, xi and vertical axis, yi. The formula, Eq. (1), used in Euclidean distance is as below:

$$d(x,y) = \sqrt{\sum_{i=1}^{m}(y_i - x_i)^2} \quad (1)$$

2.3 Confusion Matrix

The accuracy of an algorithm can be further evaluated using confusion matrix to evaluate the performance of the classification. Table 2 shows the confusion matrix for the two-class classifier that provide the visualization of the performance of the algorithm. Through the table, two sets of data will be compared with each other and show the number of instances that are correctly and incorrectly predicted. There are four basic terms that should be defined to complete the confusion matrix. The first type, true positives (TP), is the test result correctly predicted the presence of the condition. Second type, false positives (FP), corresponds to test result incorrectly predicted the presence of the condition and, it is false. The third type, true negatives (TN), refers to test result correctly predicted the absence of the condition and, it is true. The fourth type, false negatives (FN), refers to test result incorrectly predicted the absence of the condition and, it is false.

Table 2: Probability of Events for Monitoring Appliances

		Actual	
		+	-
Predicted	+	TP	FP
	-	FN	TN

3. RESULT AND ANALYSIS

3.1. Power Consumption of Appliances

After the analysing the power signals of the teleworking appliances, one observes that some of the appliances exhibit very similar power value distributions which causes difficulty in discriminating the appliances especially in cases where the power values fall in the range of more than one category. The dataset power consumption values and number of samples for each type of event are listed in Table 3. Fig. 2 shows the distribution of power values for sixteen different events of the appliances where it illustrates the extent of which the distribution of power values of the events overlapped with each other in graphical manner. The overlapped power value distributions pose difficulty to pre-define the threshold of the appliances.

Table 3: Power consumption values and number of samples for each event

			Power Rating	
Events	Appliances	No. of samples	Min (Watt)	Max (Watt)
1	All OFF	25	1.8	10.14
2	P	25	12.76	40.81
3	F	25	20.67	42.73
4	P, F	25	55.49	97.04
5	L	25	53.8	77.28
6	L, P	25	55.08	62.85
7	F, L	25	77.07	102.36
8	F, P, L	25	86.51	118.23
9	WH	25	1553.65	1576.06
10	WH, P	25	1559.42	1603.54
11	WH, L	25	1601.97	1613.39
12	WH, P, L	25	1597.37	1629.35
13	WH, F	25	1604.69	1620.4
14	WH, F, P	25	1616.02	1655.93
15	WH, F, L	25	1650.11	1672.17
16	WH, F, L, P	25	1681.78	1702.6

3.2 Classification of Teleworking

The experiment has been conducted by applying event-based detection as feature extraction and a machine learning model for data classification. From the training set size of 60% to 10%, it is observed that the training set size of 50%, at the number of nearest neighbours, k=5 produces the highest accuracy at 62%. Table 4 records the prediction accuracy for different k values. The highest percentage prediction accuracy with the corresponding training data set size, k value, is analysed.

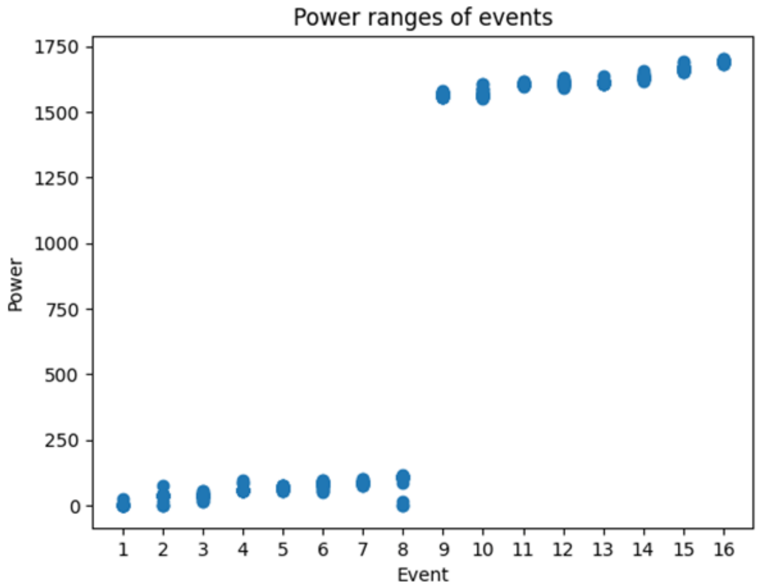

Fig. 2. Power distributions of the 4 appliances according to events

Table 4: k-NN prediction accuracy from varying training set size and k-value

Training (%)	k =1	k=2	k=3	k=4	k=5	k=6
10	60.28	57.77	50.55	41.667	46.11	40.55
20	60.625	55.0	50.312	53.75	55.31	47.19
30	58.93	57.86	55.714	55.714	55.714	60.714
40	60.42	60.0	61.25	62.92	60.83	62.08
50	59	58.5	57.5	60.5	62	59.5
60	60	56.875	57.5	59.375	60.625	60.625

3.3 Classifier Performance

To define the performance of the classification algorithm, confusion matrix was used. The matrix table as shown in Table 5, summarizes the number of testing data that are correctly classified and misclassified. In the analysis of confusion matrix, the predicted appliances are mapped to the actual appliances. The diagonal values represent the instances that are correctly predicted while others are wrongly predicted with other events.

From the confusion matrix in Table 5, it is observed that the classifier has difficulty in predicting between Event 2 and Event 3. There are 7 power events that belong to Event 2, but they are misclassified as Event 3 by the K-NN classifier algorithm. There are also 7 power events that belong to Event 4 but classified as Event 5 by the classifier. On top of that, from the confusion matrix table, it is observed that the K-NN classifier has difficulty in classifying Event 7. There are 9 power events of Event 7 that are misclassified as Event 6. This proved that the classifier is unable to discriminate Event 7 and Event 6. There are also 7 power events of Event 10 that are misclassified as Event 9. Besides that, there are also 6 power events in Event 11 and Event 13 that are misclassified as Event 12. It has already been observed that the appliances have similar power ranges and cause overlapping of power values. Overlapping of power values causes difficulty for the classifier to classify which switching events are occurring.

Table 5: Confusion Matrix for KNN Classifier

		Actual															
	Event	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
PREDICTED	1	12	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0
	2	0	9	0	0	0	1	0	0	0	0	0	0	0	0	0	0
	3	0	7	7	1	0	0	0	0	0	0	0	0	0	0	0	0
	4	0	0	0	9	0	0	1	0	0	0	0	0	0	0	0	0
	5	1	0	0	7	5	1	0	0	0	0	0	0	0	0	0	0
	6	0	0	1	1	1	2	9	0	0	0	0	0	0	0	0	0
	7	0	0	0	0	0	3	10	1	0	0	0	0	0	0	0	0
	8	1	1	1	0	0	0	0	8	0	0	0	0	0	0	0	0
	9	0	0	0	0	0	0	0	0	6	7	0	0	0	0	0	0
	10	0	0	0	0	0	0	0	0	6	6	0	0	1	0	0	0
	11	0	0	0	0	0	0	0	0	0	0	7	0	5	0	0	0
	12	0	0	0	0	0	0	0	0	0	0	6	2	6	0	0	0
	13	0	0	0	0	0	0	0	0	0	0	1	0	9	1	0	0
	14	0	0	0	0	0	0	0	0	0	0	0	1	0	11	1	0
	15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	1
	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11

3.4 Monitoring Working Event of Employees for Teleworking

After loading the data to the K-NN algorithm, the classified data will undergo a process where the timestamp of when the working event occurred was used to classify if the employee clock-in 'On Time' or 'Late' from the working event. Every company implements its own time and attendance policies based on the needs of the organization. This approach helps the employers to keep track of employees' working from home attendance and the implementation of this system can be useful for an organization to evaluate an employee's performance. In this project, the official working hours are specified to start at 8.00am.

Firstly, the program will classify Event 1, Event 2, Event 3 as 'Not Working'. This is due to the overlapping of power usage between fan and phone charger, which is Event 2 and Event 3. Since these two will be perceived as the same event by the algorithm, a condition was set where these two appliances need to be combined with other appliances to be considered as working. Next, the program classified the working event as 'On Time' if the employee clocked in at 8.00am sharp or earlier as shown in Fig. 3.

The implementation of this teleworking system could differ depending on the companies' policies and management style. However, regardless of the policies and management style, companies still need to process attendance of each employee working from home to improve operations and increasing productivity. Fig. 4 depicted the total of late ins by an employee in percentage. Having this information helps the management to determine the compliance rate of remote employees.

The labor law in Malaysia is regulated by Employment Act, 1995. The law governs the term and conditions of employment such as working hours, holidays, annual leave, and other employment conditions. By implementing an effective attendance system for work from home setting, the management will be able to analyze attendance anomalies. Attendance anomaly refers to any time discrepancy apart from the official attendance policy. After analyzing the attendance anomaly situation in the company, appropriate actions could be taken by the company to improve their operations.

	TIME	DATE	POWER	Prediction	Time in	Hour	Minute	Status
0	7:55:00	1/12/2022	77.28	6	2022-12-01 07:55:00	7	55	On time
1	8:01:00	2/12/2022	73.39	5	2022-12-02 08:01:00	8	1	Late
2	7:57:00	5/12/2022	60.94	4	2022-12-05 07:57:00	7	57	On time
3	8:07:00	6/12/2022	85.79	7	2022-12-06 08:07:00	8	7	Late
4	8:00:00	7/12/2022	50.76	4	2022-12-07 08:00:00	8	0	On time
5	7:59:00	8/12/2022	1569.25	9	2022-12-08 07:59:00	7	59	On time
6	8:20:00	9/12/2022	1561.44	10	2022-12-09 08:20:00	8	20	Late
7	7:50:00	12/12/2022	1557.21	10	2022-12-12 07:50:00	7	50	On time
8	8:00:00	13/12/2022	1601.97	11	2022-12-13 08:00:00	8	0	On time
9	7:51:00	14/12/2022	1686.34	16	2022-12-14 07:51:00	7	51	On time
10	7:59:00	15/12/2022	1692.79	16	2022-12-15 07:59:00	7	59	On time
11	8:22:00	16/12/2022	111.67	8	2022-12-16 08:22:00	8	22	Late
12	8:23:00	19/12/2022	26.45	3	2022-12-19 08:23:00	8	23	Not working
13	8:24:00	20/12/2022	2.66	1	2022-12-20 08:24:00	8	24	Not working
14	8:00:00	21/12/2022	33.36	3	2022-12-21 08:00:00	8	0	Not working
15	7:56:00	22/12/2022	53.55	4	2022-12-22 07:56:00	7	56	On time
16	8:02:00	23/12/2022	35.59	2	2022-12-23 08:02:00	8	2	Not working
17	8:00:00	26/12/2022	35.06	2	2022-12-26 08:00:00	8	0	Not working
18	7:51:00	27/12/2022	1616.96	13	2022-12-27 07:51:00	7	51	On time
19	8:11:00	28/12/2022	80.55	6	2022-12-28 08:11:00	8	11	Late
20	7:59:00	29/12/2022	155.47	8	2022-12-29 07:59:00	7	59	On time
21	10:51:00	30/12/2022	10.65	1	2022-12-30 10:51:00	10	51	Not working

Fig.3. The classified data showing staff working state.

On time	50.000000
Not working	27.272727
Late	22.727273

Fig. 4. The result of Teleworking monitoring system shows 22% late clock-in of an employee.

This work can be refined to develop a system that is more accurate in predicting working events of employees working from home. One of the suggestions was to count the duration of appliances switched ON during the day to monitor how many hours the employee worked in a day at home. This will ensure the accuracy to monitor working activity of the employees. Therefore, more data should be analyzed in the future for more accurate results in monitoring working events of the employees. Next, this project can also be improved by using more features such as harmonics or V-I trajectory and so on to further improve the classification of appliances.

4. CONCLUSION

In summary, from this project, the methods to improve the efficiency of employees' monitoring by the employer and at the same time respecting the privacy of employees have been discussed and implemented. By classifying the working events in the power consumption of electrical appliances used in teleworking activities, employees monitoring can be implemented.

For future work, this project can be refined to develop a system that is more accurate in predicting working events of employees working from home. One of the suggestions was to count the duration of appliances switched ON during the day to monitor how many hours the employee worked in a day at home. This will ensure the accuracy to monitor working activity of the employees. Next, this project can also be improved by using additional features to obtain the highest predictive performance. Besides that, more data should be analyzed in the future for more accurate results in monitoring working events of the employees.

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