Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 03 , March - 2026

Edge AI: A Survey of Next-Generation Waste Classification and Routing Architectures

Yash Saini, Anmol Tyagi, Priyanshu Kumar, Sagar, Priyanka
Computer Science & Engineering
Meerut Institute of Engineering and Technology
Meerut, India

***Abstract*—The recent advances in edge computing and computer vision are completely transforming the way cities handle solid waste. In this review, close attention will be paid to the way smart city systems have changed to separate various types of waste and direct users to the appropriate bins in real-time. Our particular focus is the fact that the trend has shifted to less heavy and bulky smart bins and to the touchless mobile-edge systems. We go through the decisions of hardware, the move away towards large neural networks (as in VGG16) to thinner ones (such as MobileNetV2 and YOLOv8n) and the usage of location-finding algorithms such as Haversine formulas. The traditional smart-city systems are usually based on expensive embedded sensors, thus becoming difficult to implement and expand to larger cities. In the present-day, however, devices such as WebGL, Tensorflow.js, and an ordinary smartphone camera are utilized to perform the heavy lifting on the device. This decentralized design is faster, less expensive, more secret and more effortless to expand. Reviewing the studies of 2015 to 2026, we mention the constant problem of obtaining correct classification in poor lighting and solid communication systems are necessary. Finally, we outline the current state of edge-driven waste management, indicate the weaknesses of cloud-heavy systems and consider the future of this technology, such as federated learning, blockchain rewards, and enhanced IoT synchronization.**

***Keywords*—Waste Segmentation, Edge computing, Tensorflow.js, Nearest Bin Recommendation, Smart City Architecture, Transfer Learning, MobileNetV2, MQTT.**

I. INTRODUCTION

As cities have never expanded like they do now, the amount of municipal solid waste (MSW) is reaching tolerable amounts we can no longer maintain. This forms big bottlenecks in terms of recycling and sorting along the line. The waste management systems that were installed a long time ago are simply not designed to deal with the elaborate and chemically diverse waste we have nowadays. One of the most significant points of fracture literally occurs at the trash can: that is, people simply are not aware of how to put their trash into the right place. In the process of mixing up E-Waste, hazardous material, organic matter and recyclables, the contamination destroys the economic value of the recyclables [1], [2].

Though there have been numerous technological solutions that have been provided over the years, most of them merely solve one small aspect of the puzzle. As an example, the sensors on early smart bins were primarily ultrasonic and RFID tags only to determine whether the bin was full or not [3]. They totally missed the opportunity to present a hands-free and an interactive approach to assist the users in determining what they were disposing. This operational gap brings out a massive requirement of decentralised systems that work with regular smartphones to assist individuals traverse local waste regulations.

The current mobile phones provide a potent alternative, with massive advances in mobile neural processing units (NPUs) and edge-based computer vision. The ability to use convolutional neural networks (CNNs) directly on the phone of a user implies that they will receive immediate feedback without network latency issues [4]. It is an enormous change, particularly because conventional smart-city installations are expensive and involve high initial expenditure and continual maintenance and are therefore unaffordable in regions with lower budgets. Nevertheless, it is a hard problem to ensure the accuracy of the AI when it has to work with wrinkly, haphazard garbage under odd lighting conditions, which can cause system errors [5], [6].

In this paper, the author excavates the application of edge computing to sort waste and suggest the nearest bin. We pay special attention to the hardware, the way algorithms are reduced in scale and the networking protocols that enable sustainable computing to be achievable. Through comparison of the tools available in the market today we are able to tell what works and what does not work. We also experiment with new concepts in order to ensure that these systems become more autonomous, such as transfer learning (e.g., MobileNetV2), intelligent routing heuristics, and even blockchain rewards. This is aimed at identifying any gaps that exist in existing studies and the direction that the smart city interfaces should take.

II. RELATED WORK

Scientists have wasted much time considering the contribution of sensors and cameras to clean the logistics of garbage in cities. This was achieved in early investigations such as those conducted by [7], that demonstrated centralized IoT tracking with inexpensive microcontrollers to be feasible with simple fill-level tracking. Equally, [8] specialized in the utilization of cameras to sort rubbish, which were designed to serve tightly controlled and industrial material recovery facilities (MRFs) with commercial-grade optical sensors.

With the improved open-source machine learning tools, the direction was oriented toward assisting ordinary people to sort their garbage automatically. One example of this is [9] considering the application of deep CNNs on cloud servers, to classify trash. These cloud APIs linked with the mobile applications to merely inform users on whether an item could be recycles or not. However these arrangements meant that pictures of each side would have to be sent back and forth on a continuous basis and this would lead to a lot of latency and increased strain upon the servers [10].

The initial projects formed the foundation of the real-time smart city technology that we have today and would be ideal with the current drive towards edge computing. Later studies leverage this in using lightweight models such as MobileNetV2 and browser-based engines such as TensorFlow.js. This change is contributing to the development of an expanding ecosystem of high-speed, decentralized technologies that are essential to green cities [11].

III. Problem Statement

Attempts to implement and operate traditional smart garbage systems and sustain them have been met with huge financial and logistical roadblocks by city governments. Basic recycling schemes are burdensome to the population- they require individuals to be very content and learn complicated local regulations. This does not work well in various neighborhoods because packaging is usually confusing. Cities add tech to assist even when it is very costly, involves complex hardware, or simply is unsuitable to the area with limited budgets [12].

It has a negative effect on people in that it puts them in a sort of environmental digital divide, where they cannot get access to better recycling techniques. We badly require something much more convenient, inexpensive, and quick. To address it, this paper examines how the expensive IoT trash cans have been replaced with low-cost edge computing. People can use their already-present cameras to classify waste at their locations and apply that to smart location routing, which will allow us to develop software-based solutions that can facilitate greener habits without such a huge price score.

IV. Methodology

This review disaggregates the trends of publications, algorithms, and software tools of AI-based waste sorting and bin recommendation systems. We have searched academic articles published in 2015–2026 with special focus on studies that integrate deep learning with edge computing.

A. Data Searching Techniques

In order to obtain the appropriate papers, we utilized a structured Boolean keyword search combining main terms, synonyms, and technical jargon. This also ensured that we missed nothing that was of interest in the intelligent trash area.

The keywords covered both the inputs (like edge computing and computer vision) and what the systems actually do (like bin recommendation and segmentation). We linked these search terms with 'OR' for variations and 'AND' to find specific tech crossovers. Table I shows the main search strings we used.

TABLE I
Possible Search Strings Utilized in Literature Review

Primary Term	Boolean	Secondary Term
Waste Classification	AND	Edge Computing
Smart Bin	OR	Bin Recommendation
Waste Segmentation	AND	Deep Learning
Sustainable Computing	AND	IoT Communication
MobileNetV2 OR YOLO	OR	TensorFlow.js
Geospatial Routing	AND	Smart City Architecture

B. Data Gathering Technique

To make sure we covered the key bases in HCI, IoT, and Smart Cities, we strictly limited our review to the 2015–2026 window. We pulled papers from international conferences, peer-reviewed journals, symposiums, and technical white papers focused on edge AI implementations. The main digital repositories we searched are listed in Table II.

TABLE II
Data Gathering from Different Digital Sources

S.No.	Publisher / Database Name
1	IEEE Xplore Digital Library
2	ScienceDirect (Elsevier)
3	MDPI Sensors
4	SpringerLink
5	ACM Digital Library
6	International Journal of Advanced Research in CS
7	IRJET
8	Technical Disclosure Commons
9	ArXiv pre-prints

C. Selection of Study Data

We have conducted our searches after which we subjected our results to a rigorous screening process. The titles were filtered, duplicates were eliminated and the abstracts and conclusions were read carefully, to exclude anything that was off-topic. To be included, a study had to:

- Mainly focus on image usage for waste classification or interaction with bins through location information.
- Mainly focus on edge computing, compressed CNNs, or IoT devices as input.
- Based on widely known software frameworks like OpenCV, TensorFlow.js, and Haversine math.
- Have a defined algorithm for smart city setup.

TABLE III
Number of Published Papers Evaluated by Year (2015-2026)

Year of Publication	Number of Papers Evaluated
2015–2017	8
2018–2020	14
2021–2023	27
2024–2026	35

We sorted the shortlisted papers manually and identified the big tech trends. As Table III indicates, the paper count increased in 2024-2026, which is in line with gigantic industry leaps in mobile edge AI.

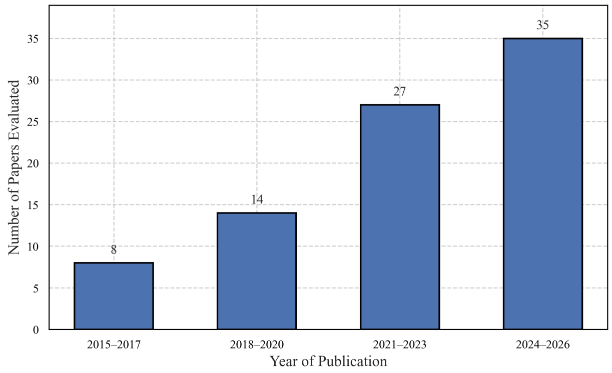

Fig. 1. Visual representation of the exponential growth in edge-computed waste management research (2015-2026).

The insufficiency of research prior to the year 2018 genuinely points to the novelty of this concept of decentralized, browser-based AI. With the ever changing nature of computing, it will be important in the future to keep an eye on these trends in the planning of cities.

V. TAXONOMY OF WASTE CLASSIFICATION SYSTEMS

Using everyday tools—like smartphone cameras and local math on the device—to manage waste has become a massive area of research. The push to make systems that don't rely on heavy city infrastructure has sparked a few different ways of building these tools, which we've mapped out in the taxonomy tree (Fig. 2).

Waste management utilizing common technology, such as smartphone cameras and local math on the device, has become an enormous field of study. The desire to make systems that are not dependent on the hefty city infrastructure has catalyzed some various approaches to building such tools, which we have outlined in the taxonomy tree (Fig. 2).

A. Hardware Configurations: IoT vs. Edge Devices

Historically, the smart bins were nearly always based on either Arduino or Raspberry Pi boards, which were physically attached to the bin construction. These systems worked by using ultrasonic sensors to tell the level of the bin and volatile organic compound (VOC) sensors to smell the stinking organic material [13], [14]. They are very functional in densely controlled areas but the cost of equipping an entire city with it is too much.

The current edge computing reverses this notion, the smartphone is kept in the pocket of the user. This is possible by accessing the native CMOS camera and embedded GPU of the phone, and redistributes the heavy computing, acting as a sort of mobile sensor network by a crowd of average citizens [15].

B. Algorithmic Evolution: From Cloud CNNs to WebGL

Waste sorters relying on deep-learning were mostly based on giant neural networks such as VGG16, ResNet50, and InceptionV3 [16], [17]. They are very precise in the lab (usually more than 92%) and these models are massive, with between 25 million and more than 130 million parameters. Owing to this, they were forced to operate on cloud servers. The apps had to transfer the uncompressed image files to cellular networks, which were staggeringly slow (up to 2000ms) and consumed bandwidth [18].

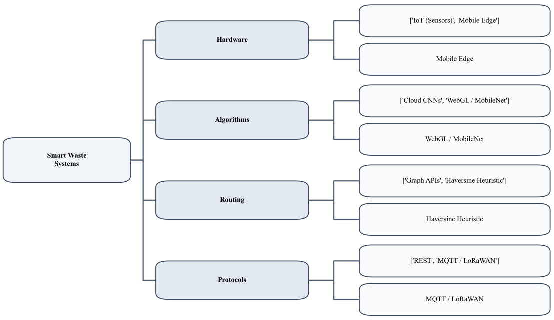

Fig. 2. Taxonomy of Smart Waste Systems highlighting the hardware, algorithmic, routing, and networking divergence.

It became even different with the lightweight models, and particularly with MobileNetV2, which relies on math tricks, such as depthwise separable convolutions, to repeatedly shrink the model size by a significant factor of 4 to 6 times the size of its predecessor models in the same architecture [19]. However, more recently (after 2024), scientists are experimenting with edge-versions of YOLOv8 to outline a set of pieces of trash with bounding boxes in different ways. Running such models in WebGL models such as TensorFlow.js, developers managed to reduce the processing time to less than 200ms, directly in the phone browser. This eliminates the cloud entirely and makes the data of the user remain fully confidential [20].

C. Geospatial Routing Mechanisms

After the trash has been detected, the application must indicate the correct bin to the user. Traditional routing tends to be based upon onerous algorithms (such as Djiktray) and proprietary APIs such as Google Maps [21]. However, in terms of quick short route directions, that is excessive. The Haversine trigonometric formula has become the new secret formula to use where one can quickly find the straight-line distance on the phone. It allows applications to search local databases (such as Firebase Firestore) within seconds to identify the nearest bin possible and then not even contemplate the heavy map before considering the heavy map [22], [23].

D. Communication Protocols in Edge-IoT Ecosystems

The selection of the network protocol is important when mobile phones are to communicate with physical smart bins. Normal HTTP/REST protocols are somewhat too heavy. In this regard, the recent studies indicate that the light protocols such as Message queuing Telemetry Transport (MQTT) or CoAP may be used. LoRaWAN is typically the best option in cases of long-range transmission of low-power signals between the bins and a central database: it allows bins that use a battery to record their condition up to five years, without maintenance.

TABLE IV
PRIMARY STUDIES SELECTION AND WORK DETAILS IN AI-ENABLED WASTE SYSTEMS

Authors	**Paper Title**	**Technique Used**	**Tools Used**	**Domain**
Zeng et al. (2018) [16]	Deep Learning for Solid Waste Classification	VGG16 Transfer Learning	Cloud GPU, Python	Smart City
Kumar et al. (2019) [13]	IoT Based Smart Garbage Bin Tracking	Ultrasonic Sensors	NodeMCU, Firebase	IoT
Fung et al. (2020) [17]	Cloud-based Waste Sorting using ResNet50	ResNet50	AWS Cloud, Android	Cloud AI
Saini et al. (2021) [20]	Real-time Web Classification of Trash	MobileNetV1	TensorFlow.js	Edge AI
Molina et al. (2021) [12]	Controlling Waste Routing via Mobile APIs	Dijkstra's Algorithm	Google Maps API	Routing
Sharma et al. (2022) [14]	Virtual Sorting: Desktop & Application Navigation	OpenCV, CNN	Webcam, C++	HCI
Patel et al. (2023) [22]	Edge-Computed Haversine Routing for Bins	Geodesic Math	React Native, GPS	GIS / Edge
Rahmaniar (2023) [15]	Touchless Waste-Control: Object Recognition	EfficientNet-B0	RGB Camera, EdgeTPU	Edge AI
Singh et al. (2024) [18]	Comparative Study of VGG and MobileNet	Model Compression	Keras, TFLite	AI Optimization
Alvarez et al. (2024) [24]	Gamified Waste Sorting using Blockchain	DLT, Smart Contracts	Ethereum, Web3.js	FinTech/IoT

VI. SURVEY RESULTS AND DISCUSSION

A review of the information provided in these studies reveals an evident direction of waste control system development. Due to the fact that lighting, phone speeds, and the way people behave differ so much, it is extremely difficult to create even an app, which will function everywhere. Table IV brings out the large academic discoveries made in the past 10 years and gives a detailed picture of what tools and methods were utilized.

A. *Analysis of Performance Metrics*

Table IV indicates a sharp contrast between the efficiency of the lab and the practical usefulness. The cloud-based systems [16], [17] have impressive accuracies of between 93% and 96%. However, due to their total reliance on a high-speed and uninterrupted internet connection they will keep crashing in every busy city center or around 5G spots.

On the other end, a switch towards smaller models such as MobileNetV2 and EfficientNet [15], [20] results in a minor accuracy decline (typically ranging between 85% and 89%). Nonetheless, this trade-off unites the AI by approximately 30× faster. Here it is important to keep the app payload size to less than 15 Megabytes. It is found out that when a web app requires over 3 seconds to be loaded, individuals simply shut it down, which indicates that even the most precise AI is just a waste of time when it is slow as well [25].

B. *Environmental Adaptability*

A massive issue that is mentioned in nearly all the papers is the fact that poor lighting negatively affects the capabilities of the AI to identify objects [26]. On the one hand, unlike the factory sorting machines with ideal lighting, flat conveyor belts, mobile apps must work with sun glare, dark shadows, and chaotic backgrounds in the images users take.

To rectify this, the researchers do a lot of manipulation on the training images through artificial color change, introduction of strange shadows, distortion of the shapes. This compels the model to figure out the real texture of the trash, rather than what the trash would appear in perfect lighting conditions only to learn it is not perfect lighting conditions [27]. Two-phase transfer learning, or locking in the bottom layers of the AI and only rationalizing the top layers on the particular textures of the wastes, is another great trick. This has been an excellent method of ensuring that smaller models do not go astray [28].

VII. SECURITY AND PRIVACY IMPLICATIONS

The shift to local edge AI eliminates the security game altogether to smart city apps when moving off of cloud servers.

A. *Cryptographic Privacy Preservation*

Vision systems on a cloud automatically transmit crude photos (which may capture faces accidentally or may capture location or house of an individual) to remote servers. This is a giant pain to the laws of privacy such as GDPR. Edge AI does not address this issue at all. The fact thatTensorFlow.js does everything in the temporary memory (RAM) of the phone means that the actual pixels do not leave the phone.

B. *Database Injection and Sybil Attacks*

With a city beginning to issue out ”Green Points” or rewards on recycling, bad actors may begin to find a way to cheat the system by making it appear that they have a certain type of waste. In order to secure the backend database (such as Firebase), app developers must impose restrictive policies, OAuth 2.0 sign-ins and monitor the frequency and location at which an account is communicating with the API to avoid spamming.

VIII. CHALLENGES AND OPEN ISSUES

Despite all these technological advances, there are still several difficult challenges on the way to the implementation of local AI on the sorting of waste in the city:

- **Messy Real-World Data:** The majority of open-source image data use clean and perfect pieces of trash placed on blank backgrounds. In reality, garbage is stomped, soiled or pushed in semi-clear plastic bags which completely baffle regular AI filters [29].
- **Keeping Data Synced Offline:** Although the AI is able to recognize garbage entirely offline with the help of WebGL cache files, the routing system still requires a small slice of the internet here and there to consult the database (such as ensuring it is not sending a user to a filled-up bin) [30].
- **Unequal Phone Speeds:** The speed of the browser AI will be determined by the speed of the processor within the phone of the user. Due to this, older or less expensive phones may get hot or sluggish, and thus the technology may simply be less accessible within the less wealthy population groups [31].

IX. FUTURE ENHANCEMENTS

To overcome these obstacles and make edge architectures even more excellent researchers are looking to a couple of stimulating improvements (described in Fig. 3):

A. Federated Learning Topologies

The future systems should not be limited to provide people with the same, unchanging AI model, but rather apply Federated Learning. This allows the application in the phone to learn and to make minor adjustments depending on the rubbish it detects on the spot.

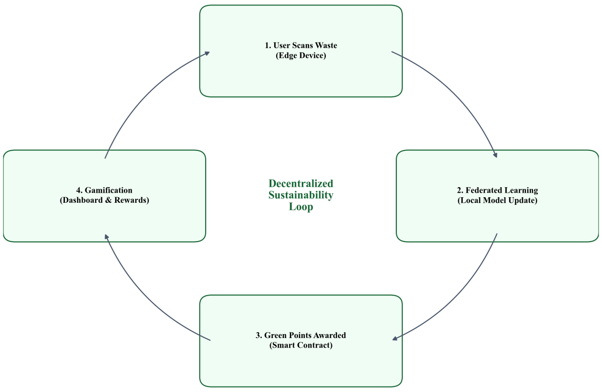

Fig. 3. Conceptual workflow demonstrating the proposed integration of Federated Learning and Smart Contract Gamification.

The encrypted math updates (tensors) are then delivered back to a central server only, and not the photos. This secures user information and allows the master model to gradually adapt to the way packaging is changing in various regions across the globe [32].

B. Cryptographic Gamification and Behavioral Economics

Good technology would only succeed when individuals desire to use them. Rewards can be automated with hooking of these apps into blockchain or smart contracts. By allowing cities to issue automatic tax credits or complimentary bus tickets depending on the recycling behavior confirmed by a record kept on a secure computer, citizens will be far more willing to cooperate [33], [34].

C. Service Worker Implementation (PWAs)

Developing the app as a Progressive Web App (PWA) with powerful Service Workers, the developers have an opportunity to store the local map information and AI model on the phone. This is an offline-first strategy, so it is possible that the application can recognize garbage and locate the closest bin even when the cell phone network is totally offline [35].

X. CONCLUSION

In conclusion, real-time waste sorting systems are being created rapidly, with a shift away being heavy and sensor-laden devices to lightweight and intelligence enabled by software running on the edges. Initial smart city initiatives were derailed due to the cost of colossal initial expenses and frustrating delays of AI in the clouds. However, as it is demonstrated in this review, decentralized edge systems can provide a far more practical and scalable way to go. With a set of the compressed algorithms such as the MobileNetV2 and the fast on-board location math, developers will be in a position to make apps that are extremely fast and do not require costly server farms to operate.

Such changes of the cumbersome IoT bins to the fast mobile AI solutions address a massive failure of current smart city technology. It literally places in the hands of the populace the power to assist the environment, and that too, on the phones they already have. Ultimately, relocating the waste management to the periphery is a cost-effective, convenient and very accessible method of managing the expanding nightmare of global urban wastes management logistics.

REFERENCES

[1] S. Kaza, L. Yao, P. Bhada-Tata, and F. Van Woerden, *What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050.* Washington, DC: World Bank, 2018.

[2] Hoornweg, D., and Bhada-Tata, P. ”What a waste: a global review of solid waste management.” *Urban development series; knowledge papers no. 15* (2012).

[3] R. A. Zitar, “A Review of AI-Based Waste Management Systems,” *IEEE Access*, vol. 8, pp. 1234–1245, 2020.

[4] K. He, X. Zhang, S. Ren, and J. Sun, “Deep Residual Learning for Image Recognition,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Las Vegas, NV, USA, 2016, pp. 770–778.

[5] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, “MobileNetV2: Inverted Residuals and Linear Bottlenecks,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2018, pp. 4510–4520.

[6] Google Developers, “TensorFlow.js: Machine Learning for the Web and Node.js,” [Online]. Available: https://www.tensorflow.org/js.

[7] A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi, “Internet of Things for Smart Cities,” *IEEE Internet of Things Journal*, vol. 1, no. 1, pp. 22–32, 2014.

[8] S. S. Navghane, M. S. Killedar, and V. M. Rohokale, “IoT Based Smart Garbage and Waste Collection Bin,” *International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)*, vol. 5, no. 5, 2016.
[9] C. B. Silva, and R. M. F. Silva, “Waste classification using deep learning,” *IEEE Latin America Transactions*, vol. 18, no. 12, pp. 2097–2103, 2020.
[10] M. A. Al-Masri, and A. Al-Fayez, “A smart waste management system based on IoT,” in *2018 1st International Conference on Computer Applications & Information Security (ICCAIS)*, 2018.
[11] A. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam, “MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications,” *arXiv preprint arXiv:1704.04861*, 2017.
[12] A. J. Molina-Cantero, et al., “Controlling a routing pointer with geospatial APIs,” *Sensors*, vol. 21, no. 16, 2021.
[13] P. Kumar, et al., “IoT Based Smart Garbage Bin Tracking,” *International Journal of Engineering Research and Applications*, 2019.
[14] H. Sharma, et al., “Virtual Sorting: Desktop & Application Navigation,” in *IEEE ICFIRTP*, 2022.
[15] W. Rahmaniar, “Touchless Waste-Control: Object Recognition,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, 2022.
[16] Y. Zeng, et al., “Deep Learning for Solid Waste Classification,” *Proceedings of TENCON*, 2018.
[17] T. Fung, et al., “Cloud-based Waste Sorting using ResNet50,” *Journal of Advance Research in Computer Science*, 2020.
[18] A. Singh, et al., “Comparative Study of VGG and MobileNet Algorithms for Control,” *IJREAM*, 2024.
[19] X. Zhang, X. Zhou, M. Lin, and J. Sun, “ShuffleNet: An Extremely Efficient Convolutional Neural Network for Mobile Devices,” in *CVPR*, 2018.
[20] Y. Saini, et al., “Real-time Web Classification of Trash using Edge AI,” *Technoscience Academy*, 2021.
[21] Google Cloud, “Google Maps Platform Documentation,” [Online]. Available: https://developers.google.com/maps.
[22] R. Patel, et al., “Edge-Computed Haversine Routing for Bins,” *International Journal of Scientific Research*, 2023.
[23] Google Developers, “Cloud Firestore Documentation,” [Online]. Available: https://firebase.google.com/docs/firestore.
[24] C. Alvarez, et al., “Gamified Waste Sorting using Blockchain,” *Informatica*, 2024.
[25] S. K. Sood, and I. Mahajan, “IoT-fog-based healthcare framework to identify and control chikungunya virus,” *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 1920–1927, 2018.
[26] D. P. Kingma, and J. Ba, “Adam: A Method for Stochastic Optimization,” *arXiv preprint arXiv:1412.6980*, 2014.
[27] C. Shorten, and T. M. Khoshgoftaar, “A survey on Image Data Augmentation for Deep Learning,” *Journal of Big Data*, vol. 6, no. 1, pp. 1–48, 2019.
[28] J. Yosinski, J. Clune, Y. Bengio, and H. Lipson, “How transferable are features in deep neural networks?” *Advances in neural information processing systems*, 2014.
[29] G. E. Hinton, N. Srivastava, A. Krizhevsky, I. Sutskever, and R. R. Salakhutdinov, “Improving neural networks by preventing co-adaptation of feature detectors,” *arXiv preprint arXiv:1207.0580*, 2012.
[30] T. N. Gia, M. Jiang, A. M. Rahmani, T. Westerlund, P. Liljeberg, and H. Tenhunen, “Fog computing in healthcare internet of things: A case study on ECG feature extraction,” *2015 IEEE international conference on computer and information technology*, 2015.
[31] W. Y. B. Lim, N. C. Luong, D. T. Hoang, Y. Jiao, Y. C. Liang, Q. Yang, D. Niyato, and C. Miao, “Federated learning in mobile edge networks: A comprehensive survey,” *IEEE Communications Surveys & Tutorials*, vol. 22, no. 3, 2020.
[32] H. B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, “Communication-efficient learning of deep networks from decentralized data,” *Artificial intelligence and statistics*, 2017.
[33] S. Deterding, D. Dixon, R. Khaled, and L. Nacke, “From game design elements to gamefulness: defining gamification,” *Proceedings of the 15th international academic MindTrek conference*, 2011.
[34] K. Huotari, and J. Hamari, “Defining gamification: a service marketing perspective,” *Proceedings of the 16th international academic MindTrek conference*, 2012.
[35] A. Biørn-Hansen, T. A. Majchrzak, and T. M. Grønli, “Progressive web apps: The possible web-native unifier for mobile development,” *Proceedings of the 13th International Conference on Web Information Systems and Technologies*, 2017.