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ESS-IoT: The Smart Waste Management System for General Household

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ABSTRACT

With the urban population's growth, unethical and unmanaged waste disposal may negatively impact the environment. In many cities, a massive flow of people in municipal buildings or offices has generated vast amounts of waste daily, which correlates to the enormous expenses of waste management. The critical issue for better waste management is waste collection and sorting. In this study, the Electronic Smart Sorting- Internet of Things (ESS-IoT) is proposed to assist people in better waste management. The ESS-IoT system uses Raspberry Pi 4b as the microcontroller with three modules, and it is designed with two main functions: waste collection and waste classification. The two main functions have been deployed separately in the literature, while this study has combined both functions to achieve a more comprehensive smart bin waste disposal solution. Waste collection is triggered by the overflow alarm mechanism that employs ultrasonic and tracker sensors. On the other hand, the waste classification is implemented using two classification algorithms: Random Forest (RF) prediction model and Convolutional Neural Network (CNN) prediction model. An experiment is conducted to evaluate the accuracy of the two classification algorithms in classifying various types of waste. The waste materials under investigation can be classified into

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four categories: kitchen waste, recyclables, hazardous waste, and other waste. The results show that CNN is the better classification algorithm between the two. Future work proposes the research extension by introducing an incentive mechanism to motivate the household communities using a cloud-based competition platform incorporated with the ESS-IoT system.

Keywords: IoT, machine learning, overflow mechanism, waste collection, waste classification, waste management

INTRODUCTION

With the advancement of modern society, waste management has gradually become a costly issue worldwide. Solid waste has also become a global issue concerning economic sustainability and environmental pollution (Ferronato & Torretta, 2019). One-third of the waste (34%) comes from high-income countries with growing populations. By the middle of the 21st century, the world's waste production is expected to reach 27 billion tons, of which 1/3 will come from Asia ("Global waste," 2018). In Asia, China and India generate more than 90% of the waste generated in the continent. India generates 133,700 tons of waste daily, where approximately only 91,572 tons are collected. The Indian government has paid a lot of money for recycling (Rana R, 2015). More than two-thirds of the cities in India are surrounded by garbage. Urban garbage dumps across the country have occupied 550,000 square kilometers of land. A quarter of the cities no longer have suitable places to stack garbage.

China's 40,000 townships and nearly 600,000 administrative villages generate more than 280 million tons of domestic waste each year. As a result, domestic waste in China has exceeded 8 billion tons. In Malaysia, economic growth has caused environmental burdens, including waste generation, greenhouse gas emissions from the energy system, and open burning (Nanda & Berruti, 2021). Aja and Al-Kayiem (2014) forecasted that Malaysia's solid waste had reached 33,000 tonnes per day, and expectedly 51,655 tonnes of waste per day will be generated by 2025 (Department of Statistics Malaysia, 2020).

This paper proposes an IoT-enabled smart waste management system, Electronic Smart Sorting-Internet of Things (ESS-IoT). Firstly, the system provides a solution to the waste disposal responsibility of waste in general household areas. Although 100,000 free dustbins were given to each household in several cities in Malaysia, the public still disposed of their waste irresponsibly. Only 24% was recycled or separated, and 76% of the waste was sent to landfills. Moreover, the waste overflow problem frequently happens due to the uncollected waste on time, which causes air pollution; wild insects and animals will consume and collect the overexposed waste, including different types of organic and inorganic waste that are potentially hazardous to the environment and public health

(Ivan, 2021). Secondly, the waste sorting problem is among Malaysian problems in waste disposal decisions. The assortment of waste is essential to avoid contamination, where the effectiveness depends on the behavior that requires education and cultivation (Low et al., 2016). Besides, people also face the problem of waste classification on municipal solid waste, which is one of the leading causes of environmental issues (Rana, 2015). To better understand the responsibility of waste disposal, people must learn the types of waste for better classification. However, achieving effective waste sorting and classification takes longer without a smart solution to detect waste disposal materials.

The proposed ESS-IoT system mainly has two main functions. The first is to improve existing waste collection procedures to minimize the hazards of hazardous waste accumulation and reduce the cost of waste collection. The system will collect the waste only if the capacity is up to 80%. The system also functions as a reminder for waste sorting or cleaning and clearing the waste before it overflows (Kumar et al., 2016). Secondly, to help residents sort waste when discarding it through visual imagery analysis with machine learning. This feature can also help reduce the workload of waste collection staff when sorting waste. Different types of waste can be handled in different ways more efficiently and reduce the cost of waste collection from the waste collection companies from sending unmanaged waste to landfills.

Sustainable waste management requires a long-term commitment from the public to establish a good habit of their waste disposal. The proposed ESS-IoT system will only focus on the technical side of waste bin management. Therefore, the motivation to use the ESS-IoT system is crucial for users to apply it in their homes. Any smart system assisting waste or resource separation should be a better move. Separation using manual or labor force should be assisted with innovative systems or fully through smart facilities. Any smart recognition system can be used at the household bins facilities for monitoring and reviewing the type of waste disposed of. Warning or alarms can be triggered when improper management or disposal of recyclable resources or materials to the garbage bins.

RECENT TECHNOLOGIES IN WASTE MANAGEMENT

Recently, many scholars have researched waste disposal technology (Dugdhe et al., 2016), but the research on waste bin monitoring is somewhat lacking. However, some of the technologies proposed by the previous researchers have good application prospects in this regard. Furthermore, in recent research, material waste collection and classification have been done individually (Al-Masri et al., 2019; Mirchandani et al., 2018), whereas both are yet to be combined.

Anagnostopoulos et al. (2020) proposed the city's smart waste bin project supported by the Internet of Things (IoT). Sushmitha et al. (2018) have considered bins with Wi-Fi-based sensors, and Fachmin et al. (2015) proposed a smart bin system to detect if the trash bin is full. The smart bin system collects data through multiple sensors transmitted via the Internet to detect waste overflow that may cause garbage toxicity and pollute the air if it does not collect. In some cases, the trash bin may not be full, but the trash in the bin has generated harmful gas. If this happens, the trash bin must be cleaned in advance (Anagnostopoulos et al., 2020). With a more efficient detection of waste overflow, a more organized duty cycle technique is also applied in the waste collection system to reduce power consumption and maximize the working time of the system. Therefore, collecting the waste is important as the application of a smart bin system with sensors has been proposed in several studies to encourage the participation of citizens (Pelonero et al., 2020).

The data collected by these sensors is sent to a central server via WiFi. Therefore, it needs internet services to function as it is. First, the communication mode of this system is based on WiFi, which means that the application scope of this system is relatively small, and it is unlikely to be widely used in a modern city. Besides, waste classification with the captured camera has been carried out by Al-Masri et al. (2019). Classification has been used on two types of smart bins to identify the waste: an artificial intelligence tool to label images based on a given trained set, and Microsoft's Custom Vision was used to classify the waste. A practical classification with IoT and modules is believed to be an advantage in overcoming waste classification caused by urbanization.

Wahab et al. (2014) proposed a collection monitoring system that rewards users based on the type and weight of waste in the trash bin. This system can encourage residents to sort garbage. If the user puts the wrong type of trash in a trash bin, the user's score will be deducted. However, this system is somewhat conceptual. Some aspects can be improved, such as multi-sensor systems or computer vision detecting garbage types. Besides, Fachmin et al. (2015), Chandra and Tawami (2020) have implemented the waste collection design. Ruiz et al. (2019) and Hanbal et al. (2020) have focused on waste image classification. However, the literature mentioned above shows only collection or classification; in other words, both works have been done separately. On the contrary, in this study, we combine both mechanisms of collection and classification to create an ESS-IoT smart bin that turns out to be a complete solution to fit our real-world daily waste disposal scenario. Besides, this study also proposes the potential of incorporating a reward system in future research to maximize the efficiency and participation of the citizens in recycling and therefore create a more comprehensive and smarter household waste management. Not only that, but this study also aims to motivate the community to recycle by creating a combined mechanism of collection and classification by skipping the hassle of checking the type of waste and the type of bins for different types of waste.

METHODOLOGY

The ESS-IoT system has two main functions, waste collection and waste classification. With respect to waste collection, trash bins in public places need to be cleaned up before the waste overflows. The overflow of waste in the trash bin will cause health problems for citizens and environmental problems. We apply and compare the performance of the Random Forest (RF) prediction model and Convolutional Neural Network (CNN) prediction model regarding waste classification. The RF algorithm builds multiple decision trees and merges them to get a more accurate and stable prediction (Hanbal et al., 2020). It is a supervised learning methodology for splitting, association, regression, and other assignments by influencing multiple decision trees during the training and testing process, then analyzing which class represents the mode of classification or predictive regression of decision trees. As a deep learning approach, the Convolutional Neural Network (CNN) has been widely used in image processing and classification tasks (Zeiler et al., 2014; Akshaya & Kala, 2020). Its effectiveness exceeds the expectation of enhancing feature representation capacity (Lim & Chuah, 2018) and quality prediction promotion (Shaily & Kala, 2020). More explanation of the theoretical aspects of RF and CNN can be found in Wu et al. (2021).

The ESS-IoT system consists of three modules: control, sensor, and servomotor. Figures 1 and 2 show the prototype of ESS-IoT. The control module comprises Raspberry Pi 4b and its extended board. The Raspberry Pi 4b has a Broadcom BCM2711, Quad-core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz, 4Gb LPDDR4-320 SDRAM has a built-in power supply system, an additional power supply module is not essential, and it is running Raspberry Operating System (OS). The Raspberry pi camera v2 camera module has a Sony IMX219 8-megapixel sensor. The camera module can be used to shoot high-definition video and still photos. The primary function of the control module is to process the information collected by the sensors and give commands to the servomotor module based on this information.

The sensor module comprises a camera, a display screen and four tracker sensors. The primary function of the sensor module is to collect data for the control module to process through the camera and sensor. It can be said that the system relies entirely on sensor modules to obtain external information. For example, tracker sensors are used to detect the fullness of trash bins. A tracker sensor is an infrared tracking sensor often used to make tracking smart cars. The tracker sensor uses ITR20001/T infrared reflection sensor. The infrared emitting diode of the ITR2001/T sensor continuously emits infrared rays. When objects reflect the emitted infrared rays, they are received by the infrared receiver and output analog values. The output simulation value is related to the distance of the object and the color of the object. By calculating the analog value of five outputs, the position of the trace line can be judged.

The servomotor model is SG90 which has an operating voltage ranging from 4.8V to 6V, operating speed is 0.1s/60^{o} and works on brushed DC motor type. The module comprises a servomotor, trash bins and several wires. The main function of this part is to execute the commands issued by the control module to control the opening and closing of the trash bin lid. Servomotors are divided into two major categories: DC and AC servo motors. The main feature of this device is that there is no rotation when the signal voltage is zero. The waste materials were fresh and from the researchers' household disposal during the usual condition and activities at home.

At first, the trash can is tested with the waste collection. Then, the depth of the trash bin is measured if the trash bin is over 7 cm, 6 cm, 4 cm or below 3 cm. Figure 3 explains the flowchart of ESS-IoT waste collection. After testing out the overflow mechanism in the phase of waste collection, the ability of ESS-IoT on waste classification is tested using the solid waste from the household residential areas. In order to assimilate the real-world domestic waste disposal scenario, we collect many different types of materials for classification. As an example, for domestic kitchen waste, we carry out single-type classification and mixed kitchen waste classification. It is because, in actual life, residents usually dispose of kitchen waste by placing all the kitchen waste together, which is more similar to mixed kitchen waste. The same methodology goes to classifying other categories of waste, where materials are classified on their own or mixed, as reported in Tables 2, 3 and 4.

The waste classification feature in the ESS-IoT system is implemented using two different techniques, which are the Convolutional Neural Network (CNN) and Random Forest (RF) classifier. An experiment was carried out to evaluate the performance of these two techniques. A one-dimensional 9-layer CNN is considered in the experiment. CNN is a network that consists of the input layer, convolution layer, pooling layer, fully-connected layer, and output layer. On the other hand, the RF builds many decision trees and randomly selects attributes from random samples. Data samples of each waste material are split into 60% training and 40% testing. In the phase of waste classification, the average classification performance of 100 trials is recorded.

For all the experiments, the lids of the different color trash bins will open based on the classification result of the object. As illustrated in Figure 2, a green bin is dedicated to kitchen waste, a blue bin for recyclable waste, a red for hazardous waste, and a grey for other waste.

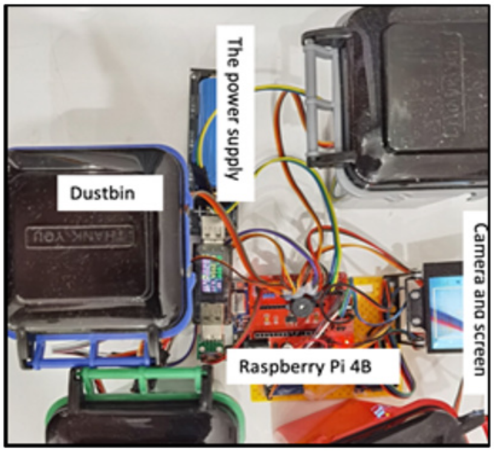

Figure 1. The prototype of the ESS-IoT system (Top view)

Figure 2. The prototype of the ESS-IoT system during the classification test (Front view)

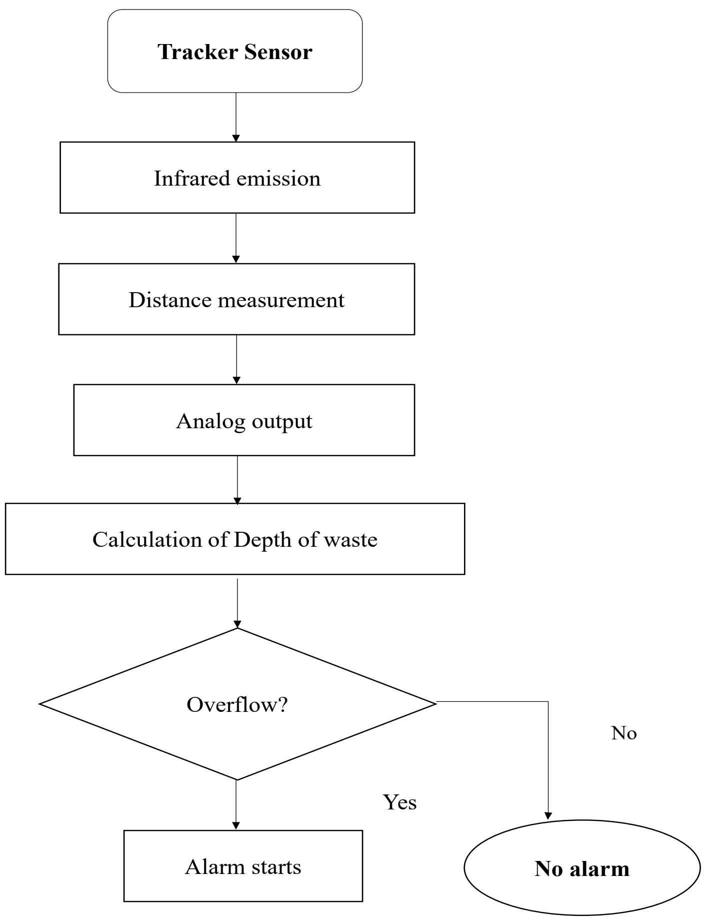

Figure 3. Flowchart of the ESS-IoT system algorithm for waste collection

RESULTS

Trash Overflow Alarm

One of the core functions of the ESS-IoT system is to trigger waste collection via an overflow alarm mechanism, which exists to detect whether there is too much garbage in the trash bin. When rubbish piles up in the trash bin, it will produce unpleasant odors and produce many bacteria in the trash bin. In addition, the mosquitoes and flies produced in trash bins can spread pathogens of infectious diseases and endanger the health of residents. This mechanism will notify and remind relevant personnel to dispose of the overflowing garbage bin as soon as possible, ensuring a cleaner and healthier living environment for residents. The realization of this function mainly depends on the tracker sensor. Table 1 shows the results of the overflow mechanism of 5 distances of depth from the sensor, less than or equal to 3 cm, 4 cm, 5 cm, 6 cm and more than or equal to 7 cm. The ESS-IoT system misses two alarms out of 20 tests when the test condition is five centimeters away, which is the critical distance. Overall, the performance is excellent, with close to 100% accuracy.

Table 1
Results of overflow alarm mechanism

Distance	Test count	Number of alarms	Accuracy
Greater than or equal to 7 cm	20	0	100%
6 cm	20	0	100%
5 cm	20	18	90%
4 cm	20	20	100%
Less than or equal to 3 cm	20	20	100%

Waste Classification

The waste classification feature in the ESS-IoT system is implemented using two different techniques, which are the Convolutional Neural Network (CNN) and Random Forest (RF) classifier. The dataset under investigation can be classified into four categories: kitchen waste, recyclables, hazardous waste, and others. The data samples comprise various melon peels, leftovers, and mixed kitchen waste for the kitchen waste category. The data samples for the recyclable waste category include plastic bottles, glass bottles, scrap metal, scrap paper, and other forms of plastics commonly used daily. The data samples for the hazardous waste category consist of ordinary hazardous wastes such as batteries, fluorescent tubes, wastewater silver thermometers, and expired medicines. These kinds of wastes require special safe treatment. Other waste includes bricks, ceramics, muck, porcelain fragments, animal excrement, disposable items and other wastes that are difficult to recycle. The images are captured by placing the object on a white poster board and using sunlight or room lighting. All the images have been resized to a spatial resolution of 512 × 384. The results are recorded in Table 2 for kitchen waste, Table 3 for recyclables, Table 4 for hazardous waste, and Table 5 for other types of waste.

Table 2

Classification result of kitchen waste (green bin)

Category: Kitchen Waste		CNN Classification		RF Classification	
Type	Material	Average Accuracy	Average Responses Time (s)	Average Accuracy	Average Responses Time (s)
Peel	Watermelon rind	94%	1.72	64%	3.55
	Durian skin	89%	1.69	58%	4.32
	Banana peel	90%	1.70	61%	4.17
Leftovers	Gruel	87%	1.65	69%	3.89
	Rice	82%	1.74	48%	3.55
	Chicken bone	91%	1.68	57%	4.03
Mixed kitchen waste	Peel and gruel	89%	1.78	49%	4.34
	Peel and rice	82%	1.69	67%	3.98
	Peel and chicken bone	92%	1.74	73%	4.12

The study demonstrates the ability of ESS-IoT to handle different categories of waste. Table 2 shows the types of kitchen waste used for classification and how they are applied (single type or mixed waste) during the classification process. Table 2 reports the classification results of CNN and RF classifiers in terms of average accuracy and average response time of ESS-IoT. It can be observed that peel wastes are more correctly classified than leftovers. It could be due to the appearance of leftovers being a bit slimy and different textures that render the classification task more challenging. Using a CNN classifier, the classification accuracy rate can vary between 82% to 94% depending on materials for kitchen waste. In actual life, residents usually dispose of kitchen waste by placing all the kitchen waste together, which is more similar to mixed kitchen waste. ESS-IoT is also applied to classifying mixed kitchen waste to assimilate a real-world scenario. The results are reasonably impressive, with an average accuracy rate of 87.7%.

Table 3

Classification result of recyclables (blue bin)

Category: Recyclables		CNN Classification		RF Classification	
Type	Material	Average Accuracy	Average Responses Time (s)	Average Accuracy	Average Responses Time (s)
Metal	Can	96%	1.59	62%	4.61
	Iron sheet, iron nail	84%	1.64	54%	4.32
	Copper wire	87%	1.70	63%	4.75
Wastepaper	Book	94%	1.70	73%	3.90
	Newspaper	96%	1.74	71%	4.51
	Wrapping paper	90%	1.69	54%	3.74
Plastic	Plastic bags or plastic packaging	97%	1.75	78%	4.35
	Mineral water bottles	95%	1.72	76%	4.66
	Plastic toys	87%	1.64	43%	3.41
Waste glass	Glass cup	95%	1.69	65%	4.96
	Glass bottle	96%	1.78	69%	4.81
	Mirror, lens	90%	1.67	50%	3.79

In the second category, which is the recyclables, Table 3 shows that the CNN model has a high accuracy rate (an average of 89% or higher) in identifying recyclables. However, the model has relatively low accuracy in identifying iron nails and copper wires. The reason could be due to the small size of this waste or its slender shape so that the control module cannot extract the necessary information from the photos.

Table 4

Classification result of hazardous waste (red bin)

Category: Hazardous Waste		CNN Classification		RF Classification	
Type	Material	Average Accuracy	Average Responses Time (s)	Average Accuracy	Average Responses Time (s)
Used batteries	Button batteries	79%	1.77	68%	4.32
	Lithium battery	89%	1.72	60%	4.61
	Power bank	82%	1.64	54%	4.17

Table 4 *(Continue)*

Category: Hazardous Waste		CNN Classification		RF Classification	
Type	Material	Average Accuracy	Average Responses Time (s)	Average Accuracy	Average Responses Time (s)
Expired drugs	Capsule	93%	1.79	36%	4.64
	Pill	85%	1.58	45%	4.33
	Medical gauze	91%	1.65	48%	3.79
End-of-life mercury measuring instruments	Mercury thermometer	94%	1.69	58%	4.21
	Mercury sphygmomanometer	96%	1.70	65%	4.29
Waste fluorescent tube	Fluorescent tube	95%	1.63	72%	3.98
	Halogen lamp	96%	1.71	64%	4.07

Table 5

Classification result of other waste (grey bin)

Category: Other Waste	CNN Classification		RF Classification	
Material	Average Accuracy	Average Responses Time (s)	Average Accuracy	Average Responses Time (s)
Brick and Ceramics	89%	1.63	65%	4.39
Muck	94%	1.73	72%	4.16

Table 4 compares the classification accuracy of CNN and RF classifier in identifying the various hazardous wastes. The classification accuracy rate of the used batteries is slightly lower than that of the other types of items in the category, with an average of 83.33%. On the other hand, the CNN classifier shows excellent accuracy in end-of-life mercury measuring instruments and fluorescent tubes, with an average accuracy of close to 95%. Last but not least, in terms of other waste, it can be observed from Table 5 that the CNN model shows a much better classification rate for identifying other waste which is not fit into any of the three categories mentioned above; the average accuracy rate ranges from 89 % to 94%. Thus, it can be concluded that ESS-IoT can perform well in real-life applications.

DISCUSSION

Discussion and Implication

The bigger issue of the waste problem is separation at the source. Not all residents or populations practice this habit. Technology-based assistance such as the one proposed in this study that can be developed to curb the issue of waste separation will be highly demanded, especially when the volume of recycled items is in piles and unmanaged. Smart systems would contribute to better waste management since manual separation is time and labor-intensive. On the waste collection aspect, ESS-IoT has the detection of waste overflow that has an accuracy of 90 – 100% that will notify the waste collection party to change the route of waste collection, the reduction of frequency in traveling around the household area can reduce the cost associated to fuel consumption (Bansode et al., 2021). We believe appropriately planned waste collection save waste not only collection costs but also labor cost. In the long run, a smart overflow detection mechanism assists the public in deciding on waste disposal and controlling the animals from fetching and scattering the waste that may be an extra cost to the municipalities.

The ESS-IoT system uses IoT and machine learning for waste collection and classification tasks. IoT has enabled sensors to track the depth of waste and cameras to shoot high-resolution images for visual imagery analysis for waste classification by CNN and RF classifiers. Experimental result has shown the effectiveness of the proposed system with an accuracy of 90 - 100% to detect five different garbage levels in a trash bin and give an alarm if the bin is full.

In terms of waste classification, the CNN classifier shows higher accuracy than the RF classifier. CNN classifier shows a better classification rate. However, CNN training requires a significant amount of labeled data to be trained. Collecting labeled data is costly. Furthermore, the labeling criteria may differ from dataset to application, even for the same applications. It is critical to reduce the amount of data to be labeled and allow CNN training with partially and flexibly labeled data. Shifting from heavily supervised to weakly supervised learning is recommended to make CNN more applicable to the ESS-IoT system (Wang et al., 2020).

Limitation and Future Works

This study only tested five different garbage levels in a trash bin. Alarms are triggered on almost all 20 tests, except for the two tests of 5cm distance from the detector. Nevertheless, the test shows promising results, which bodes well for the future of the proposed system.

The ESS-IoT system has several limitations on the classification of the materials. First, up to the current stage of the study, the ESS-IoT only focuses on four categories, 13 types and 31 kinds of materials closely related to general household waste, which are different from commercial and industrial waste that contain highly contaminated chemical substances, heavy metal, radioactive substances and toxic fumes and smoke.

General household waste also leads families in the municipalities to practice ethics and manage household waste disposal that could be brought to the workplace culture and the industry. Therefore, the ESS-IoT system is proposed to extend its future works to the general household with an integration of a cloud-based community incentive system where families around the different households (i.e., terrace, semi-detached, condominium, flat and bungalow communities) can gather and compete with each other to receive incentives or rewards. It is aimed to develop a sustainable habit within the community through extrinsic motivation.

CONCLUSION

The ESS-IoT system uses IoT and machine learning for waste collection and classification tasks. Experimental result has shown the effectiveness of the proposed system in waste management, i.e., overflow mechanism to properly trigger waste collection and disposal according to waste type classification. There are still many areas to explore with the possibilities of the microcontroller nowadays that could extend to numerous versatile modules that effectively solve daily activities. The incorporation of machine learning, like the proposed ESS-IoT, has also extended the potential of analysis from the gathered data. It has also fulfilled the demand of current data-centric fast-growing cities.

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REFERENCES

Aja, O. C., & Al-Kayiem, H. H. (2014). Review of municipal solid waste management options in Malaysia, with an emphasis on sustainable waste-to-energy options. *Journal of Material Cycles and Waste Management, 16*, 693-710. https://doi.org/10.1007/s10163-013-0220-z

Al-Masri, E., Diabate, I., Jain, R., Lam, M. H., & Reddy, N. S. (2019). Recycle.io: An IoT-enabled framework for urban waste management. In *Proceedings. 2018 IEEE International Conference on Big Data, Big Data* (pp. 5285-5287). IEEE Publishing. https://doi.org/10.1109/BigData.2018.8622117

Anagnostopoulos, T., Zaslavsky, A., Ntalianis, K., Anagnostopoulos, C., Ramson, S., Shah, P., Behdad, S., & Salmon, I. (2020). IoT-enabled tip and swap waste management models for smart cities. *International Journal of Environment and Waste Management*, *28*(4), 521-539. https://doi.org/10.1504/IJEWM.2021.10042472

Akshaya, B., & Kala, M. T. (2020). Convolutional neural network based image classification and new class detection. In *Proceedings of 2020 IEEE International Conference on Power, Instrumentation, Control and Computing* (pp. 1-6) IEEE Publishing. https://doi.org/10.1109/PICC51425.2020.9362375

Bansode, P., Rasal, P. V., Waste, S., & City, S. (2021). Smart waste management for smart city using IoT. *Journal of Science and Technology, 6*(1), 53-58.

Chandra, R. P., & Tawami, T. (2020). Design of smart trash bin. In *IOP Conference Series: Materials Science and Engineering: Material Science Engineering* (Vol. 879, p. 012155). IOP Publishing Limited. https://doi.org/10.1088/1757-899X/879/1/012155

Department of Statistics Malaysia. (2020, November 27). *Compendium of Environment Statistics, Malaysia 2020* (Press Release). Department of Statistics Malaysia. https://www.dosm.gov.my/v1/index.php?r=column/pdfPrev&id=TjM1ZlFxb3VOakdmMnozVms5dUlKZz09

Dugdhe. S., Shelar, P., Jire, S., & Apte, A. (2016). Efficient waste collection system. In *Proceedings of the International Conference on Internet of Things and Applications (IOTA)* (pp. 143-147) IEEE Publishing. https://doi.org/10.1109/IOTA.2016.7562711

Fachmin, F., Low Y. S., & Yeow W. L. (2015). Smartbin: Smart waste management system. In *IEEE Tenth International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP*) (pp. 1-2). IEEE Publishing. https://doi.org/10.1109/ISSNIP.2015.7106974

Ferronato, N., & Torretta, V. (2019). Waste mismanagement in developing countries: A review of global issues. *International Journal of Environmental Research and Public Health, 16*(6), Article 1060. https://doi.org/10.3390/ijerph16061060.

Hanbal, I. F., Jeffrey, S. I., Neal, A. O., & Hu, Y. (2020). Classifying wastes using random forests, gaussian naïve bayes, support vector machine and multilayer perceptron. *International Conference Series: Material Science Engineering, 803*, Article 012017. https://doi.org/10.1088/1757-899X/803/1/012017.

Ivan, L. (April 07, 2021). Council to give out free rubbish bins to residents *The Star.* https://www.thestar.com.my/metro/metro-news/2021/04/07/council-to-give-out-free-rubbish-bins-to-residents

Kumar, N. S., Vuayalakshmi, B., Prarthana, R. J., & Shankar, A. (2016). IoT based smart garbage alert system using Arduino UNO. In *Proceedings of 2016 IEEE Region 10 Conference (TENCON)* (pp. 1028-1034). IEEE Publishing. https://doi.org/10.1109/TENCON.2016.7848162

Lim, M. G., & Chuah, J. H. (2018). Durian types recognition using deep learning techniques. In *Proceedings of the 9th IEEE Control and System Graduate Research Colloquium (ICSGRC)* (pp. 183-187). IEEE Publishing. https://doi.org/10.1109/ICSGRC.2018.8657535

Low S. T., Tee S. Y., & Choong W. W. (2016). Preferred attributes of waste separation behaviour: An empirical study. *Procedia Engineering, 145*, 738-745. https://doi.org/10.1016/j.proeng.2016.04.094

Mirchandani, S., Wadhwa, S., Wadhwa, P., & Joseph, R. (2018). IoT enabled dustbins. In *Proceedings of the 2017 International Conference on Big Data, IoT and Data Science* (pp. 73-76). IEEE Publishing. https://doi.org/10.1109/BID.2017.8336576

Nanda, S., & Berruti, F. (2021). Municipal solid waste management and landfilling technologies: A review. *Environmental Chemistry Letters, 19*(2), 1433-1456. https://doi.org/10.1007/s10311-020-01100-y

Pelonero, L., Fornaia, A., & Tramontana, E., (2020). From smart city to smart citizen: Rewarding waste recycle by designing a data-centric IoT-based garbage collection service. In *Proceedings of 2020 IEEE International Conference on Smart Computing (SMARTCOMP)* (pp. 380-385). IEEE Publishing. https://doi.org/10.1109/SMARTCOMP50058.2020.00081

Rana, R., Ganguly. R., Ashok, K. G., (2015). An Asssessment of solid waste management in Chandigarh City, India. *Electronic Journal of Geotechnical Engineering, 20*, 1547-1572.

Ruiz, V., Sanchez, A., Velez, J. F., & Raducanu, B. (2019). Automatic image-based waste. In J. M. F. Vicente, J. R. A. Sanchez, F. D. L. P. Lopez, J. T. Moreo & H. Adeli (Eds), *From Bioinspired Systems and Biomedical Applications to Machine Learning* (pp. 422-431). Springer Nature. https://doi.org/10.1007/978-3-030-19651-6

Shaily, T., & Kala, S. (2020). Bacterial image classification using convolutional neural networks. In *Proceedings of the IEEE 17th India Council International Conference (INDICON)* (pp. 1-6). IEEE Publishing. https://doi.org/10.1109/INDICON49873.2020.9342356

Sushmitha, N., Veena, R. C., Ajay, K., Ajith, D., & Yasaswi, K. (2018). An IoT based waste management system for smart cities. *International Journal of Emerging Technologies and Innovative Research, 5*(12), 202-205.

The World Bank. (2018, September 20). *Global waste to grow by 70 percent by 2050 unless urgent action is taken: World Bank report*. (Press Release). https://www.worldbank.org/en/news/press-release/2018/09/20/global-waste-to-grow-by-70-percent-by-2050-unless-urgent-action-is-taken-world-bank-report

Wahab, M. H. A., Kadir, A. A., Tomari, M. R., & Jabbar, M. H. (2014). Smart recycle bin: A conceptual approach of smart waste management with integrated web based system. In *Proceedings of 2014 International Conference on IT Convergence and Security (ICITCS)* (pp. 1-4). IEEE Publishing. https://doi.org/10.1109/ICITCS.2014.7021812

Wang, S., Chen, W., Xie, S. M., Azzari, G., & Lobell, D. B. (2020). Weakly supervised deep learning for segmentation of remote sensing imagery. *Remote Sensing, 12*(2), Article 207. https://doi.org/10.3390/rs12020207

Wu, M., Lu, Y., Yang, W., & Wong, S. Y. (2021). A study on arrhythmia via ECG signal classification using the convolutional neural network. *Frontiers in Computational Neuroscience, 14*, 1-10. https://doi.org/10.3389/fncom.2020.564015

Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In D. Fleet, T. Pajdla, B. Schiele & T. Tuytelaars (Eds.), *Computer Vision-ECCV 2014, Lecture Notes in Computer Science*, (Vol. 8689). Springer. https://doi.org/10.1007/978-3-319-10590-1_53