



An Examination Of Machine Learning Approaches For Enhancing Efficiency In Smart Waste Management Systems

Shubham Kumar¹, Bidhan Kumar Singh¹, Aniket Kumar², Aman Kumar³ and Swati Gupta⁴

Department of Computer Sciences¹, Vivekananda Global University, Jaipur

Department of Allied Healthcare Sciences², Vivekananda Global University, Jaipur

Department of Business Management³, Vivekananda Global University, Jaipur

Department of Life Sciences⁴, Vivekananda Global University, Jaipur

Abstract

Unused disposal is a hard work for Economically developing countries alike. Biggest problem is that the public garbage cans often overflow well before they are due to be emptied again. This results in elevated levels of smokes, beetles, and houseflies produced by waste management which can cause some serious health disease. A comprehensive analysis is conducted in the latest research, focusing on the integration of machine learning techniques in enhancing smart waste management practices. With this technology, the system may optimize waste disposal by selecting the most efficient route using machine learning. ML-IoT-based design includes equipment that measures weight of rubbish adjusted to network environment as well as containing information about waste management Comparing these studies should give readers a complete understanding of the smart waste management domain.

Keywords: Smart Waste Management, Intelligent Waste Management, IoT, Smart Bin.

Introduction

In a recent study, it was estimated by the World Bank that the amount of trash produced around the world every year is 2.01 billion tonnes. Due to the rapid growth of the population, it is expected to increase by 70% and reach nearly 3.40 billion tonnes by 2050. [1] These numbers can completely change the way societies function. As we produce more trash, we also spread more diseases. Both developed and developing nations are grappling with one major issue: what to do with all this garbage? The World Health Organization (WHO) highlights that inadequate waste management contributes to severe health risks, including respiratory infections, carbon monoxide poisoning, gastrointestinal issues, vector-borne diseases like malaria and dengue fever, and tuberculosis. Moreover, improper disposal of hazardous electronic or medical wastes can lead to lung or skin infections, transmission of HIV/AIDS, Hepatitis B & C viruses, and other infectious diseases. WHO now compares polluted air to 'the new tobacco,' emphasizing its status as a significant yet often overlooked public health crisis.

Refuse collection, disposal and recycling/reusing should be done properly for effective waste management [2].

Previously, waste controlling scarcity led to garbage collection; full bins, which were not collected; no information flow; low recycling rates as well as a lot of gas, bugs and houseflies. In this era of revolutionary technology, we require Smart (automation) Waste Management systems, which are cloud-based programs connecting fleets with the bins' users through central administration. [3].

Objective: Enhance asset and fleet management, boost operational efficiency, reduce labor expenses, and ensure timely bin emptying through advanced technology. Increase transparency and promote cleanliness in urban areas of smart cities. The utilization of intelligent IoT-based hardware paired with cloud-based software solutions is shown to reduce waste collection expenditures by as much as 50%, resulting in cleaner streets. [3].

The city's administrators using SWM can Monitor the bins, monitor historical and real-time load levels, check battery levels, optimize collection routes using learnings from historical collection, geographic point of collection, response latencies, fire events, overflow status and other factors, as well as predict the analyses by using machine-learning algorithms as we collect more data. A machine-learning algorithm will enable us to do more than optimize the collection – it will use experience of the learning system (The anticipated trends of waste generation, the expected cycles of waste production, the foreseeable rhythms of waste creation) to inform what is going to happen over the next 1 Day. The routes of collection can soon be optimized and be better than if we monitor in real time. [4].

Compared to the previous work, the research work being done to smarter garbage management is proceeding faster. Although a lot of systematic reviews have not done which should be covered during the investigation. So this research project will, help to contribute to the comprehensive analysis section as well because this study will help the upcoming research work, which belongs to that field. The impulse of writing this research work comes from the absence of reviews in the previous study, then the objective of doing this systemic literature review on “smart waste management with the use of machine learning (ML) is to introduce a smart - waste management system SWM. Secondly, who will help to understand the gaps in the smart waste management system. The primary objective is to identify the recurring themes or patterns associated with particular terms that align with the focus areas of the study, thereby consolidating the findings of prior research. The research inquiries (RQ) for this investigation are: -

- **RQ.1:** What are the predominant methods employed to encourage efficient waste management practices?
- **RQ.2:** What obstacles do develop nations currently face in implementing intelligent waste management systems?
- **RQ.3:** What solutions are presently being suggested for smart waste management?

The intelligent waste management system is described in Section 2 along with the overview of work. SLR methods to be used for the review are detailed in Section 3— including criteria for paper inclusion/exclusion, Exploration method, source curation, and data retrieval. Details on the literature systematic review findings are provided in Section 4; research question responses are outlined in Section 5; and conclusion can be found in Section 6. This approach aims to ensure that findings are well presented: making it easier for readers to understand and appreciate the results.

The investigation involves coming up with the appropriate methodology, comparing what other studies consider when choosing what to include or exclude in their reviews, seeking out established research standards based on identified benchmark right practices, pulling out data and making sense out of it. The review meticulously gathers, compiles and analyzes a total of 50 papers related to smart waste management that were published in top journals and conferences between January 2017 and May 2022. The study adheres to the guidelines of systematic literature review as defined by

Kitchenhand [5] which is further influenced by the work presented in [6] This research highlights the growing trend of smart waste management adoption, emphasizing the effectiveness of specific tools and techniques, particularly those leveraging machine learning. However, there is notable emphasis within current research on particular areas like system and tool development, overshadowing aspects such as the implementation of smart waste management solutions. The study establishes research benchmarks to address this issue.

Literature review

The emergence of the Internet of Things (IoT) has opened avenues for more intelligent and effective waste management solutions. One of its notable applications lies in utilizing IoT to monitor and mitigate the environmental repercussions of waste. Through the integration of technology, enterprises are increasingly embracing a sustainable trajectory, prioritizing recycling initiatives and holistic waste management practices.

The Functionality of IoT Sensors in Waste Management: Monitoring and Mitigation of Waste Generation. IoT sensors integrated onto waste containers are reshaping waste management practices. These sensors accurately gauge waste volume, transmitting real-time data to waste management entities. This not only optimizes waste collection through predictive fill-level forecasting but also aids in comprehending waste generation trends. Analyzing this data empowers businesses and local authorities to enact source reduction strategies, bolster recycling initiatives, and foster responsible waste disposal habits among the populace. Moreover, by aligning waste production with disposal costs, it incentivizes waste reduction and adoption of eco-friendly practices.

In summary, IoT sensors present a dynamic and efficient approach to curbing the environmental impact of waste. By furnishing precise waste generation data, streamlining waste collection schedules, and advocating for waste reduction tactics, IoT technologies are spearheading the evolution of waste management towards sustainability and resource efficiency. In an era where efficiency and sustainability are at the forefront of urban planning and development, real-time trash monitoring systems leverage the Internet of Things (IoT) to revolutionize waste management. A notable study introduces a commercially available IoT-based waste monitoring system that employs advanced data analytics to optimize waste collection operations.

The integration of IoT in waste management introduces several advantages. Firstly, it enables precise monitoring of waste levels in bins through devices like Raspberry Pi and ultrasonic sensors, providing immediate data on trash accumulation. This information is crucial for dynamic scheduling, allowing waste collection services to prioritize full bins and avoid unnecessary pickups, thereby reducing operational costs and carbon footprint. Moreover, the real-time data coupled with machine learning analysis aids in predicting future waste generation patterns, further enhancing scheduling efficiency and reducing the likelihood of overflow. This system not only streamlines waste collection but also encourages data-driven decisions, promoting a cleaner and more sustainable urban environment.

The adoption of IoT for real-time trash monitoring epitomizes the intersection of technology and environmental stewardship. By optimizing collection schedules and reducing waste overflow, cities can significantly lower their environmental impact while improving service to residents. This innovation marks a substantial step forward in the quest for smarter, sustainable urban living.

In the research, the author [8] used commercial

off-the-shelf (COTS) Raspberry Pi modules and proposed a feasible, cost-effective and scalable solution for future municipalities' deployments. During 10 days of operation, the suggested design was shown to enhance fuel efficiency by up to 46% as well as reduce collection times by up to 18%.

Furthermore, some effort has been made towards safeguarding the Internet of Things environment from cyber-attacks.

According to a recent tendency, smart waste management systems are being merged with low-cost internet of things

infrastructures. In this work, authors [7] have developed a distinct garbage bin level-based probability prediction approach for waste management with graph theory that can improve shortest path waste using ML. A novel IoT based machine learning methodology is presented which predicts probability by collecting real-time waste material with chronological input-based data.

Indications from this study imply the use of sigmoid function for predicting possibility of waste accumulation while Dijkstra's algorithm is adopted to optimize the path for collecting garbage from trash cans. This has employed thresholds of filling heights based on findings of the algorithm to determine where dustbins should be concentrated and how much money can be made. The most interesting method in this research combines graph theory with Logistic regression analysis. Third-Generation Long Range Radio (LoRa) and a low-cost designed circuit are included in the system technology for practical real-world applications, which allow fast system modifications. Operational costs are cut down by this technology, enables timely data collection, and assists in enhancing workers' productivity. Such a system can be set up at a relatively cheap price, with moderate complexity, and it will be implemented widely across all university campuses [7].

In this study, they describe how automated machine learning could solve manual problems with SWMS [9]. In this paper, a lot of attention is given to detecting when a recycling bin needs to be emptied using sensor data. What was suggested here was that we base our approach off of the data [9]. First, the current proposed solution for the problem was evaluated. Then this solution was optimized by gathering a dataset. To solve the problem, ML algorithms were used and then feature engineering was done to see if more features would help optimize the results. It made sense that from 86.8%, 47.9% and 99.1%, 98.2% respectively with top-performing answers; classification can be improved with precision or recall compared to the current manually engineered framework. Machine learning can also be used for discovering whether additional features may improve machine learning algorithms' outcomes [9]. Within this paper study these authors have considered control systems which received information from induction algorithms in ML so as to boost acceptance of systems [10]. From the acoustic test and light transmission, initial sensor data can tell apart between clear and unclear objects. Smart waste management, recycling, and waste sorting are among the AI and ML techniques described by the author [10]. Another data transmission option could be RFID tags as well as RFID readers according to the author. This serves both as a data storage medium and a transmission medium through RFID tags. By detecting different shapes, sizes, abnormalities and levels of contamination, the machine has been trained to identify glass, metal and plastic. The substance was placed in each configuration using several sensors arrays. In this article an intelligent garbage bin that alerts relevant authorities about increase in waste is described by the authors [11]. The feature only directs waste trucks to collect garbage when the dustbin is almost full. Machine learning' concept was used here to determine what type of waste will be produced in near future by collecting data on area's waste generation habits. On top of this graphical representation of continuous data analysis sent through cloud is also done. If the dustbin has more rubbish than permitted by the authorities, they will instantly receive an email and a text message. Time and money would be saved by the relevant authorities.

In line with [12], managing waste is becoming a difficult task for concerned authorities due to industrialization and population explosion. Both small and large-scale waste management have equal potential in terms of environmental impact. The problems of smart city SWMS can be solved through IoT based SWMS for residential neighborhoods using ML techniques. Dustbins from various residential communities need to be monitored as indicated by the authors [12]. This research paper focuses on monitoring multiple dustbins in different residential areas.

The dustbin itself houses sensors that monitor bin capacity, metal level, and air hazardous gas levels. The proposed work also involves recording waste statistics and predicting future waste production rates in neighborhoods, which can be used to determine the best size for the dustbin as well as recycling waste.

Authors [13] of this study look at it from a machine learning point of view, pointing out how hard it is not to take advantage of the vast amounts of data generated by smart cities. Their main concern is on how one could misuse unlabeled data and that semi-supervision is necessary when dealing with problems in smart cities.

Moreover, they advocated for a three-level learning framework to be adopted by smart cities, aligning with the varying significance of big data across different levels of complexity, thereby providing diverse levels of knowledge abstraction. Additionally, instead of disregarding unlabeled data, they proposed a structured integration with labeled data to achieve convergence in policy control. Authors [14] are currently developing smart trash cans designed for household use.

Waste segregation has been significantly facilitated by the integration of numerous sensors and machine learning-based models into the system. Whenever an individual approaches the trash bin, equipped with a camera fixed on its lid, the lid automatically opens. Utilizing image processing algorithms, the bin's system can identify and analyze the trash, prompting the slots to open for waste disposal. According to [15], this method represents the sole suggested approach for integrating Internet of Things (IoT) with deep learning paradigms, offering a promising solution within the realm of waste management. By amalgamating IoT technology with deep learning systems, a novel and efficient solution for garbage management is presented. Deep learning techniques enable the application of advanced machine learning methods to distinguish between bio-waste and non-bio waste, as mentioned in [15]. The authors propose the development of an intelligent garbage alarm system, which involves preparing an image classification dataset, training neural networks, creating TensorFlow models, and deployment. Machine learning will play a pivotal role in categorizing waste into two distinct categories: biodegradable and non-biodegradable waste.

Review Methods

In this research or review article, we tackle the pertinent issues, offer an insight into smart waste management systems, and examine the background of the subject.

There are numerous motivations for undertaking a systematic review. The prevalent factors are outlined below. The subsequent points highlight key disparities between a systematic literature review and a conventional literature review.

- Develop a systematic process for on-site verification
- Determine, add or delete selection criteria
- Search methods that provide compelling results
- attract a certain level of attention
- Leverage data extraction and synthesis

A. Systematic review protocol

The systematic search commences with a thorough review process and employs systematic review methodologies. This section encompasses the search strategy, research inquiries, and criteria for inclusion and exclusion. Previous sections have addressed related work and research queries, while subsequent subsections will delve into further discussion. The diagram below illustrates the comprehensive search framework employed.

B. Inclusion and exclusion criteria

To ensure the relevance of study findings within the context of our research objectives, we established specific inclusion and exclusion criteria. The pilot study yielded a total of 50 datasets from the digital search database utilized. The inclusion keywords/strings employed were "Smart Waste Management," "Machine Learning," "Deep Learning," and "IoT," while exclusion keywords included "Waste Recycling," "Wastewater treatment," and "Sewage treatment." We considered research papers (from journals, workshops, and conferences) written in English and published in electronic databases between January 2017 and May 2022. Tutorial introductions, poster presentations, panel discussions, and abstracts were excluded. Additional details on the inclusion and exclusion criteria are provided in Table 1.

C. The Search Strategy

Methodology: This study employs two primary methods: an automated keyword-based search and a manual reference-based search, both categorized as primary search (PS) and secondary search (SS) respectively. For primary research references, a manual search was conducted. In automated searches, the keyword "Smart waste management" was utilized, while in manual searches, additional keywords such as "Smart waste management using machine learning" were included. Paper selection was based on primary search criteria, incorporating the title, abstract, and keywords, resulting in the identification of 50 papers, as illustrated in Figure 1. All the references were indexed by Mendeley which identified the records from the output. Mendeley removed all the duplicates and listed the results of the searches in a bibliography. The method of data selection has been carried out accurately with the study containing two categories that we have identified, eliminating the reasons for 20 studies. However, we failed to find full text for other 10 articles. Out of 10 articles, 20 were excluded because the full text of the articles was not found. Finally, 10 papers were used to apply the quality assessment criteria and those studies were used in forming a data synthesis.

D. The Study Selection Process

Toll-gate method was used to identify the studies found for more review. Table 2 demonstrates the distribution of included primary studies in different publications sources visually. We observe that the maximum number of papers were collected from IEEE Xplore before the toll-gate processes were initiated (20), Following ScienceDirect with 6, Springer Link with 4, ResearchGate with 3, and Wiley with 1, these sources were exclusively utilized in secondary searches. However, subsequent to applying inclusion and exclusion criteria, IEEE Xplore yielded 5 papers, while another source contributed 2 papers, with 1 paper each from Elsevier, Springer, and Wiley, as detailed in [5].

E. The Evaluation of Quality (EQ)

In order to prepare the quality evaluation forms for evaluating the individual studies, we conducted 6 quality evaluations.

- QA1. A learning suggests the smarter bin for waste collection.
- QA2. An author is suggesting to use of machine learning to recycle the trash.
- QA3. A smart garbage alarms. It can be used to detect metals, methane gas (CH₄), and the garbage bin emitting smoke.
- QA4. Instead of/with sensors, the author of an article suggested a self-describing object technique for the detection of the object in a nice bin.
- QA5. An author suggests the model classification based on accuracy and efficiency.

- QA6. An author addressing the tasks in smart waste management.

The total score of each article was calculated with the total points of 6 queries mentioned above which were high, medium and low on their scaling. The Individual articles scoring mechanism was Y(yes)=2, P(partial)=1, and N(no)=0. The criteria of >6 and $=6$, the total score of all the articles, are considered high. >3 and <6 , if a study got the score above 3 and less than 6, we can consider it medium. Otherwise, the study will be categorized as low if it scored below 3. Every article was assessed and 4 (S7-S10) articles were distributed individually for the independent evaluation of these articles for the evaluation to the other author of this paper. This study will be a comprehensive guide for smart waste management through machine learning. See table 3 for QA as an output of the quality assessment mentioned above, we were able to include 10 original studies in this SLR as per our systematic quality assessment criteria. The remaining studies above 2/3 were high score studies, which we had to left in our SLR from the quality point of view. We will discuss the remaining high-scored studies in the SLR based on the quantity of evaluation rating for quality. [4]

F. Data Extraction and Formulation

Data collection and management involved thoroughly reviewing all studies to extract pertinent information, which was subsequently stored in Microsoft Excel spreadsheets. Each study was assigned a unique identifier (e.g., S1, S2, S3, etc.) within the Excel spreadsheet column. During the review process, the following details were recorded in accordance with Table 4: Study ID, study title, author(s), publication year, database provider, source, document type, and citation count.

TABLE II
Quality Evaluation For SLRS

Study No.	QA1	QA2	QA3	QA4	QA5	QA6	Total	Score
7	Y	N	P	N	N	N	3	Med.
8	Y	N	P	N	Y	Y	7	High
9	Y	N	P	N	Y	Y	7	High
10	Y	Y	Y	Y	Y	N	10	High
11	Y	N	P	N	N	N	3	Med.
12	Y	N	Y	N	Y	Y	8	High
13	Y	N	N	N	N	Y	2	Low
14	Y	Y	N	P	Y	Y	9	High
15	Y	Y	P	Y	Y	N	9	High
16	Y	N	P	Y	N	Y	7	High

TABLE III

Distribution of research across different publications pre- and post-application of quality assurance standards

Source of study	Amount before QA	Amount after QA
IEEE Xplore	20	5
Elsevier	6	-
Springer database	4	1
ResearchGate portal	3	1
Wiley	1	1
Other	16	2
Total Amountt	50	10

IV.SLR Results

This unit investigates activities conducted prior to a more inclusive literature review. We report spreadsheet results in this section: publishing origins, the EP step, citations, methodologies, and research methods. We introduce our study context in this section. The following paragraph describes our study.

A. PUBLICATIONS SOURCES

As a rule, the investigations indicated that research findings from their high-profile conferences and at high-profile journals are likely to mirror from the most cited sources. Therefore, most of the extracted studies were as illustrated in figure 2 below. In this case, 40% of the primary research was evident in four journal articles, while three conference papers accounted for 30%. As a result, research articles comprised 20%, and 10% were contributions to book chapters

B. CITATION COUNT

Number of citations is actually an important indicator of the total number of citations your paper received. As shown in Figure 3 for our works. Our citation count was obtained from Google Scholar, as already mentioned. As such, information displayed in the bar chart is not designed for comparative purposes. Specifically, in the cited works list, there is one work with the largest Citations count: 177, but they are followed by 32 and then two works are cited 16 times each, two works are cited 13 times each, and so on. A relatively small number of citations means that the research was published quite recently, that is, in 2019-2020. So, generally speaking, we expect that in the future, the rate of citing this research will grow, since most of the studies date from the last 5 years, this suggests that the latest evaluated studies are very relevant even today in May 2022.

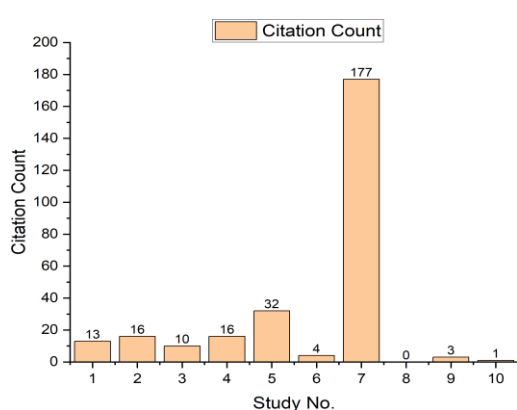


Fig.2.

C. Temporal View

There is evidence in Figure 3 of how studies are spread across the years. As Figure 3 displays the publication year it is observable that there was an increased publication of studies captured on smart waste management in the previous year. This is a clear way of indicating the development of Recent interest in this area for the past two years. Therefore, one can figure out that there is an increase in the number of last year's publications from figure 3 since there were only two more publications during the period 2017 to 2019

D. Research Methodologies

"Figure 4 depicts the study methodologies identified within the analyzed papers. Both qualitative and quantitative approaches were present in roughly equal measures among the included studies."

The distribution of study methods is as follows:

- * 50% measurable
- * Three out of ten qualitative
- * A fraction of 10% conceptual works
- * 10% mixed (qualitative and quantitative)

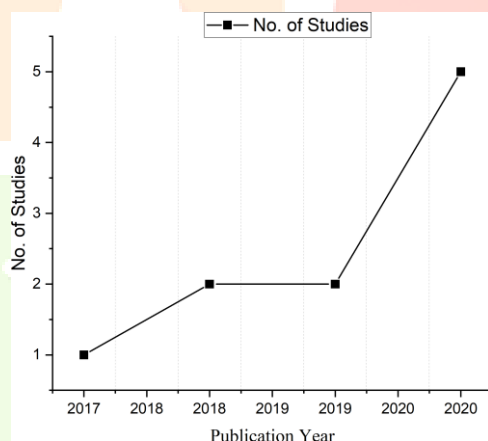


Figure 3: Temporal Patterns of Initial Research

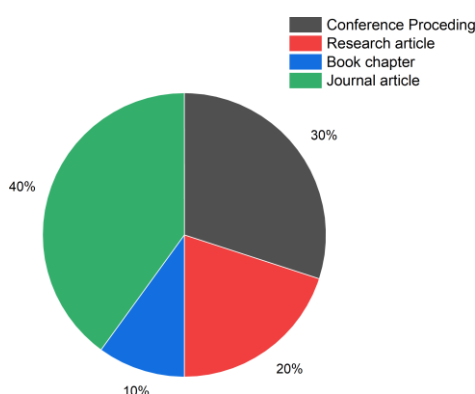


Figure 4: Research Reports: Investigative Studies, Research Findings

Conclusion

We conducted a comprehensive review of studies spanning from 2017 to 2022, focusing on the application of machine learning in smart waste management. This report presents our research findings. Figure 1 illustrates the step-by-step methodology employed to select or exclude studies. Our initial examination of a vast literature corpus yielded a primary collection of 10 publications addressing smart waste management using machine learning techniques.

IoT integration emerges as a dominant theme in smart waste management, with three studies exploring recycling, waste segregation, and IoT applications to enhance environmental impact. Six articles center on machine learning-based trash management alarm systems, proposing algorithms to monitor waste generation and adjust pricing and volume to mitigate or amplify future waste accumulation.

Notably, the past two years have witnessed a surge in research on machine learning for smart waste management (2019-2020), as depicted in Figure 4. While only two studies were published between 2017 and 2019, the number of publications has notably increased. Additionally, the review covers various research methodologies in waste management, with 50% of studies adopting quantitative approaches, 30% qualitative, and 10% mixed methods, as illustrated in Figure 5.

The findings of this study are anticipated to be valuable for professionals, scholars, and practitioners seeking insights into smart waste management. Furthermore, we hope this research may stimulate further inquiries in the field.

References

- [1]Kaza, Silpa, et al. What a waste 2.0: a global snapshot of solid waste management to 2050. World Bank Publications, 2018.
- [2]Kaza, Silpa, and Lisa Yao. "At a glance: a global picture of solid waste management." 2018. 17-38.
- [3]Anagnostopoulos, Theodoros, et al. "Challenges and opportunities of waste management in IoT-enabled smart cities: a survey." *IEEE Transactions on Sustainable Computing* 2.3 (2017): 275-289.
- [4]Hu, Ya-Han, and Kuanchin Chen. "Predicting hotel review helpfulness: The impact of review visibility, and interaction between hotel stars and review ratings." *International Journal of Information Management* 36.6 (2016): 929-944.
- [5]Kitchenham, Barbara, and Stuart Charters. "Guidelines for performing systematic literature reviews in software engineering." (2007).
- [6]Ahmed, Awais, A. Aziz, and M. Muneeb. "Electronic payment system: A complete guide." *Journal of Multidisciplinary Sciences* 1.2 (2019): 1-17.
- [7]Bakhshi, Taimur, and Muhammad Ahmed. "IoT-enabled smart city waste management using machine learning analytics." 2018 2nd international conference on energy conservation and efficiency (ICECE). IEEE, 2018.
- [8]Anh Khoa, Tran, et al. "Waste management system using IoT-based machine learning in university." *Wireless Communications and Mobile Computing* 2020 (2020).
- [9]Rutqvist, David, Denis Kleyko, and Fredrik Blomstedt. "An automated machine learning approach for smart waste management systems." *IEEE transactions on industrial informatics* 16.1 (2019): 384-392.
- [10]Gupta, Praveen Kumar, et al. "The use of modern technology in smart waste management and recycling: artificial intelligence and machine learning." *Recent advances in computational intelligence*. Springer, Cham, 2019. 173-188.

- [11]Baby, Cyril Joe, et al." Smart bin: An intelligent waste alert and prediction system using machine learning approach." 2017 international conference on wireless communications, signal processing and networking (WiSPNET). IEEE, 2017.
- [12]Dubey, Sonali, et al. "Waste management of residential society using machine learning and IoT approach." 2020 International Conference on Emerging Smart Computing and Informatics (ESCI). IEEE, 2020.
- [13]Mohammadi, Mehdi, and Ala Al-Fuqaha. "Enabling cognitive smart cities using big data and machine learning: Approaches and challenges." IEEE Communications Magazine 56.2 (2018): 94-101.
- [14]Patel, Dhruv Nrupesh, et al. "Smart Waste Segregation using ML Techniques." International Journal of Innovative Science and Research Technology-2019 (2020).
- [15]Rahman, Md Wahidur, et al. "Intelligent waste management system using deep learning with IoT." Journal of King Saud University-Computer and Information Sciences (2020).
- [16]Lakshmi, V. Srinithi Santhana, et al. "Smart garbage alert system using machine learning." Int. J. Eng. Appl. Sci. Technol 5 (2020): 487-489.

