Smart garbage bin: Garbage growth behavior prediction

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Abstract: Presently in the heart of many major cities globally, there exist several smart garbage systems based on the Internet of things (IoT). Likewise, there are different traditional garbage management systems at levels of cities and municipals with fixed collection schedules. However, to learn garbage growth behavior in a single house level at different times and predicting future amounts for the next collection schedule is paramount. Therefore, in this study, we design and develop a smart garbage bin embedded with ToF (time of flight), DHT22 (temperature and humidity), and load cell sensors and Wi-Fi interface. With the prototype of the garbage bin, we conducted a preliminary deployment of a customized smart garbage bin in a student laboratory. Using a Wi-Fi gateway data were sent into a ThingSpeak cloud platform, thus enhancing the smart bin system's ubiquity. A machine learning method for continuous-time series forecasting ARIMA with a fixed forecast slide window size of 2-4-7 days on the split training size was applied in learning the garbage growth and predicting future garbage behavior. The ARIMA model was evaluated based on the performance measurement values of average mean absolute error and standard deviation. Training the model with N=20 number of observations given with the 4-window size provided the average mean absolute of 5.17 cm and the standard deviation of 0.33 cm, thus was considered the best accuracy on the garbage growth prediction. The ARIMA model found to be suitable for predicting future garbage growth behavior; therefore, enhancing flexibility in the garbage collection schedule and the frequency of changing garbage bags in the smart bin.

1. Introduction

In recent times, many studies on Internet of Things (IoT), "smart cities" and "smart homes" have been conducted. Over decades, the main goal has remained the same, to apply ubiquitous sensing to enhance the human experience [1]. Owing to the characteristics and merits of IoT services, garbage management has also become a significant domain attracting a number of IoT studies. The current IoT applications for improving domestic garbage management services such as Radio Frequency Identification (RFID) [2], [3] as well as proximity sensors [4], [5] have been helping users to take data-driven actions ahead of time through real time monitoring, transfer of data into specified storage as well as sending notifications to the relevant authorities using communication technologies such as GSM and Wi-Fi. On the other hand, cities and municipals have also introduced long term garbage generation analysis and predictions models [6], [7], [8] for best route plan of garbage collection and future data predictions.

Apart from this technological revolution of IoT smart garbage management systems as shown in **Fig. 1**, different countries have different traditional garbage management systems at various levels such as cities and municipals levels. Japan as a case base for this study is known as an exceedingly clean and eco-friendly country [24]. The cities, towns, and districts have completely different garbage management systems that are said to be efficient and effective. Taking a walk in a Japanese city, one would rarely find a public garbage bin. In most cases, distinct types of bins are installed in an area comprising of burnable, plastic, pet bottles and cans garbage bins. The disposal and sorting is strict and complex.

Likewise, at the household level, every household is responsible of proper management and disposal of own garbage. This is by sorting and disposing garbage in a specific colored bag that are then put outside the house on the right collection day based on the city's fixed garbage collection schedule as is set by a particular city (Fig. 1). For example, in Ikoma city found in Nara prefecture [25] burnable garbage are scheduled to be collected twice a week on Mondays and Thursdays, while plastic garbage is collected once a week whereas the rest garbage such as glass, cans, pet bottles, fragile items and toxic waste are collected twice a month. Nonetheless, such existing systems are city based and unfriendly in learning garbage growth behavior for a single house at different times in a day, a week, or a month. This results in unnecessary garbage collection trips, thus adding up to the cost of operation and lack of proper household garbage growth records that are essential for appropriate city planning and management.

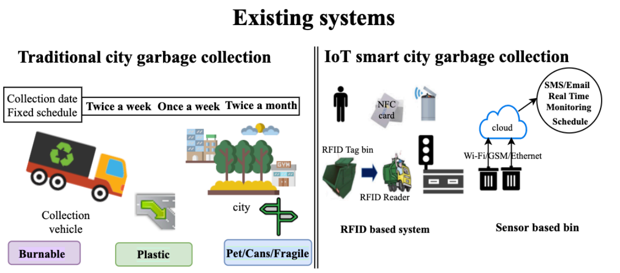

Fig. 1 Overview of traditional and smart city garbage management systems

Interestingly, there is yet inadequate studies on IoT based

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garbage management systems that can learn growth behavior of garbage in a smart bin and predict its future growth at a single house, in realization of garbage generation in a season such as day of a week for example a weekend; time of the day such as morning time or evening time, rather than solely monitoring the level of garbage to notify the authority or owners based on their configurations. For instance, garbage disposal at a university laboratory would fluctuate based on many factors such as a day of the week. It is obvious that while there would be so much garbage on weekdays, there is less on weekends.

This paper aims to introduce a customized smart garbage bin capable of Big data collection of user's garbage disposal routine using some sensors and Wi-Fi communication technology. Further, to establish and predict a house based garbage growth behavior patterns and collection schedule. The understanding of garbage disposal growth rates and predictions of growth behavior is vital for practical and efficient garbage management.

2. Related work

This section presents a thorough discussion on existing IoT based smart garbage management solutions.

IoT based smart garbage solutions have been implemented at the heart of major cities in the world such as Seoul-Republic of Korea, Varese- Italy, Hong Kong, Barcelona- Spain, Singapore, and Stockholm- Sweden [5], [9], [10]. In these cities, smart bins are equipped with sensors that provide users with ability to know the fill-level (volume) of each waste container in real time. These bins are equipped with a live monitoring platform which helps the waste collection staff to plan ahead on how collections should be implemented, targeting only the locations of full garbage bins [10].

Mostly, there are different technological approaches for implementing such application solutions. For instance, studies in [4],[11] developed a smart and wireless waste management system using a load cell, ultrasonic sensors, and GSM module, which used to notify either the bin is full or emptied. Besides, the work in [12] developed a cloud-integrated and wireless waste management system for smart cities involving a combination of infrared (IR), ultrasonic sensor, temperature sensor, (MQ2) gas sensors and load cell in monitoring and storing the information about waste status in a bin. Some approaches focus on RFID technology where the smart bin embedded with RFID tags, and the collection vehicle is installed with the RFID reader to detect smart bins during waste collection in the city [13],[3],[14].

Likewise, to implement measures on reduction and recovery of waste, [2] introduced iBags using RFID. Further, other studies used RFID technology to build smart garbage management system such as in Seoul, Korea [10] and The Hong Kong Polytechnic University [9] where NFC card was launched, for users to open the bin a verification process is done by pairing up with the user's card and charged based on weight measured.

Broadening to the approaches of IoT based garbage management, machine learning techniques have also been involved. Whereby a study [15] applied a linear regression model on prediction future garbage generation using level values from the ultrasonic sensor and population as main variables. Also, some studies [16],[6] applied decision tree and Time-series algorithms respectively in predicting and modeling future garbage generation and plan for the best route for garbage collection using sensor filling level as an influential variable for predictions. Moreover, efforts are devoted at municipal and city levels on predictions and modeling of future garbage generation and collection at their levels in overall [7],[8],[17]. This provides benefits to the authorities in estimating and allocating essential resources needed in the future for garbage management and formulating alternative strategies to influence the attainability of sustainable goals [6].

However, these approaches have been exclusively helping users conduct real-time monitoring, taking data-driven action ahead of time, sending a notification for full waste bins, predicting, and planning for the best garbage collection route. Yet, it is indeed vital to understand and learn the growth behavior of garbage in a smart bin and predict future growth at the single house level in a season. This remains significant for future decision making in ensuring effective as well as efficient garbage management. Hence, we developed a customized smart garbage bin, suitable for Big garbage data collection, learn garbage growth behavior, and predict future garbage growth amounts.

3. Methods and tools

3.1 System requirements

In this section, we describe system requirements for the proposed customized smart garbage bin. Based on the discussions in Sections 1 and 2, there are the following two main requirements for a smart bin system:

Req 1: It should detect a particular garbage variable and upload it to the specified cloud storage at a defined programming time interval via a wireless gateway. Also, ensure real-time data visualization.

Req 2: It should be able to conduct data analysis and predictions of future garbage growth.

3.2 Proposed smart garbage system

The proposed system's block diagram comprises three main layers, as shown in **Fig. 2**: Hardware layer, Cloud service layer, and Processing and control layer. In particular, the smart bin collects bin's status data and then instantly sends it to the cloud platform via a gateway. Later, machine learning methods are applied for data analysis and prediction. The following is the explanation of each part of the proposed system. On the other hand, **Fig. 3** provides an overview of the proposed smart garbage bin system.

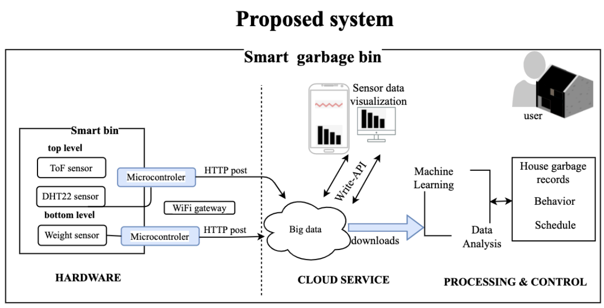

Fig. 2 Block diagram for proposed smart garbage system

Table 1 A summary of studies used different technologies in the development of IoT-based smart garbage systems

Reference	Wi-Fi	GSM	RFID	ZigBee	Ultrasonic sensor	Infrared sensor	Load cell	DHT11/22	MQ2/135	Camera	ToF
[18]	*O*	*X*	*X*	*X*	*X*	*O*	*O*	*X*	*X*	*X*	*X*
[19]	*X*	*O*	*X*	*X*	*X*	*X*	*O*	*X*	*X*	*O*	*X*
[3]	*X*	*O*	*O*	*X*	*O*	*X*	*X*	*X*	*X*	*X*	*X*
[2]	*X*	*X*	*O*	*O*	*X*	*X*	*X*	*X*	*O*	*O*	*X*
[20]	*X*	*O*	*X*	*O*	*O*	*X*	*O*	*X*	*X*	*X*	*X*
[10]	*X*	*X*	*O*	*X*	*X*	*X*	*X*	*X*	*X*	*X*	*X*
[4]	*X*	*O*	*X*	*X*	*O*	*X*	*O*	*X*	*X*	*X*	*X*
[9]	*X*	*X*	*O*	*X*	*O*	*X*	*O*	*X*	*X*	*X*	*X*
[12]	*X*	*O*	*X*	*X*	*O*	*X*	*X*	*O*	*O*	*X*	*X*
[21]	*O*	*X*	*X*	*X*	*O*	*X*	*X*	*X*	*X*	*X*	*X*
[14]	*X*	*X*	*O*	*X*	*O*	*X*	*X*	*X*	*X*	*X*	*X*
[22]	*X*	*O*	*X*	*X*	*O*	*X*	*X*	*O*	*X*	*X*	*X*
[11]	*X*	*O*	*X*	*X*	*O*	*X*	*O*	*X*	*X*	*X*	*X*
[23]	*O*	*X*	*X*	*X*	*O*	*X*	*X*	*X*	*X*	*X*	*X*
our system ∗	*O*	*X*	*X*	*X*	*X*	*X*	*O*	*O*	*X*	*X*	*O*

∗ *O = YES, X = NO*

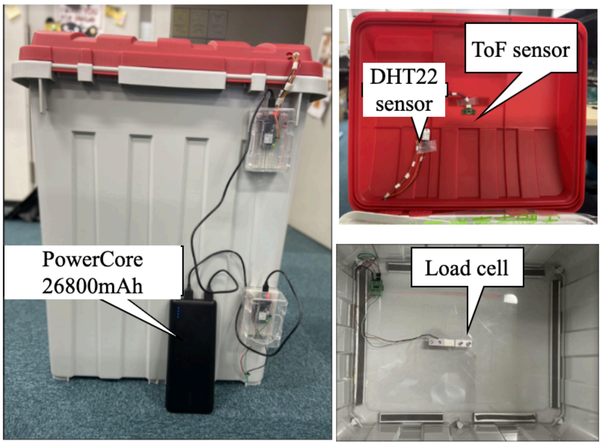

Fig. 3 Smart garbage bin overview

3.2.1 Hardware layer

The Hardware layer comprises the hardware used in developing the proposed smart garbage bin system with two levels; bottom and top shown in Fig. 2. By which Adafruit feather m0 Wi-Fi atsamd21 + atwinc1500 Microcontroller placed in the heart of the system connected to the sensors. The Adafruit feather m0 has a built-in Wi-Fi module hence providing ubiquity, ease of setup of the system. We considered exploring other related studies used different technologies in the development of IoT-based smart garbage systems see **Table 1**, where communication technologies such as RFID, GSM, Wi-Fi, and ZigBee enhanced garbage data transfer during real-time monitoring. Besides, sensor technologies such as ultrasonic, infrared, load cell, and DHT22, provided the measurements of the garbage status. The review from other related studies found that the ToF sensor has not yet commonly considered in developing an IoT-based smart garbage system. In contrast, ultrasonic and infrared sensors are found to be popular. Thus, in the present study, we ultimately chose the time of flight (ToF) sensor. The ToF sensor is not affected by the colour of the target object compared to the infrared sensor. Also, compared to the ultrasonic sensor ToF sensor does not critically depend on the angle of incidence, and not disturbed by environmental noise; thus, it has greater readings and accuracy. Therefore, in the proposed system, the smart bin cover is embedded with the ToF, DHT22 (temperature, and humidity) sensors Fig. 3. The ToF sensors measure the increase of garbage fill levels in a smart garbage bin in the centimeter unit of measurements plus DHT22, which measures the inside temperature and humidity condition of garbage in the bin. The temperature and humidity need to be monitored because the garbage may decompose and may produce a pungent smell. Further, the bottom part of the smart garbage bin Fig. 2 comprises the load cell, which is responsible for detecting the increase of the garbage weight in the bin. Power Core 26800mAh Anker external battery supply sufficient power to the system. Arduino IDE software was used as the programming environment for the sensors. **Table 2** shows the type of sensor used and purpose.

Table 2 Sensor used in development of smart garbage bin

Sensor	Purpose
1. AE-VL53L0X(ToF)	Measure fill level of garbage in a bin
2. DHT22	Measure temperature and humidity in a bin
3. Load cell	Measure increase of weight of garbage in a bin

3.2.2 Cloud service layer

In attaining the first requirement, a ThingSpeak cloud platform was used. ThingSpeak is an open-source cloud platform that provides cloud space for IoT projects. Using the Wi-Fi gateway connection from the hardware layer, all of the sensed data from the smart garbage bin were continually uploaded, stored, and visualized into the Thingspeak cloud space via the provided Write-Application Programming Interface *(W-API)*. Besides, a ThingView mobile application linked to Thingspeak via *(W-API)* enhanced easy data visualization and real-time garbage monitoring.

3.2.3 Processing and control layer

The processing and control layer backs the achievement of the second requirement of the smart garbage bin system. A Time-series machine learning algorithm for continuous data named an autoregressive integrated moving average (ARIMA) was applied. **Fig. 4** is a flow chart of the predictive model for future garbage growth behavior patterns of a single house. The flow chart includes data preparation, machine learning model building, performance measurement, and the model's deployment.

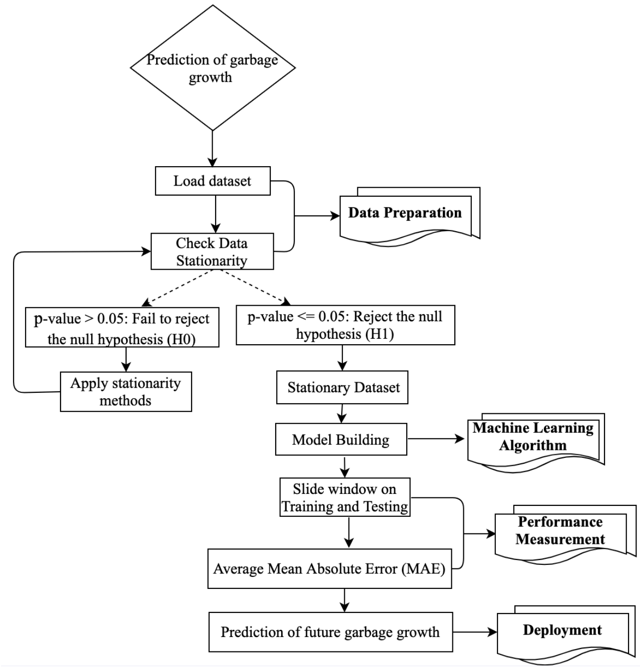

Fig. 4 The flow chart of modelling steps used in this study

4. Deployment and data collection experiment

In evaluating the performance of the developed smart garbage bin in Fig. 3, we explored a way of successfully utilizing the smart bin system in terms of the number of days *(times)*, type of user, and garbage growth. In addition to the smart garbage bin's validation and feasibility, some key questions studied foremost. These are: how a big data collection of garbage growth of a single house being conducted?; how to learn the trends/patterns of garbage growth?; and how to estimate the future amount of garbage generation for the next schedule and changing of garbage bags?

To respond to the questions above, we conducted a preliminary deployment of the smart garbage bin in a university laboratory consisting of 42 research students who use the laboratory daily. As a routine, students visit the laboratory from Mondays to Fridays, on or after morning to night hours, while few visit the lab on Saturdays and Sundays. At these times, they do different activities, including eating, drinking, and cleaning, which in the end, produce garbage.

The lab is placed with three types of garbage bins: burnable, cans, and plastics. However, for this study, the focus stood on burnable garbage only. Burnable garbage includes: food waste, paper waste fruit/vegetable peel, eggshells, old clothes, and any other food item that may leave an unpleasant odor if left in the bin for too long.

5. Model building

The foremost way to model continuous time series data using an autoregressive integrated moving average (ARIMA) model is to check the stationarity of the observation, which can be used in feature engineering and feature selection on time series problem when using the machine learning method. We applied an augmented statistical dickey-fuller (ADF) test in checking the stationarity of our time series dataset with a 2-day rolling window. The interpretations of the results shown in **Fig. 5** based on using the p-value from the test. The time series dataset is considered stationary if the p-value is $p \leq 0.05$, and the critical values at 1%, 5%, 10% confidence intervals are as close as possible to the ADF statistics. In our test, the ADF test gave the p-value of 0.006, and the test statistic was less than the 1% critical value. Thus, it suggests that we can reject the null hypothesis with a significance level of less than 1%; therefore, the dataset is stationary. Consequently, we used the ARIMA model to predict future garbage growth using a fixed-sized slide forecast window on training and to test the model. ARIMA is a popular model and widely used in the statistical method for continuous-time series forecasting [26]. The ARIMA model consists of the three components: autoregression (AR), integrated (I), and moving average (MA), which is explicitly specified in the model as a parameter like ARIMA*(p, d, q)*. An auto correlation function (ACF) provides the MA value, and partial auto correlation function (PACF) provides the AR. The akaike information criterion (AIC) value allows us to compare how well the model fits the data. The lower the value, the better the model. Therefore, we built our model with the ARIMA *(2, 1, 0)* with the AIC value of *205*.

```
Results of Dickey-Fuller Test:
Test Statistic                 -3.548993
p-value                         0.006814
#Lags Used                      7.000000
Number of Observations Used    21.000000
Critical Value (1%)            -3.788386
Critical Value (5%)            -3.013098
Critical Value (10%)           -2.646397
dtype: float64
```

Fig. 5 Dickey-Fuller test statistic results

6. Results and discussion

6.1 Cloud data visualization

In our preliminary deployment of a smart garbage bin in a university laboratory, data from three sensors, ToF, DTH22, and load cell, were continuously collected and stored in the ThingSpeak cloud storage over 30 days at a 1-minute interval. For smooth live streaming and garbage data monitoring, a ThingView mobile application shown in **Fig. 6** linked to the ThingSpeak cloud storage via *W-API*, provided good data visualization.

6.2 Daily garbage growth

During the deployment, we studied the garbage's growth using the fill-level values sensed by the ToF sensor from the top level of the smart garbage bin in a time series interval of each day. As a reference, **Fig. 7** reveals both slow and high variations of the garbage growth behavior, which depended on the use of smart garbage bin on a particular day by the students in the laboratory. Further, we determined the trended frequency of changing the garbage bags on different peak values as Fig. 7 illustrates, whereas, the small green boxes indicate the lowest peak value *(5.6 cm)* from the bottom when the smart bin was empty. The dark red small boxes indicate the highest peak values of garbage

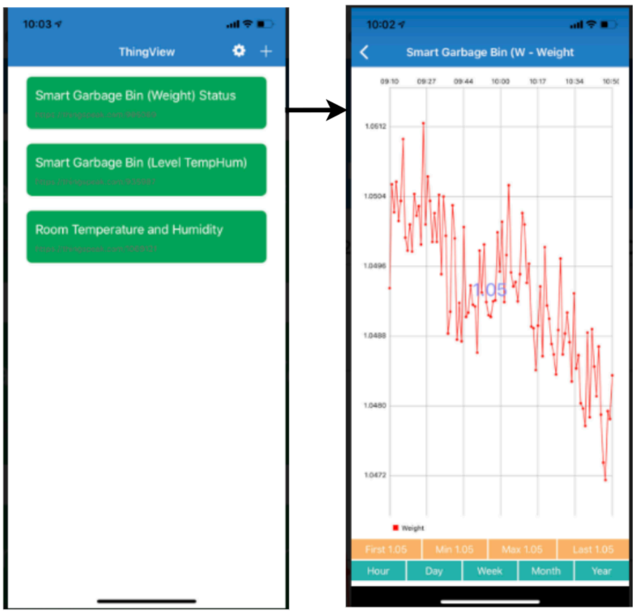

Fig. 6 Daily garbage growth data visualization using ThingView app

where the change of garbage bag occurred, such trend frequency of changing the garbage bag learned as irregular behavior in the smart bin system. The change of the garbage bag can also be due to bad smell resulting from decomposed garbage in the smart garbage bin.

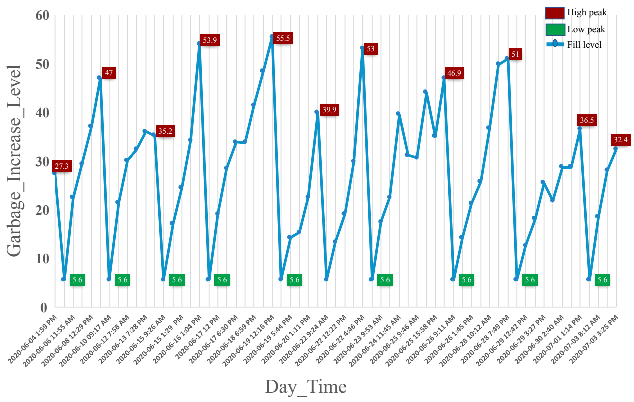

Fig. 7 Garbage growth and frequency of change of a bag in the smart bin

6.3 Garbage growth prediction

To predict the future amount of garbage growth for the next collection schedule and the change of garbage bag. We applied the ARIMA model using a sliding window forecast method to train the model on the fill-level dataset, which consisted of a total of thirty number of the observations provided by the ToF level sensor. Initially, we started by splitting the whole number of observations into different training size, and each training size takes a given forecast window size as an input for testing and predicting **(Forecast)** future garbage growth behavior. As shown in **Table 3**, the number of observations (N) was split into ten days, fifteen days, and twenty days as training size. Therefore, a fixed forecast slide window size of 2, 4 or 7 days was applied to each N-number of observations to forecast the garbage growth. **Fig. 8**, **Fig. 9**, and **Fig. 10** illustrate the prediction of garbage growth on training the ARIMA model with the ten, fifteen, and twenty N-number of observations. The result shows that the predicted garbage values follow the actual values of the initial observations. Additionally, **Fig. 11** demonstrates prediction outcomes of garbage growth on each number of training size; N=10, N=15, N=20 with given forecast window size. We have observed that the ARIMA model is suitable for predicting future garbage growth behavior in the single house because the prediction follows the actual observations and able to provide predictions with few amounts of data; also, the model was capable of gathering the fluctuations on observed data, and the averaged accuracy error decreases with respect to the simultaneous increasing forecast window size and training size. Moreover, the ARIMA model is a flexible method, which uses past data to predict the future where its application does not require much data. Thus, in the present study, the ARIMA model using the slide forecast window was used, provided flexibility and functional result.

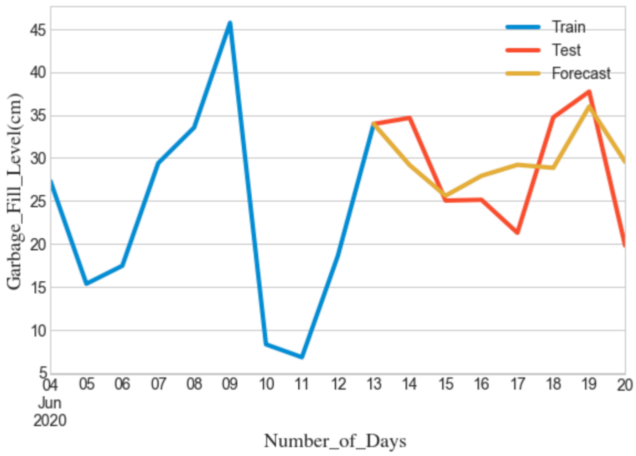

Fig. 8 Garbage growth prediction with ten number of observations

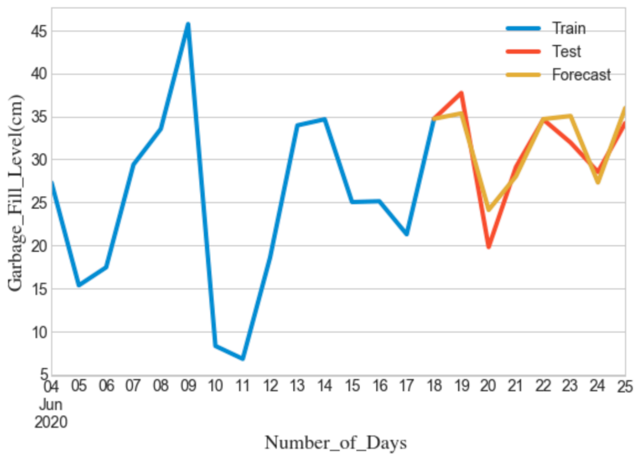

Fig. 9 Garbage growth prediction with fifteen number of observations

6.4 Performance measurements

To analyze the prediction's relevant facts, we calculated the error of the model on each training size (N-number of observations) given the slide forecast window. There are many standard methods that can be applied to evaluate the performance of

Fig. 10 Garbage growth prediction with twenty number of observations

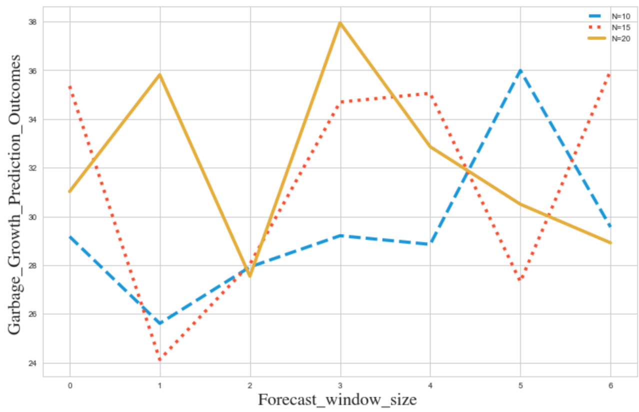

Fig. 11 Prediction outcomes of garbage growth on different N-number of observation

the ARIMA model. In that regard, we conducted a performance measurement of our model using mean absolute error (MAE) and standard deviation (SD) in the centimeter unit of measurements (cm). As shown in Table 3, the forecast window started with the size of two, then slid to four and, finally, seven window sizes on the same training size; N=10, N=15, N=20, therefore, the performance was observed and compared from few to higher numbers of observations (N). We obtained the model performance accuracy by using three different training iterations; thus, MAE was recorded and averaged. **Fig. 12** is an error bar graph achieved during model performance measurements, training the model with ten number of observations using the window size of two indicates satisfactory performance, but the number of observation is lower. Thus, training the model with twenty number of observations given with the window size of 4 days, as shown on Table 3, provided the best accuracy on the garbage growth prediction with (N=20, Average MAE=5.17 cm, SD=0.33 cm). The results show that the simultaneous increase of both the training and forecast window sizes provides fewer errors. With the less number of prediction errors during the ARIMA model's performance measurement indicates the predicted values are closer to the actual observation that offers high efficiency in predicting the future amount of garbage growth behavior on daily practical use. In contrast, the higher error value above 10% of the smart bin's maximum fill level, which was best achieved by the model, can impact the timing of garbage bag change during garbage disposal and garbage collection schedule.

Table 3 ARIMA model performance measurement

Training size (N) (day)	**Forecast window size** (day)	**Average MAE** (cm)	**SD** (cm)
10	2	3.67	0.75
10	4	4.63	0.76
10	7	5.34	0.62
15	2	7.54	0.18
15	4	6.11	1.42
15	7	5.56	1.19
20	2	5.08	3.24
20∗	4	5.17	0.33
20	7	5.34	0.55

∗ *is considered as the best performance accuracy*

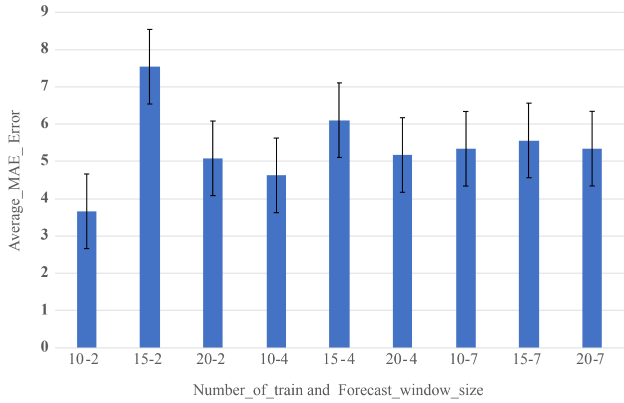

Fig. 12 An error bar graph during model performance measurement

7. Conclusion

This study aims to learn garbage growth behavior in a single house using IoT sensors and to store the data in a cloud platform for further processing with the machine learning model. The prediction of garbage growth's future behavior will enhance a flexible collection schedule; thus, authorities will reduce operational costs by eliminating unnecessary garbage collection trips. Therefore, we have designed and developed a customized smart bin capable of storing the garbage data in a cloud platform that was preliminarily deployed in a student laboratory. Data from ToF (time of flight), DHT22 (temperature and humidity), load cell sensors via Wi-Fi gateway were collected over thirty days and stored into the ThingSpeak cloud platform. Further, we have applied a time series model ARIMA with a fixed slide forecast window size used on each N-number of observations in predicting the future amount of garbage growth for the collection schedule and changing of the garbage bag during the disposal. The result found that the ARIMA model is suitable for predicting future garbage growth behavior in a single house because the predicted garbage values follow the actual values of the initial observations. Also, the model was capable of gathering the fluctuations on observed data, and its application did not require much data.Moreover, the model performance accuracy error decreased with respect to the simultaneous increasing window size and training size. As future work, we will build a model for supporting behavior change of users on garbage disposal by providing control on throwing garbage and considering seasonality fluctuation factors of an area. Also, we will add other sensors such as an accelerometer for counting the smart bin's opening during the disposal of garbage and route optimization for garbage collection in a city as well as increasing devices lifetime by optimizing energy.

References

[1] G. Laput, Y. Zhang, and C. Harrison, "Synthetic sensors: Towards general-purpose sensing," in *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, 2017, pp. 3986–3999.

[2] P. Reis, R. Pitarma, C. Goncalves, and F. Caetano, "Intelligent system for valorizing solid urban waste," in *2014 9th Iberian Conference on Information Systems and Technologies (CISTI)*. IEEE, 2014, pp. 1–4.

[3] N. S. Kumar, B. Vuayalakshmi, R. J. Prarthana, and A. Shankar, "Iot based smart garbage alert system using arduino uno," in *2016 IEEE Region 10 Conference (TENCON)*. IEEE, 2016, pp. 1028–1034.

[4] S. Thakker and R. Narayanamoorthi, "Smart and wireless waste management," in *2015 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS)*. IEEE, 2015, pp. 1–4.

[5] S. Longhi, D. Marzioni, E. Alidori, G. Di Buo, M. Prist, M. Grisostomi, and M. Pirro, "Solid waste management architecture using wireless sensor network technology," in *2012 5th International Conference on New Technologies, Mobility and Security (NTMS)*. IEEE, 2012, pp. 1–5.

[6] J. Ferrer and E. Alba, "Bin-ct: Urban waste collection based on predicting the container fill level," *Biosystems*, vol. 186, p. 103962, 2019.

[7] M. Kannangara, R. Dua, L. Ahmadi, and F. Bensebaa, "Modeling and prediction of regional municipal solid waste generation and diversion in canada using machine learning approaches," *Waste Management*, vol. 74, pp. 3–15, 2018.

[8] S. A. Ali and A. Ahmad, "Forecasting msw generation using artificial neural network time series model: a study from metropolitan city," *SN Applied Sciences*, vol. 1, no. 11, p. 1338, 2019.

[9] C. K. M. Lee and T. Wu, "Design and development waste management system in hong kong," in *2014 IEEE International Conference on Industrial Engineering and Engineering Management*. IEEE, 2014, pp. 798–802.

[10] I. Hong, S. Park, B. Lee, J. Lee, D. Jeong, and S. Park, "Iot-based smart garbage system for efficient food waste management," *The Scientific World Journal*, vol. 2014, 2014.

[11] S. V. Kumar, T. S. Kumaran, A. K. Kumar, and M. Mathapati, "Smart garbage monitoring and clearance system using internet of things," in *2017 IEEE International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials (ICSTM)*. IEEE, 2017, pp. 184–189.

[12] M. Talha, A. Upadhyay, R. Shamim, and M. S. Beg, "A cloud integrated wireless garbage management system for smart cities," in *2017 International Conference on Multimedia, Signal Processing and Communication Technologies (IMPACT)*. IEEE, 2017, pp. 175–179.

[13] B. Chowdhury and M. U. Chowdhury, "Rfid-based real-time smart waste management system," in *2007 Australasian Telecommunication Networks and Applications Conference*. IEEE, 2007, pp. 175–180.

[14] A. Papalambrou, D. Karadimas, J. Gialelis, and A. G. Voyiatzis, "A versatile scalable smart waste-bin system based on resource-limited embedded devices," in *2015 IEEE 20th Conference on Emerging Technologies & Factory Automation (ETFA)*. IEEE, 2015, pp. 1–8.

[15] C. J. Baby, H. Singh, A. Srivastava, R. Dhawan, and P. Mahalakshmi, "Smart bin: An intelligent waste alert and prediction system using machine learning approach," in *2017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*. IEEE, 2017, pp. 771–774.

[16] T. Bakhshi and M. Ahmed, "Iot-enabled smart city waste management using machine learning analytics," in *2018 2nd International Conference on Energy Conservation and Efficiency (ICECE)*. IEEE, 2018, pp. 66–71.

[17] N. Sun and S. Chungpaibulpatana, "Development of an appropriate model for forecasting municipal solid waste generation in bangkok," *Energy Procedia*, vol. 138, pp. 907–912, 2017.

[18] S. Navghane, M. Killedar, and V. Rohokale, "Iot based smart garbage and waste collection bin," *International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)*, vol. 5, no. 5, pp. 1576–1578, 2016.

[19] G. Prajakta, J. Kalyani, and M. Snehal, "Smart garbage collection system in residential area," *IJRET: International Journal of Research in Engineering and Technology*, vol. 4, no. 3, pp. 122–124, 2015.

[20] M. A. Al Mamun, M. Hannan, A. Hussain, and H. Basri, "Wireless sensor network prototype for solid waste bin monitoring with energy efficient sensing algorithm," in *2013 IEEE 16th International Conference on Computational Science and Engineering*. IEEE, 2013, pp. 382–387.

[21] M. Adam, M. E. Okasha, O. M. Tawfeeq, M. A. Margan, and B. Nasreldeen, "Waste management system using iot," in *2018 International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE)*. IEEE, 2018, pp. 1–4.

[22] H. N. Saha, S. Gon, A. Nayak, S. Moitra *et al.*, "Iot based garbage monitoring and clearance alert system," in *2018 IEEE 9th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*. IEEE, 2018, pp. 204–208.

[23] P. J. Ayaskanta Mishra, Nisha Ghosh, "Internet of things based waste management system for smart cities: A real time route optimization for waste collection vehicles," *International Journal of Computer Sciences and Engineering*, vol. 7, pp. 496–503, 4 2019. [Online]. Available: https://www.ijcseonline.org/full$_{p}aper_{v}iew.php?paper_{i}d = 4064$

[24] available from ⟨https://www.tofugu.com/japan/garbage-in-japan/⟩ (accessed 2020-06-29)

[25] available from ⟨https://www.city.ikoma.lg.jp/cmsfiles/contents/⟩ (accessed 2020-06-29)

[26] available from ⟨https://towardsdatascience.com/time-series-forecasting-using-auto-arima-in-python-bb83e49210cd⟩ (accessed 2020-06-01)