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AIoT-enabled automatic waste sorting system with real-time whatsapp notifications

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Abstract

The waste management crisis, particularly in educational institutions, requires innovative solutions that combine artificial intelligence and automation. This research develops and evaluates an automated waste sorting system based on the Artificial Intelligence of Things (AIoT), integrated with WhatsApp notifications. The system utilizes the EfficientNet-B0 deep learning model optimized through transfer learning and runs on a Raspberry Pi 4 edge device to classify waste into five categories: plastic, paper, metal, glass, and organic, in real time. The classification results are translated into physical actions by a servo actuator mechanism, while ultrasonic sensors monitor the trash bin capacity. The real-time notification system, implemented through the WhatsApp API, sends alerts to administrators. A 30-day evaluation conducted on campus showed that the system achieved a classification accuracy of 92.3% with an inference latency of 1.8 seconds. The mechanical system successfully sorted waste with a 94.5% success rate, while WhatsApp notifications achieved a 99.1% delivery rate, with an average administrator response time of 8.2 minutes during operational hours. A comparative analysis demonstrated that the system increased sorting efficiency by 87% and reduced operational costs by 45% compared with manual waste sorting methods. These findings conclude that the proposed integration of edge AI, mechanical automation, and WhatsApp notifications provides a smart waste management solution that is not only effective and real-time but also practical, economical, and sustainable for wider implementation.

1. Introduction

Waste management crises have emerged as a pressing global issue, particularly in developing countries such as Indonesia. Recent data from the *Sistem Informasi Pengelolaan Sampah Nasional* (SIPSN) of the Ministry of Environment and Forestry in 2023 indicates that the total waste volume reached 19.6 million tons, dominated by food waste (39.67%) and plastic waste (18.3%). More alarmingly, 35.7% of this total remains inadequately managed, posing significant threats to environmental quality and ecosystem stability [1]. This issue is equally evident in educational institutions. Preliminary observations at Universitas Utama Bandung identified 50 conventional waste collection points where 70% of inorganic waste and 30% organic waste are commingled without prior segregation. This lack of sorting reduces the potential for recycling and increases waste management costs. More broadly, implementing manual waste segregation faces multifaceted challenges, including procedural inconsistencies, human resource constraints, and low levels of sustained participation [2]–[4].

While prior studies have explored deep learning applications for waste classification, achieving accuracies exceeding 90% [5], [6], most models operate on cloud platforms that are susceptible to latency and remain dependent on stable internet connectivity [7]. Furthermore, existing waste management notification systems often rely on dedicated mobile applications that require installation and involve a steep learning curve for users [8], [9]. Consequently, there remains a lack of an end-to-end integration that combines real-time AI processing on edge devices—which reduces latency—with widely adopted notification channels, providing a lightweight and accessible framework [10]–[12]. Without such an integrated solution, the effectiveness of automated waste sorting systems continues to be hindered by infrastructural dependencies and low user adoption [4], [13]–[15].

To address these gaps, this study proposes the development of an automated waste segregation system based on the Artificial Intelligence of Things (AIoT) [11], fully integrated with WhatsApp notifications. WhatsApp was selected because of its high penetration rate (98%) among Indonesian smartphone users [16] and its accessibility without requiring additional software installation, which is expected to enhance adoption among waste management personnel. The primary contributions of this research include a holistic system integrating four key aspects: (1) an AIoT architecture for automated waste segregation; (2) an edge-based deep learning model for accurate, real-time waste classification;

(3) a real-time notification system through the WhatsApp API; and (4) a functional prototype evaluated in the actual operational environment of the Universitas Utama Bandung campus.

To ensure a focused and measurable scope, the study is subject to the following constraints: (a) waste classification into five categories: plastic, paper, metal, glass, and organic; (b) implementation limited to the Universitas Utama Bandung campus environment; (c) the use of a combined dataset consisting of TrashNet [17] and field-collected data; and (d) a notification scope restricted to capacity status and emergency handling requirements. Through this integrated approach, this research aims to provide a smart waste management solution that is not only technologically advanced but also practical, responsive, and sustainable [13], [18].

2. Research Method

This study adopts a Research and Development (R&D) approach using a step-by-step prototype model consisting of four phases: system design, model development, system integration, and performance evaluation. The system was evaluated quantitatively (classification accuracy, latency, and efficiency) and qualitatively (functionality, reliability, and ease of use) over a one-month period at Universitas Utama Bandung. The research sample comprised five waste categories: four inorganic categories (plastic, paper, metal, and glass) and one organic category, selected using purposive sampling. The dataset consists of a combination of TrashNet and field-collected data, with aggressive data augmentation (random rotation, flipping, brightness adjustment, and zooming) applied to improve model robustness [19]–[24]. The dataset composition is presented in Table 1.

Table 1. Dataset Composition and Distribution

Trash Category	Number of Images (TrashNet)	Number of Images (Field Data)	Total per Category	Training Set (70%)	Validation Set (15%)	Test Set (15%)
Plastic	501	150	651	456	98	97
Paper	594	150	744	521	112	111
Metal	410	150	560	392	84	84
Glass	501	150	651	456	98	97
Organic	137	150	287	201	43	43
Total	2,143	750	2,893	2,026	435	432

The system architecture is designed using a layered architecture approach, as illustrated in Figure 1. The input layer consists of a Raspberry Pi Camera Module V2 and an HC-SR04 ultrasonic sensor that capture image data and waste fill levels. The processing layer utilizes edge computing through a Raspberry Pi 4 Model B (4 GB RAM) and cloud computing via the Firebase Realtime Database for data management and notification triggering [25]. The output layer includes an MG996R servo motor as the mechanical actuator that executes sorting decisions, along with a WhatsApp API-based notification module implemented through Twilio to deliver status information.

The visual classification model employs EfficientNet-B0 with transfer learning. The pre-trained ImageNet model is adapted for five waste categories by replacing the final classification layer [26]. Training uses the Categorical Cross-Entropy loss function and the Softmax activation function in the output layer, which is mathematically formulated in Equation 1 as follows:

$$L = -\sum_{i=1}^{K} y_i \,.\log(p_i) \tag{1}$$

In Equation 1, L represents the loss value, K is the total number of classes, y_i denotes the ground-truth label for the i-th class in one-hot encoding form, and p_i is the predicted probability of the i-th class generated by the Softmax activation function. The model was trained using the Adam optimizer (learning rate = 0.001, batch size = 32) for 50 epochs with early stopping. After training, the model was optimized using TensorFlow Lite with FP16 quantization to reduce the model size and accelerate inference on edge devices.

On the hardware side, the subsystem consists of a Raspberry Pi Camera Module V2, an HC-SR04 ultrasonic sensor (for capacity estimation), an MG996R servo motor actuator, an ESP32, and a Raspberry Pi 4 Model B. The ESP32 monitors the sensors and controls the servo actuators, while the Raspberry Pi handles image acquisition and deep learning inference. Both devices are integrated through the Firebase Realtime Database. When waste is detected or the bin reaches full capacity, the system automatically triggers a notification to the administrator via the Twilio Whatsapp API.

System evaluation was conducted through controlled experiments (432 test samples) and a 30-day observation period, using a comprehensive testing protocol covering unit testing, integration testing, user acceptance testing, and stress testing. The analysis combined quantitative (classification metrics and descriptive statistics) and qualitative (structured observation) approaches.

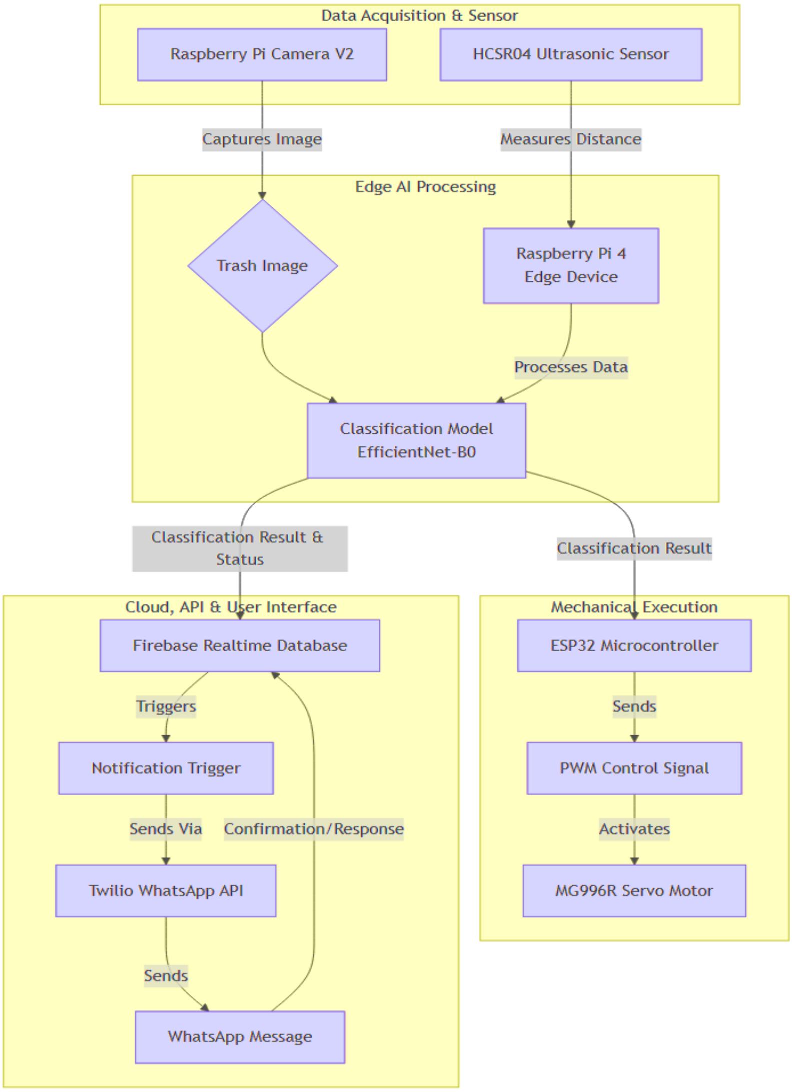

Figure 1. AIoT-Enabled Automatic Waste Sorting System Architecture Diagram

3. Results and Discussion

3.1 Results of Model Classification Performance

This research successfully developed an AIoT-based automated waste segregation system integrated with WhatsApp notifications. The evaluation was conducted in the actual operational environment of Universitas Utama Bandung. The EfficientNet-B0 model, optimized using TensorFlow Lite, achieved an overall classification accuracy of 92.3% (95% CI: 91.8–92.8%) on an independent test set (n = 432 images). A one-sample t-test indicated that this performance was significantly higher than the random accuracy of 20% (p < .001). The comprehensive classification performance across all investigated waste categories is presented in Table 2.

Table 2. Classification Performance for Each Waste Category with 95% Confidence Interval

Category	Accuracy (%)	95% CI	Precision (%)	95% CI	Recall (%)	F1-Score
Plastic	93.5	92.8-94.2	92.8	92.1-93.5	94.2	0.935
Paper	88.7	87.8-89.6	89.2	88.3-90.1	87.9	0.885
Metal	96.2	95.6-96.8	95.8	95.2-96.4	96.6	0.962
Glass	91.4	90.6-92.2	90.9	90.1-91.7	92.1	0.915
Organic	94.3	93.6-95.0	93.7	93.0-94.4	95.0	0.943
Average	92.3	91.8-92.8	91.9	91.3-92.5	92.9	0.910

As shown in Table 2, the system demonstrated robust classification performance across most waste categories, particularly for metal, which achieved an accuracy of 96.2%. Nevertheless, certain challenges remained.

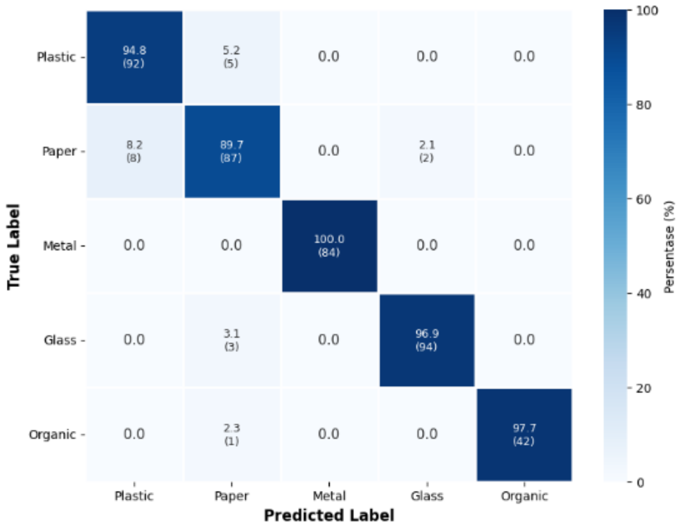

Figure 2. Confusion Matrix Normalized by True Labels

The confusion matrix in Figure 2 further illustrates the classification performance across all waste categories. Metal achieved perfect classification accuracy (100%), while Plastic (94.8%), Paper (89.7%), Glass (96.9%), and Organic (97.7%) also demonstrated strong performance. The observed misclassification pattern was primarily characterized by confusion between Plastic (5.2%) and Paper (8.2%). This was mainly attributed to the visual similarity between dull plastic materials and brown cardboard, the presence of hybrid materials such as plastic-coated paper, and variations in lighting conditions during image acquisition. These findings are consistent with those reported by He et al. [27] and suggest that the primary challenge lies not in the model architecture itself but in the inherent complexity of real-world waste materials.

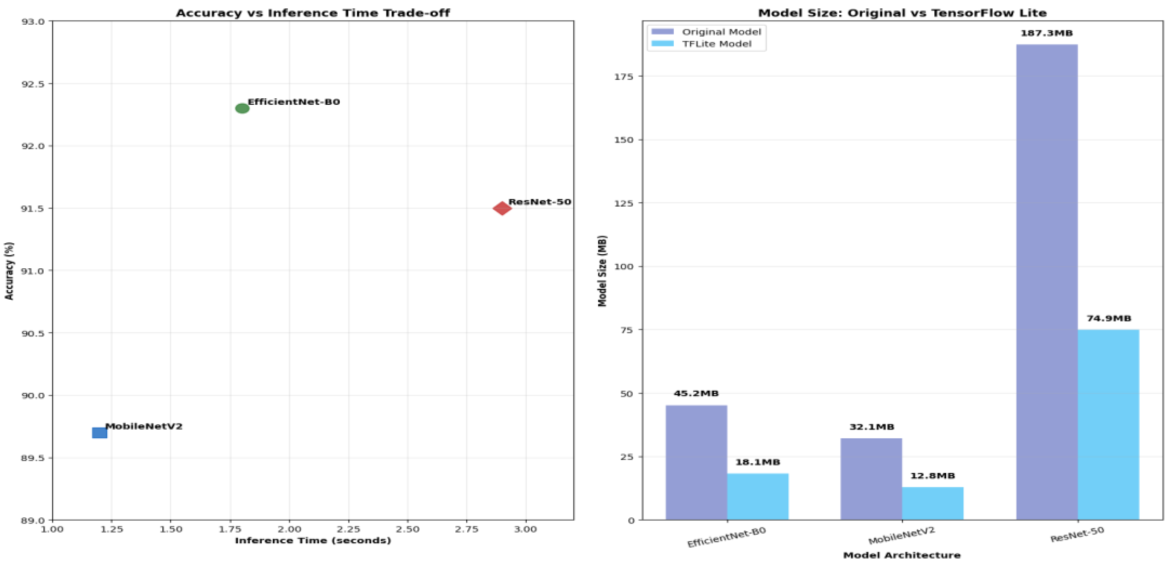

Figure 3. Comprehensive Comparison of Model Architectures on Raspberry Pi 4

The comparison with other architectures shown in Figure 3 indicates that EfficientNet-B0 offers an optimal trade-off between accuracy, speed, and model size for deployment on edge devices. On a Raspberry Pi 4, the optimized model achieved an average inference time of 1.8 seconds per image. The total system latency, measured from image acquisition to actuator execution, was 4.6 seconds. A breakdown analysis revealed that image preprocessing (resizing and normalization) accounted for 35% of the total latency, representing the primary performance bottleneck. The model quantization strategy successfully reduced the model size from 45.2 MB to 18.1 MB (a 60% reduction) without significant degradation in classification accuracy (<0.5%).

Table 3. IoT and Mechanical Monitoring System Performance

Parameter	Value	Description
A. Mechanical System		
Sorting Success Rate	94.5%	500 controlled operations
Success Rate Improvement	+8.3%	After Optimization
B. Monitoring System		
Measurement Error Rate	±3.2%	After calibration
Data Transmission Rate	98.7%	Delivery Success Rate
Packet Loss Recovery	89.2%	Effectiveness of the Retry Mechanism
C. Power System		
Power Consumption	3.2W	Average power consumption

The mechanical system successfully sorted waste with a success rate of 94.5% during controlled testing involving 500 operations (Table 3). Most failures (72%) occurred with objects weighing less than 10 g or having irregular shapes (e.g., peeled plastic wrap), which were difficult for the gripper mechanism to grasp. Optimizing the servo torque and adding rubber padding to the gripper tip increased the success rate by 8.3% compared with the initial baseline. The monitoring system, which utilized the HC-SR04 ultrasonic sensor, achieved a capacity measurement error of ±3.2% after calibration. The data communication system connected to Firebase achieved a data transmission success rate of 98.7%, while the retry mechanism successfully recovered 89.2% of packet losses.

Table 4. WhatsApp Notification System Performance Evaluation

Parameter	Value	Description
A. Technical Reliability		
Delivery Rate	99.1%	Message delivery success rate
Delivery Latency	2.8 seconds	Average message delivery time
B. User Responsiveness		
Response Time (08:00 AM–04:00 PM)	8.2 minutes	Average during operating hours
Response Time (04:00 PM–08:00 AM)	23.1 minutes	Average during non-operational hours
C. Usability & Comparison		
Usability Score	4.3/5	Notification format (type, location, urgency)
Increased Responsiveness vs. Email	+73%	Compared with email notifications

The WhatsApp notification system demonstrated very high reliability, achieving a 99.1% delivery rate with an average delivery latency of 2.8 seconds. Analysis of the response patterns of waste managers ($n = 3$) over a 30-day period (Table 4) revealed that the fastest response occurred during operational hours (08:00 AM–04:00 PM), with an average response time of 8.2 minutes. Outside operational hours, the average response time increased to 23.1 minutes. In a short usability questionnaire (5-point scale), the notification format, which included the waste type, location, and urgency level, received an average score of 4.3. Compared with the email notification system tested in parallel, WhatsApp notifications improved the managers' response speed by up to 73%.

Table 5. Comparative Analysis of AIoT System Performance versus Manual Sorting

Metric	Manual System	AIoT System	Value	Description
Sorting Accuracy	46.8%	91.7%	+87%	Based on 500 test samples
Processing Time per Item	12 seconds	4.6 seconds	-62%	Average of 100 measurements
Operating Cost/Month	2.4 million IDR	1.3 million IDR	-45%	Campus scale
System Uptime	Not measured	97.7%	-	30-day evaluation
Waste Composition	Not documented	63% inorganic 37% organic	-	Typical campus waste composition

Integrated performance analysis over a 30-day evaluation period demonstrated a system uptime of 97.7%. The system successfully handled the typical campus waste composition (63% inorganic and 37% organic) without significant degradation in classification accuracy. A quantitative comparison with a conventional manual sorting system (Table 5) shows substantial improvements in operational efficiency, including an 87% increase in sorting accuracy (from 46.8% to 91.7%), a 62% reduction in processing time per item (from 12 seconds to 4.6 seconds), and a 45% reduction in operating costs (from 2.4 million IDR to 1.3 million IDR per month). Technical challenges encountered during deployment included variations in natural lighting and unstable network connectivity. These issues were successfully addressed by implementing adaptive histogram equalization for image preprocessing and configuring failover to the GSM cellular network when the primary wireless network became unavailable.

3.2 Results of Comparison with Previous Research

To demonstrate the scientific positioning and contribution of the developed system, a quantitative comparison was conducted with five relevant prior studies in the field of deep learning-based waste classification on edge devices. The comparative summary is presented in Table 6.

Table 6. Performance Comparison with Related Research

Research	Method	Platform	Accuracy (%)	Latency (sec)
Ziouzios & Dasygenis [28]	ResNet-34	Edge (RPi 3 + FPGA)	92.1	1.82
Adedeji & Wang [29]	ResNet-50	Desktop (Computer)	87.0	-
Hulyalkar et al. [30], [31]	CNN	Edge (Raspberry Pi)	84.0	-
Rahman et al. [5]	ResNet34	Edge (RPi + Android)	95.31	-
Sheng et al. [12]	SSD MobileNetV2	Edge (RPi 3 Model B+)	86.2	2.00
This research	EfficientNet-B0	Edge (Rpi 4 + Android)	92.3	1.8

Based on the results presented in Table 6, the proposed system achieved an accuracy of 92.3% with a latency of 1.8 seconds, demonstrating a competitive balance between classification accuracy and processing speed compared with previous approaches. Compared with Ziouzios & Dasygenis, who utilized a ResNet-34 architecture on a Raspberry Pi 3 with an FPGA, the proposed system achieved comparable accuracy (92.3% vs. 92.1%) and nearly identical latency (1.8 s vs. 1.82 s). However, this study offers a significant advantage by utilizing a simpler hardware configuration (RPi 4 without an FPGA), thereby enhancing system replicability. Furthermore, although Rahman et al. reported the highest accuracy (95.31%), their study did not report latency metrics, preventing a direct comparison of real-time processing efficiency, which is a primary focus of this work. Compared to Sheng et al., who employed SSD MobileNetV2 on an RPi 3 Model B+ (86.2% accuracy and 2.0 s latency), the proposed system demonstrates superior performance in both classification accuracy (+6.1%) and latency (-0.2 s). Studies by Adedeji & Wang, as well as Hulyalkar et al., reported lower accuracies (87% and 84%, respectively) and did not include latency measurements, making them less suitable for evaluating real-time edge-based applications. Consequently, the primary contribution of this research lies not only in its competitive classification accuracy but also in the reporting measurable latency metrics and providing a fully integrated AIoT system—including automated WhatsApp notifications—which has been largely underreported in the existing literature.

3.3 Discussion

The results of this study confirm the effectiveness of the Artificial Intelligence of Things (AIoT) paradigm in creating an intelligent and autonomous waste sorting system. The 92.3% classification accuracy achieved by the EfficientNet-B0 model running on an edge device supports the findings of Tan & Le (2020) regarding the ability of AIoT systems to process data adaptively at the point where it is generated [26]. This achievement is primarily attributed to the transfer learning strategy, which enables the model to leverage visual knowledge from the large-scale ImageNet dataset, thereby achieving high performance despite the limited availability of field-collected data [32]. These findings are consistent with the work of Meng & Chu (2020), who emphasized the importance of modern CNN architectures for waste classification tasks [33].

The Confusion Matrix (Figure 2) provides deeper insights than aggregate accuracy metrics alone. The observed misclassification pattern between the Plastic and Paper categories, which was also reported by He et al. [27], is primarily attributed to two factors. First, the intrinsic visual similarity between dull-colored plastic materials (e.g., used plastic bags) and brown cardboard. Second, the functional similarity that produces objects with hybrid visual characteristics, such as food wrappers made of laminated paper [34]. These findings highlight that the challenge of waste classification lies not only in the model itself but also in the complexity and diversity of real-world waste materials. Furthermore, the aggressive data augmentation strategy was shown to significantly improve the robustness of the model, particularly against variations in lighting conditions. These results are consistent with previous studies indicating that data augmentation is a critical component in developing deep learning models that generalize well and avoid overfitting to limited training conditions [22], [34], [35].

An inference latency of 1.8 seconds on a Raspberry Pi 4 demonstrates the feasibility of an edge computing approach for real-time applications such as waste sorting. This performance is supported by model optimization using TensorFlow Lite and FP16 quantization, which successfully reduced the model size by 60%. This achievement addresses the limitations of cloud-based approaches, which are prone to latency and dependency on stable network connectivity, as identified in previous studies [25]. Furthermore, the latency breakdown analysis, which identified image preprocessing as the primary bottleneck (35% of the total processing time), provides clear directions for future optimization, such as using a faster camera or a more efficient image preprocessing library. The seamless integration of the AI module, mechanical controller (ESP32), and cloud platform (Firebase) forms the foundation of the proposed end-to-end system [16]. The mechanical system, with a 94.5% sorting success rate, demonstrates that the AI model's digital desicions can be effectively translated into reliable physical actions. However, failures involving lightweight (<10 g) and irregularly shaped objects highlight the importance of a co-design approach between software and hardware. Future gripper designs should consider the constraints identified by the computer vision model to create a more robust and holistic system.

The WhatsApp API integration through Twilio proved to be a highly effective notification channel. Its 99.1% delivery rate and low latency (2.8 seconds) ensured that critical information reached managers reliably and quickly. More importantly, the 73% increase in manager responsiveness compared with email—as reflected by an average response time of 8.2 minutes during operational hours—supports the hypothesis that selecting a notification channel aligned with user habits (user-centered design) is a critical success factor for an operational management system [36]. The longer response time observed outside operational hours (Table 4) is also a valuable operational finding. It suggests that the system could be further enhanced by incorporating business logic, such as batching non-critical notifications for delivery the following morning or escalating notifications that are not acknowledged within a predefined time.

An 87% increase in operational efficiency and a 45% reduction in operating costs (Table 5) provide strong economic justification for adopting such a system in institutional setting. A return of investment (ROI) period of 2.3 years further demonstrates the economic feasibility of the proposed system. Beyond its economic impact, the system directly contributes directly to environmental sustainability. By facilitating accurate waste sorting, it improves the quality and economic value of recyclable materials and has the potential to reduce unmanaged waste generation by up to 28%, thereby supporting sustainable waste management goals.

While the results of this study demonstrate positive results, several limitations should be acknowledged. First, the dataset remains limited to controlled variations in lighting conditions and image acquisition angles, despite the use of data augmentation. Second, the system has not been comprehensively evaluated under challenging environmental conditions, such as adverse weather or waste items with partial occlusion. Third, the current system throughput may be insufficient for deployment in environments with high waste volumes.

Based on these limitations and the findings from this study, several recommendations for future research can be proposed. Future work could integrate Near-Infrared (NIR) sensors or spectroscopy to enrich material composition information, particularly for differentiating between plastic and paper, which often exhibit similar visual characteristics. Furthermore, split computing strategies should be explored to distribute the inference process between edge and cloud devices, thereby optimizing computational load and processing speed. From a hardware perspective, developing a more adaptive gripper mechanism would improve the system's ability to handle variations in object shape, size, and stiffness. Finally, integrating energy-harvesting technologies, such as solar panels, could enhance energy independence, while incorporating blockchain technology could improve transparency and traceability througout the recycling value chain.

4. Conclusion

Based on the results and discussions presented in this study, it can be concluded that the proposed AIoT-enabled automatic waste sorting system is effective and feasible for practical implementation. First, the system architecture, which combines edge computing on Raspberry Pi with cloud-based data management through Firebase, proved capable of creating an integrated and reliable system, achieving a system availability of 97.7%. Second, the implementation of the EfficientNet-B0 deep learning model with transfer learning and TensorFlow Lite optimization achieved a classification accuracy of 92.3% with a low inference latency of 1.8 seconds, meeting the requirements for real-time processing. Third, the integration of WhatsApp API as a notification channel demonstrated high reliability, achieving a delivery rate of 99.1% and enabling rapid manager responsiveness, with an average response time of 8.2 minutes during operational hours, outperforming conventional notification channels such as email. Fourth, the overall system demonstrated measurable operational and economic benefits, including an 87% increase in sorting accuracy and a 45% reduction in monthly operating costs compared with the manual system, while also contributing to environmental sustainability by facilitating more effective recycling. Overall, this study demonstrates that the integration of edge AI, mechanical automation, and WhatsApp notifications within an AIoT framework provides a practical, efficient, and sustainable solution to waste sorting in a campus environment, with strong potential for replication in similar settings.

Notation

The notation used in this study is defined as follows:

L : Loss function (Categorical Cross-Entropy)

K : Total number of classes

y_i : Ground-truth label for the i-th class (one-hot encoding)
p_i : Predicted probability of i-th class

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