Computer Vision System Based on OpenCV for Solid Waste Classification in Piura, Peru

Matias Garcia-Olivares * and Yeran Carmen-Livia

Faculty of Engineering and Architecture, Professional School of Systems Engineering,
Universidad César Vallejo, Piura, Peru
Email: magarciao@ucvvirtual.edu.pe (M.G.O.); yliviac@ucvvirtual.edu.pe (Y.C.L.)
*Corresponding author

***Abstract*—Inadequate solid waste management poses a threat to public health and environmental sustainability in urban contexts. This study aimed to determine how a computer vision system based on Open Source Computer Vision Library (OpenCV) reduces processing time and improves accuracy in solid waste classification in Piura, Peru. An applied study with a quantitative approach was conducted with operators. Data were collected using observation guides and a validated questionnaire. The results showed significant improvements: the number of waste items classified per minute increased by 80%, and the average processing time per batch was reduced by 46.8%. The system achieved an overall accuracy of 83.2%, with classification accuracy rates exceeding 70% in all evaluated categories. It is concluded that computer vision based on OpenCV effectively optimizes both speed and accuracy in solid waste classification, thereby significantly improving urban environmental management.**

***Keywords*—artificial intelligence, sustainable development, public health, recycling, waste management**

I. Introduction

The inadequate solid waste management poses a significant threat not only to the environment but also to public health and overall urban well-being. Increasing waste generation driven by population growth, limited infrastructure for reuse, and insufficient environmental awareness, has intensified this challenge in many developing regions, As reported by Yelve and Mann [1], projections warn that global waste levels could increase by nearly 70% by 2050 if urgent measures are not taken, Gomez and Bardales [2] also indicate that inadequate disposal practices, accumulation of waste in inappropriate locations, and the presence of informal waste pickers further aggravate sanitary risks and contribute to environmental degradation. On the other hand, Vargas-Restrepo *et al.* [3] explain how waste generation is closely associated with daily human activities, ranging from food preparation to packaging use and household maintenance, which continuously produce organic and inorganic waste. Without proper management, these materials accumulate rapidly and negatively affect public spaces, human health, and the quality of life of local communities. Markets represent a critical hotspot for waste accumulation due to their intense commercial activity and constant flow of people, resulting in large volumes of mixed waste that require immediate attention. According to Zamani *et al.* [4], traditional waste classification methods performed manually by operators are slow, labor-intensive, and often inaccurate due to a lack of training and limited knowledge of proper waste segregation. This situation demands sustainable technological solutions capable of supporting more consistent classification processes while reducing operational burden under municipal working conditions. Guerra and Baca-Cajas [5] have proposed intelligent systems as viable alternatives that can achieve higher classification while consistency reducing physical effort required from waste management personnel. At the regional level, they explain that urban growth and limited infrastructure in Latin America have contributed to a projected 25% increase in the generation of municipal solid waste. This is reflected in Piura, where waste collection is conducted through door-to-door routes; however, the service is often perceived as operationally inefficient by residents. Although the municipality promotes the “Piura Recicla” program, the high dependence on manual labor continues to limit the consistency and overall performance of the segregation process. Studies conducted in Piura and Castilla by Tomiyama *et al.* [6] show that more than 60% of residents are dissatisfied with the efficiency of waste collection and transport services, with a significant proportion reporting irregular schedule and a lack of comprehensive facilities for waste management. Low levels of recycling awareness and inadequate waste management practices exacerbate environmental risks, especially in high-density areas such as municipal markets. Daily waste generation in these markets can exceed hundreds of tons, however, technological solutions remain scarce. Similarly, Olawade *et al.* [7] conducted a study in the city of Chiclayo demonstrating how poor municipal solid waste management negatively affects public spaces. Their findings indicated that more than 50% of waste is not properly collected, resulting in diseases and pollution

Manuscript received November 17, 2025; revised January 21, 2026; accepted February 10, 2026; published September 4, 2026.

doi: 10.12720/jait.17.9.1676-1690

within the urban space. Their research argued for the validity of integrating efficient technologies to strengthen the sustainability of public spaces. This contextualizes the need for computer vision-based solutions in Peru. It also demonstrates the urgency of modernizing waste classification and handling processes in cities facing recurrent accumulation problems, such as Piura. Consequently, local conditions highlight the urgent need for innovative and accessible tools to support automated waste classification.

Despite the increasing number of studies applying computer vision techniques based on OpenCV and YOLO for solid waste classification, most existing approaches primarily focus on detection accuracy under controlled or laboratory conditions, often relying on benchmark datasets. Moreover, several recent deep learning models prioritize high accuracy at the expense of increased computational complexity, which limits their suitability for real-time deployment in municipal environments with constrained infrastructure. Given the rapid evolution of object detection architectures, several studies have demonstrated that greater architectural complexity does not necessarily translate into superior performance in real-time scenarios, especially when computational resources are limited. Wang *et al.* [8] demonstrated that models with efficiency-oriented designs often achieve more stable inference times and comparable accuracy when deployed in real-world operational environments. In this context, the You Only Look Once (YOLO) family, originally proposed by Redmon *et al.* [9], was designed under a single-stage detection paradigm that prioritizes low latency and real-time responsiveness.

Most published waste classification studies validate their systems using a limited number of waste categories. Echeverry and López [10] developed a prototype named AUTORECYCLER, which classifying only 4 waste categories, thereby restricting its applicability to comprehensive municipal waste segregation. Similarly, Zamani *et al.* [4] focused on binary distinction between biodegradable and non-biodegradable materials, lacking the categorical specificity required for operational waste flow management. In addition, the majority of published studies emphasize technical detection metrics while neglecting human-centered evaluation dimensions. Aarthi and Rishma [11] demonstrated their vision-based approach without assessing operator usability perception or system acceptance among waste segregation workers.

In contrast, the present study evaluates 7 waste categories (plastic, cardboard, glass, metal, paper, medical waste, and electronic waste), providing broader categorical coverage than previous works. Furthermore, the study incorporates operator usability and system acceptance assessment alongside technical accuracy metrics, thereby addressing the human-centered evaluation dimension that has been largely overlooked in existing research.

This expanded categorical scope enables granular differentiation of waste streams required for municipal operations. Moreover, the inclusion of human-centered evaluation dimensions addresses the gap identified in prior research, providing holistic assessment of both technical performance and scalability in municipal waste management contexts.

In this context, the present study adopts YOLOv11 as the core detection model due to its balance between detection accuracy, inference speed, and computational efficiency, making it well suited for real-time waste classification under real operational conditions. The novelty of this work lies in its integrated evaluation framework, which combines technical detection metrics with operational performance indicators and a user-centered evaluation, including classification speed, processing time, usability, and system acceptance by waste segregation operators. Based on this identified research gap and the need for practical validation under real operational conditions, the specific contributions of this study are summarized as follows: (1) the implementation and evaluation of a computer vision-based waste classification system at a municipal scale, validated in a real waste segregation facility under operational conditions; (2) a user-centered evaluation framework that integrates technical detection metrics with operational performance indicators and user-focused measures, including usability and system acceptance; (3) the design and implementation of an integrated system architecture that combines a YOLOv11-based detection model, OpenCV processing, and a web-based management interface; and (4) the definition of an end-to-end operational workflow that supports real-time waste classification, data logging, and performance monitoring in a municipal recycling context.

In alignment with Sustainable Development Goal (SDG) 12—particularly target 12.5, which seeks to significantly reduce waste generation through recycling and reuse—this study proposes a computer-vision system based on OpenCV aimed at evaluating changes in classification time and accuracy in solid waste separation processes in Piura. The main research problem addresses how such a system can reduce classification time and increase precision in real operational contexts. Specifically, the study examines: (1) variations in classification time before and after system implementation; (2) the system's accuracy in waste identification; (3) its accuracy across different waste types; and (4) user perceptions regarding the system's usefulness and performance.

Following the formulation of the research problem, the study defined its objectives alignment with Sustainable Development Goal (SDG) 12—particularly target 12.5, which promotes the reduction of waste generation through recycling and reuse. The general objective was to determine how a computer-vision system based on OpenCV can reduce classification time and improve accuracy in solid-waste separation in Piura. The specific objectives were to: (1) measure the average classification time before and after system implementation; (2) evaluate the system's accuracy in solid waste classification; (3) determine the system's accuracy by waste type; and (4) assess user perceptions of the system's effectiveness.

II. Literature Review

A. Related Studies

To contextualize this research, it is essential to review previous studies that explore AI and computer vision applications in solid waste classification, as these works provide a technological foundation for the present project in Piura. At international level, Castro-Bello *et al.* [12] developed an automated computerized method for the identification of solid waste in urban parks. Their main research objective was to design a computer vision system to support solid waste classification in public areas. To achieve this, they implemented neural networks together with image processing techniques, establishing a methodological approach that included image capture, algorithm training, and system validation. Their findings reported a reduction in classification error rates when compared to manual procedures, indicating that convolutional models can provide more consistent results under controlled conditions. This study is relevant to the present work as it demonstrates the feasibility of applying computer vision technologies to support solid waste classification processes in municipal contexts such as Piura.

Similarly, Malik *et al.* [13] proposed an algorithm based on deep learning for the automatic classification of waste using real images obtained from public datasets. As a result, the prototype implemented over a neural network architecture reached stable classification performance in identifying organic and inorganic waste in different environments. Their investigation demonstrated the feasibility of deep learning for waste classification, providing evidence that models trained with large datasets can generalize effectively even in heterogeneous contexts. This strengthens the basis for the current research, as it confirms the applicability of deep-learning-based waste classification approaches.

Likewise, Arteaga *et al.* [14], conducted a study in the city of Chiclayo showing how poor urban solid waste management negatively affects public spaces. Their findings indicated that more than 50% of waste is not properly collected, leading to disease and pollution within the urban space. Their research argued for the relevance of integrating technological solutions that contribute to the more sustainable public space management. This contextualizes the need for computer vision–based solutions in Peru. It also demonstrates the urgency of modernizing waste classification and management processes in cities facing recurrent accumulation problems, such as Piura. Therefore, these studies collectively justify the implementation of intelligent systems to support municipal waste management operations.

B. Theoretical Framework

Furthermore, Cruz *et al.* [15] argued the versatility of OpenCV by presenting an intelligent solid waste detection system based on neural networks and computer vision. Their proposal incorporated sensors and digitalized images for real-time identification and classification, highlighting the adaptability of OpenCV in low-cost systems with continuous operating capacity. This reference is significant because it demonstrates how open-source computer vision libraries enable the development of functional solutions without requiring specialized infrastructure, thereby reinforcing the theoretical basis of this work.

Likewise, Lu and Chen [16] strengthened these foundations from the perspective of Deep Learning Theory by analyzing how classification systems based on computer vision have transformed waste-sorting solutions. Their critical review showed that modern approaches allow solid waste detection under real conditions, emphasizing material types through advanced architectures such as Mask Region-based Convolutional Neural Network (R-CNN). This perspective provided deeper insight how multilevel feature extraction supports accurate waste classification. Consequently, their contributions justify the application of robust models such as YOLOV5 in the current system and provide a solid theoretical basis for automating visual recognition tasks.

In addition, Merugu *et al.* [17] analyzed the role of deep learning–based feature representation in improving image similarity through autoencoder architectures. Their study highlights how latent feature extraction enables visual systems to better distinguish structurally similar objects by learning compact and discriminative representations. This contribution supports the theoretical foundation of the present work, as waste classification systems also rely on robust feature extraction to reduce visual ambiguity among materials with heterogeneous appearances.

C. Technological Framework

Similarly, Kavade *et al.* [18] developed an automated classification system assisted by OpenCV, that enabled the segregation of different types of waste—including organic, plastic, metal, and inorganic materials—using image processing techniques and lightweight neural networks. Their architecture incorporated camera interfaces, a ESP32 microcontroller WiFi module , and YOLOV5 to support waste segregation tasks and promote sustainable system operation. This proposal represents a direct technological reference, as it integrates elements similar to those used in the present study, reaffirming the suitability of deep learning combined with accessible hardware to develop scalable solutions.

On the other hand, Aarthi and Rishma [11] proposed an architecture for waste classification with robotic intervention based on computer vision. From their perspective, the system enabled waste localization and accurate information extraction through neural networks, achieving an 86% accuracy in multiclass classification under experimental conditions. Their contribution demonstrates the increasing incorporation of computer vision into robotic processes, indicating a transition toward autonomous and complex solutions. This is relevant for contextualizing the technological evolution underlying the present study, as it highlights the gradual shift from simple recognition algorithms to systems capable of performing precise interactions with real-world environments.

III. METHODOLOGY

A. Research Design

This research was structured as applied research, given its primary focus on developing a functional solution to address the tangible and real difficulties observed in solid waste classification in the municipal context of Piura. A quantitative approach was employed, which was essential for objectively measuring the impact of the intervention and validating the hypotheses through numerical data and statistical analysis. The study adopted a pre-experimental design, specifically a single-group pretest/posttest configuration, as this structure allowed for the intentional manipulation of the independent variable in order to observe its measurable effect on the dependent variable. However, this design did not include a control group, which represents a methodological limitation, as it restricts the ability to fully isolate external factors that may influence the observed outcomes. In addition, the research maintained a descriptive scope, as it sought to systematically document and characterize changes in classification indicators and operational performance throughout the intervention period.

B. Variables and Dimensions

The variables of this study were operationally defined based on established literature. The independent variable was Computer Vision System, which is conceptually described as a technology that enables the automatic identification and classification of solid waste through image analysis processed by OpenCV. The dependent variable was Solid Waste Classification, which refers to the process of separating and categorizing different types of waste according to their characteristics to facilitate proper recycling and disposal.

This dependent variable was analyzed through 3 specific dimensions to provide a comprehensive measurement. First, classification accuracy, which refers to the degree of precision with which the system measures and evaluates solid waste, encompasses indicators such as overall accuracy percentage, accuracy rate by waste type, and classification error rate [19]. Second, the classification speed, which evaluates the time required by the system to process and classify solid waste, measured through indicators such as average processing time per batch (in seconds) and the number of items classified per minute. Third, the perceived efficiency, which analyzes operators' perceptions regarding system usability and acceptance during the waste classification process.

C. Population and Sample

The population for this study included all operators at the waste segregation plant managed by the Provincial Municipality of Piura through the "Piura Recicla" program, this population was finite and readily accessible. Clear inclusion criteria were defined, such as being an active operator performing waste classification tasks at the segregation plant with regular attendance. These inclusion criteria ensured that all participants shared comparable levels of prior experience and familiarity with manual solid waste classification activities, thereby reducing variability related with differences in initial operational skills among operators. Likewise, detailed exclusion criteria were established to ensure data homogeneity, such as administrative personnel not directly involved in classification operations or workers absent during data collection periods. The total population comprised 160 operators distributed across seven associations within the program. Given the finite nature of this population, the sample size was calculated using the finite population formula, where N equals 160, z equals 1.96 for a 95% confidence level, p and q equal 0.5 for maximum variability, and E equals 0.10 for the margin of error. This calculation yielded a final sample of 60 operators who met the established criteria. The sampling strategy employed was non-probabilistic convenience sampling due to operational constraints and practical accessibility considerations. While this approach ensured feasibility and full participation during the intervention, it limits the generalizability of the findings beyond the specific context studied. Therefore, the results should be interpreted as context-specific to the municipal waste management conditions of Piura.

D. Data Collection and Instrumentation

The data collection process was structured into sequential phases aligned with the specific objectives of the study, ensuring methodological consistency and temporal separation between measurements.

For Objective A (Measurement of Classification Time Before and After Implementation), a pre-test/post-test scheme was applied. The pre-test phase was conducted from September 15 to September 19, 2025, during which 60 operators performed traditional manual waste classification tasks. Data collection was distributed across 5 consecutive days, evaluating 12 operators per day under real operational conditions. Following system installation and operator training, the post-test phase was conducted from September 22 to September 26, 2025, maintaining the same daily distribution and measurement conditions to ensure direct comparability between pre- and post-test results.

Objective B (Overall Accuracy in Solid Waste Classification) was evaluated exclusively during the post-test phase. Data were collected between September 29 and October 3, 2025, focusing on the system's global classification precision under continuous real-world operation, without comparison to a manual baseline.

Objective C (System Accuracy Level in Solid Waste Classification by Type) was also evaluated solely in the post-test phase. This evaluation was conducted from October 7 to October 11, 2025, recording correctly and incorrectly classified items across 7 waste categories to determine category-specific accuracy rates.

Objective D (System Efficiency in Solid Waste Classification), corresponding to operators perceived usability and system acceptance, was evaluated during the final stage of the study. Data were collected on October 13 and 14, 2025, using a structured dichotomous questionnaire administered to the same group of 60 operators after sustained system use.

The instrumentation consisted of 4 observation guides. Observation Guide 1 measured the number of waste items classified per minute, Observation Guide 2 recorded the average classification time per batch of 150 waste items, Observation Guide 3 evaluated overall classification precision as a percentage, and Observation Guide 4 evaluated accuracy by waste type (plastic, cardboard, glass, metal, paper, medical waste, and electronic waste). In addition, a dichotomous questionnaire composed of 10 items was used to evaluate perceived system usability and acceptance, grouped into the dimensions of usability level and system acceptance, with responses coded as Yes (1) or No (0).

The questionnaire underwent a validation process to ensure methodological rigor. Content validity was confirmed through expert judgment by 3 specialists, obtaining Aiken's V coefficients of 1.00 for all items [20]. Reliability analysis yielded a Cronbach's Alpha coefficient of 0.943 [21], indicating excellent internal consistency.

E. Data Analysis

For the mathematical analysis, raw data from the instruments were first digitized and consolidated using Microsoft Excel for initial organization. Subsequently, a combination of statistical software and programming tools were employed. Inferential hypothesis testing was executed using the Statistical Package for the Social Sciences (SPSS) Statistics version 27.0, while the Python programming language—specifically its data analysis and visualization libraries—was used to generate complex descriptive and comparative graphs. The analytical process began with descriptive statistics, calculating mean, standard deviations, minimum, and maximum values for all quantitative variables, followed by inferential testing, where the Kolmogorov-Smirnov test was applied to assess data normality, a critical step given the sample size of 60 participants. The test results revealed that 3 of 4 indicators showed non-normal distribution with p-values below 0.05, thereby confirming the use of the non-parametric Wilcoxon signed-rank test for related samples to analyze classification speed and processing time indicators, while the ordinal, non-normally distributed operator perception data also required the use of the Wilcoxon signed-rank test to compare pre-test and post-test responses. Statistical significance was established at an alpha level of 0.05 for all hypothesis tests.

F. Solution Development

The computer vision solution was conceived as an automated classification system capable of supporting real-time waste identification with limited human intervention. Its development was divided into 3 strategic components: the dataset construction and model training, the system architecture and deployment, and the operational implementation workflow.

G. Dataset Construction and Model Training

The foundation of the computer vision system was a comprehensive dataset comprising 7000 images evenly distributed across 7 waste categories: plastic, cardboard, glass, metal, paper, medical waste, and electronic waste. Each category contained exactly 1000 images that were carefully collected from the segregation plant's operational environment and supplemented with publicly available waste classification datasets to ensure diversity and representative coverage. These images were organized and annotated using Roboflow, a specialized computer vision platform that facilitated image dataset labeling, augmentation, and management. Each image was manually annotated with bounding boxes identifying waste items and their corresponding categories, thereby ensuring accurate ground truth data for model training.

The complete dataset was subsequently divided into 3 subsets following standard machine learning practices, where each of the seven categories was split into 600 training images (60%), 200 validation images (20%), and 200 test images (20%), resulting in a total of 4200 training images, 1400 validation images, and 1400 test images across all categories, This distribution is illustrated in Fig. 1, which presents the dataset distribution strategy and sample images from each waste category. Although the dataset was numerically balanced across categories to prevent class imbalance during training, a potential source of dataset bias is associated with the origin and visual diversity of the samples. A substantial portion of the images was collected from a single municipal segregation facility, resulting in relatively consistent backgrounds, object presentation patterns, and lighting conditions. While this controlled acquisition facilitated reliable annotation and stable model training, it may have limited the exposure of the model to a wider range of visual conditions commonly encountered in different operational environments. Furthermore, inherent intra-class variability among waste categories—related to differences in shape, texture, reflectance, and deformation—poses an intrinsic challenge for visual classification systems, even under balanced dataset configurations. The model training process was executed on the Google Colab cloud platform using the YOLOv11 object detection architecture, specifically the YOLOv11s model. All input images were resized to 640 × 640 pixels, and the model was trained using a batch size of 16 over 100 epochs. The Stochastic Gradient Descent (SGD) optimizer was employed with an initial learning rate of 0.01, using the default YOLOv11 loss functions for object detection. Training was accelerated using an NVIDIA Tesla T4 GPU provided by the Google Colab environment.

COLOR	CLASS NAME	COUNT
	cardboard	995
	e-waste	1002
	glass	970
	medical	1000
	metal	973
	paper	972
	plastic	989

Fig. 1. Dataset distribution and sample images by waste category.

The model training process was conducted on the Google Colab cloud infrastructure, which provided the necessary Graphics Processing Unit (GPU) acceleration to ensure computational efficiency without requiring investment in local hardware. Training was configured to run for 100 epochs using a convolutional neural network architecture based on YOLOV11, integrated with OpenCV 4.x framework for image processing and real-time detection. Throughout the training process, several performance metrics were continuously monitored to assess model convergence and mitigate the risk of overfitting. These metrics included the mean Average Precision (mAP) at a 50% Intersection over Union (IoU) threshold, the mAP computed across multiple IoU thresholds ranging from 50% to 95%, precision, defined as the proportion of correctly predicted positive instances, and recall, which measures the proportion of actual positive instances correctly identified by the system. Upon completion of the training phase, the model achieved a maximum mean Average Precision at 50% IoU of 83.2%, indicating strong detection and classification capabilities across all waste categories. These results are detailed in Fig. 2, which illustrates the evolution of training metrics over the 100 epochs, including the convergence of the training loss, validation precision, and final performance indicators, namely mAP@0.5 of 83.2%, mAP@0.5:0.95 of 53.2%, precision of 78.2%, and recall of 54.4%.

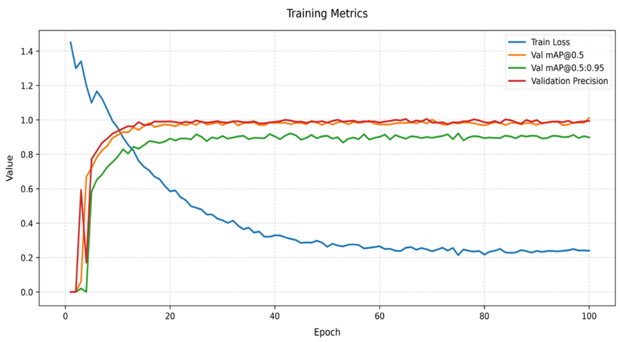

Fig. 2. Training and validation metrics of the YOLOv11 model.

The model's performance was further validated through category-wise analysis using a confusion matrix, which revealed differentiated levels of classification accuracy across waste types. Glass achieved the highest accuracy at 88%, attributable to its distinctive visual features and relatively uniform appearance. This was followed by electronic waste at 86%, metal at 85%, cardboard at 82%, medical waste at 81%, paper at 76%, and plastic at 72.5%. This variation was attributed to the inherent visual complexity of certain categories, particularly plastic, which exhibited high intra-class variability in terms of color, transparency, shape, and degrees of degradation. Fig. 3 illustrates the confusion matrix, depicting the model's classification performance across the seven waste categories, with correct predictions represented along the diagonal and misclassifications in off-diagonal cells.

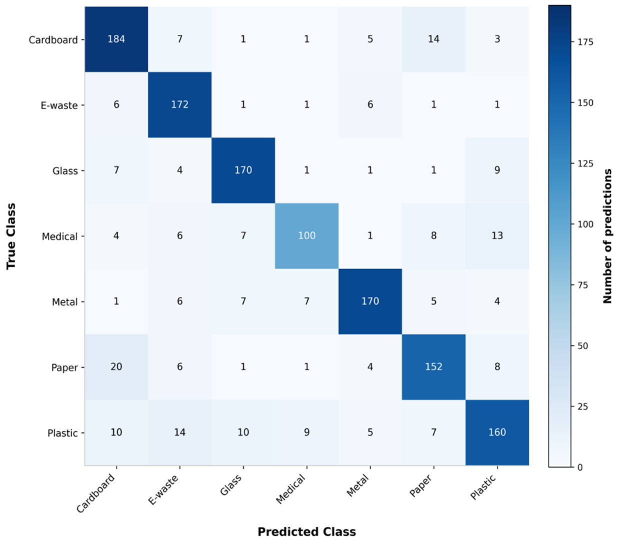

Fig. 3. Confusion matrix for waste classification results.

H. System Architecture and Deployment

The system architecture was designed using a modular approach to facilitate scalability and real-time operation in a municipal solid waste classification environment. The user interface was developed using PHP and MySQL, deployed through XAMPP (Cross-platform, Apache, MySQL, php and Perl) to store operator data, classification records, and system logs. The computer vision module was implemented in Python with OpenCV and a YOLOv11 object detection model for waste classification. Image acquisition was performed using a fixed Red, Green, Blue (RGB) camera installed in an elevated position above the waste classification area, operating at a resolution of 1920 × 1080 pixels and 30 frames per second under controlled lighting conditions. The model training process began with dataset annotation using Roboflow, where waste images were labeled and organized. Subsequently the YOLOv11 model was trained in Google Colab using the YOLOv11 library, optimizing detection performance for the specific context of solid waste classification. During inference, YOLOv11 processed video frames using a confidence threshold of 0.5 and an IoU threshold of 0.45, enabling multi-object detection per frame. The system achieved a stable real-time performance of approximately 15–20 frames per second with an average latency below 100 ms, ensuring smooth and responsive operation for operators.

Communication between the computer vision module and the web interface was managed through a Flask-based Representational State Transfer Application Programming Interface (REST API), which exchanged classification results in JavaScript Object Notation (JSON) format. The system was deployed on a local server within the facility to reduce latency, ensure data privacy, and maintain continuous operation without reliance on external internet connectivity. The complete system architecture and its interconnected components are illustrated in Fig. 4, which depicts the integration of the frontend, backend, database, and model training workflow [22].

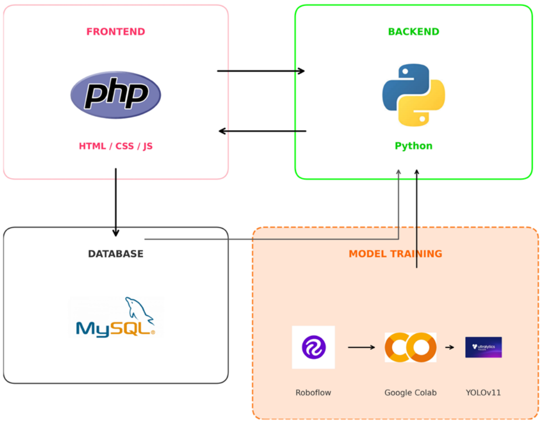

Fig. 4. System technology stack and component integration.

All system infrastructure was deployed on a local server within the waste classification facility, ensuring data privacy, reducing network latency for real-time classification operations, and maintaining system functionality independently of external internet connectivity. The object detection module leverages the trained YOLOv11 model to accurately identify waste materials. Specifically, paper detection enables the classification of printed documents and sheets. Likewise, plastics are identified and classified across different polymer forms. Glass is accurately detected and localized within the frame. In addition, cardboard is distinguished and categorized for proper segregation. As shown in Fig. 5, the detection system successfully identifies and localizes these materials under real-world operational conditions.

Fig. 5. Detection of cardboard, electronic devices, biohazardous materials, and metals.

In addition to these material categories, electronic devices are accurately detected and classified. Similarly, biologically hazardous materials are identified and localized within video frames. Metals are also detected and categorized for ensure proper segregation within the waste stream. As shown in Fig. 6, the detection system demonstrates reliable identification and localization of these material categories during real-time classification operations.

From a scalability perspective, the modular architecture of the proposed system enables its deployment in other municipal waste management contexts without requiring structural redesign. Adaptation to new cities or facilities would primarily involve retraining or fine-tuning the detection model using locally collected waste images, as well as recalibrating operational parameters such as confidence thresholds and category definitions to reflect local waste composition and management practices. This approach allows the core system architecture to remain unchanged while accommodating environmental, visual, and operational differences across municipalities, prioritizing adaptability rather than direct replication under heterogeneous urban conditions.

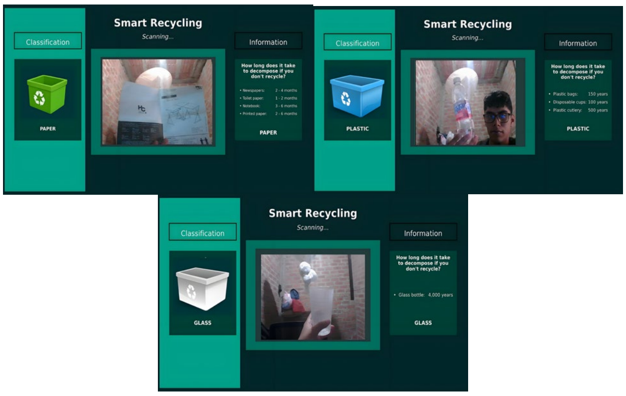

Fig. 6. Detection of paper, plastics, and glass.

IV. Results

This section presents the findings obtained during the experimental phase of the research, which was conducted at the segregation plant managed by the Provincial Municipality of Piura. The sample consisted of 60 operators who participated in the evaluations corresponding to the pre-test and post-test phases.

A. Measurement of Classification Time Before and After Implementation

The first indicator analyzed was the number of solid waste items classified per minute, which reflects operator productivity during manual sorting activities. Pre-test measurements established a baseline level of performance prior to system implementation. As shown in Fig. 7, the observed productivity levels exhibit considerable variability across waste categories, which can be attributed to inherent characteristics of manual classification processes. Specifically, decision-making time, visual ambiguity among material types, and operator fatigue contribute to fluctuations in classification speed. In addition, heterogeneity in waste appearance and varying levels of contamination increase cognitive load, resulting in slower and less consistent classification rates. These baseline conditions highlight the structural limitations of manual sorting and provide a reference point for evaluating the impact of the automated visual assistance introduced in subsequent stages.

In contrast, following system implementation, post-test results show a marked increase in the number of waste items classified per minute. As illustrated in Fig. 8, operator productivity improved consistently across all waste categories, reflecting a change in the classification rates compared to the pre-test phase. This change is attributable to the availability of real-time visual guidance provided by the computer vision system, which reduced decision-making time and classification uncertainty. By enabling faster material recognition, the system allowed operators to maintain a more continuous and stable workflow compared to manual sorting.

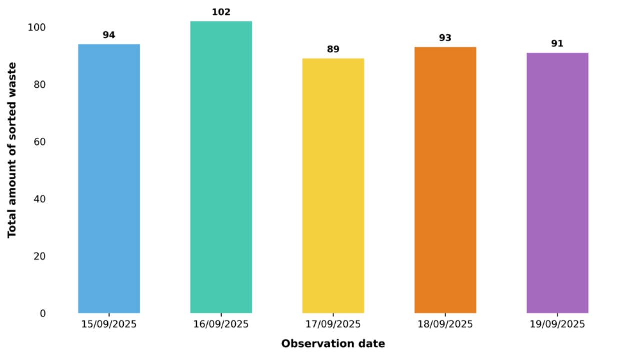

Fig. 7. Number of solid waste items classified per minute in the pre-test phase.

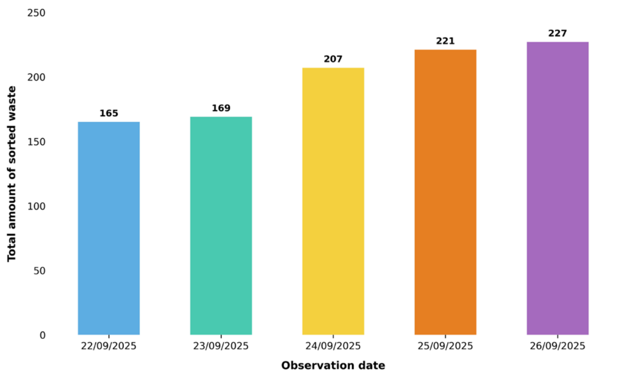

Fig. 8. Number of solid waste items classified per minute in the post-test phase.

To further analyze the results obtained after implementation of the computer vision system, a comparative graph was created to contrast the values recorded during the pre-test and post-test phases for the indicator "Waste items classified per minute," as shown in Fig. 9.

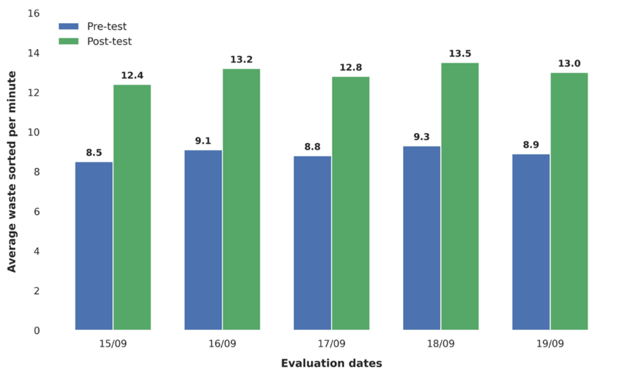

Fig. 9. Comparison of solid waste items classified per minute between pre-test and post-test phases.

Classification performance before and after system implementation was compared, revealing a consistent increase in the number of items classified per minute following deployment. Post-test values are uniformly higher across all evaluated days, indicating increased classification rates under the assessed conditions. This improvement is primarily attributed to the real-time visual assistance provided by the computer vision system, which reduced identification time and facilitated a smoother workflow.

After presenting the results related to Indicator I (number of solid wastes classified per minute), the analysis proceeded to Indicator II, which refers to the average classification time per batch of solid waste.

The second indicator analyzed was the average time required to classify a batch of solid waste, with each batch consisting of 150 items of the same type. Pre-test measurements provide a baseline representation of batch classification performance prior to system implementation. As shown in Fig. 10, the results indicate relatively high average processing times with notable variability across observations. These differences are primarily associated with individual operator pace and the manual decision-making required to identify waste types during classification. The absence of automated assistance meant that operators relied solely on visual inspection and experience, contributing to longer and less consistent processing times across the evaluated batches.

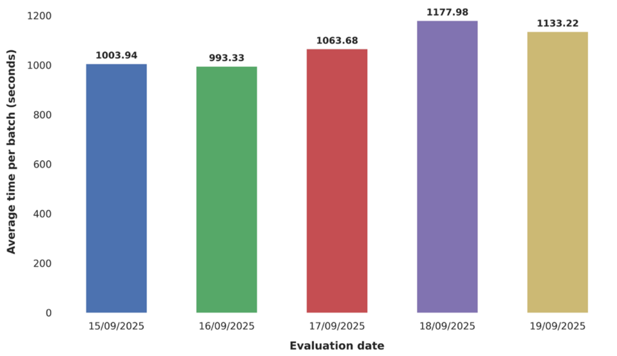

Fig. 10. Average classification time per batch in the pre-test phase.

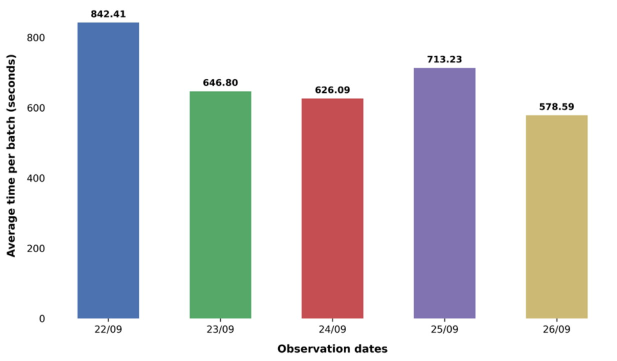

Fig. 11. Average classification time per batch in the post-test phase.

In contrast, post-test results for the second indicator, corresponding to the average classification time per batch of solid waste, show a reduction in the mean processing time per batch following system implementation. As shown in Fig. 11, the average processing time per batch exhibits a notable decrease along with increased consistency across the evaluated sessions. This reduction indicates that the computer vision system effectively streamlined the classification process by enabling operators to identify waste types more rapidly and reducing decision-making delays. The minimal variability observed across days suggests stable system performance under real operational conditions, consistent with the shorter batch processing times recorded during the post-test phase.

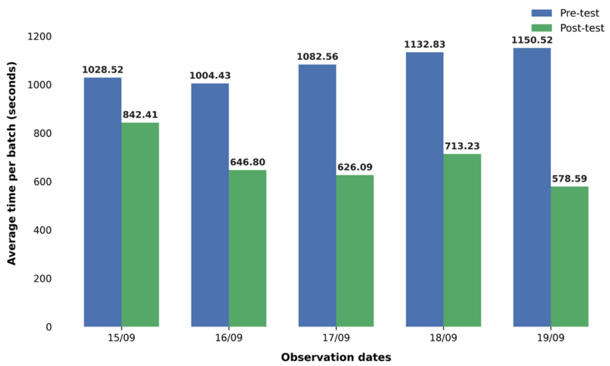

Fig. 12. Comparison of average classification time per batch between pre-test and post-test phases.

To further examine the impact of the computer vision system, a comparative analysis between the pre-test and post-test phases was conducted for the indicator "average classification time per batch of 150 items," as illustrated in Fig. 12. The comparison reveals a substantial improvement in processing efficiency following system implementation. While pre-test measurements exhibited longer and more variable classification times, characteristic of fully manual sorting processes, post-test results show a marked reduction and greater temporal stability. This shift indicates that the system effectively supported operators by accelerating batch processing and reducing operational delays, thereby contributing to a more efficient and consistent classification workflow.

An inferential analysis was conducted to evaluate changes in operational efficiency indicators before and after system implementation. As summarized in Table I, the Wilcoxon signed-rank test for related samples revealed statistically significant differences between pre- and post-test measurements for both classification speed (waste items per minute) and average classification time per batch. These results support rejection of the null hypothesis in both cases, indicating that the observed improvements are statistically significant within the sample evaluated. Overall, the findings confirm that the computer vision system contributed to measurable improvements in operational performance under real working conditions.

TABLE I. INFERENTIAL ANALYSIS OF OPERATIONAL EFFICIENCY BEFORE AND AFTER SYSTEM IMPLEMENTATION

Indicator	Null Hypothesis	Test	Sig.	Decision
Waste classified per minute	Median difference = 0	Wilcoxon signed-rank test	0.001	Reject H_0
Average classification time per batch	Median difference = 0	Wilcoxon signed-rank test	0.001	Reject H_0

B. *Overall Accuracy in Solid Waste Classification*

Following the descriptive analysis, overall accuracy was evaluated to assess the system's general effectiveness in solid waste classification after deployment. As shown in Fig. 13, accuracy values remained highly consistent across the evaluation period, exhibiting only minor fluctuations across observation sessions. Although a slight downward trend is observable, the variation is minimal and does not affect system stability during the evaluated post-test sessions under the observed operational conditions, and classification accuracy was maintained throughout the post-test phase.

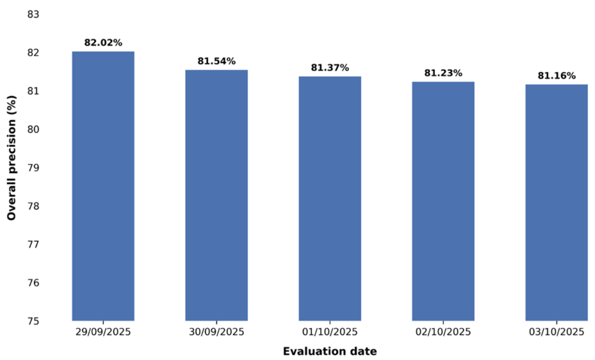

Fig. 13. Overall classification precision during the post-test phase.

Complementary descriptive statistics, summarized in Table II, further support the consistency of the system's performance. The limited dispersion observed around the mean accuracy value reflects low variability among operators during the post-test phase. This statistical stability indicates that the system maintained reliable accuracy regardless of individual differences in operator interaction. Consequently, these results suggest consistent behavior during the post-test phase, achieving stable overall accuracy under real operational conditions.

TABLE II. DESCRIPTIVE STATISTICS OF POST-TEST OVERALL CLASSIFICATION ACCURACY

Observation Session	N	Min (%)	Max (%)	Mean (%)	Standard Deviation
Session 1	12	77.48	85.62	82.02	1.58
Session 2	12	78.10	86.44	81.54	1.61
Session 3	12	78.05	85.90	81.37	1.65
Session 4	12	77.90	85.30	81.23	1.72
Session 5	12	77.48	84.95	81.16	1.79

C. *System Accuracy Level in Solid Waste Classification by Type*

This section presents the post-test results regarding system accuracy in solid waste classification by type. The analysis focuses on the proportion of correctly classified items within the evaluated waste categories, providing insight into the model's category-level performance under real-world operational conditions. Fig. 14 illustrates this analysis by showing the classification results obtained from a single operator. This representative example allows for a clear interpretation of category-level accuracy while remaining consistent with the aggregated results obtained from all evaluated operators.

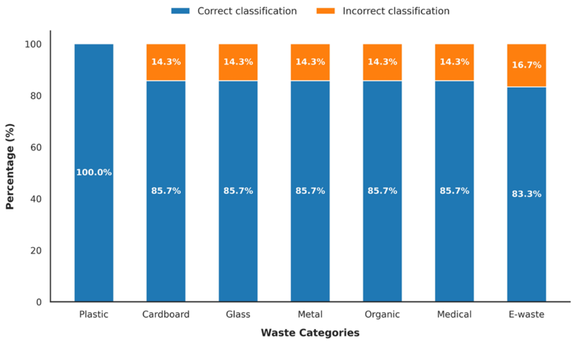

Fig. 14. System accuracy level in classifying solid waste by type.

D. System Efficiency in Solid Waste Classification

To evaluate system effectiveness, a structured 5 items dichotomous questionnaire (P1–P5) was administered to the 60 operators. Table III presents the format of the questionnaire used during data collection and is included for illustrative purposes only; therefore, the Yes/No columns are left blank, as they represent the response options rather than aggregated results. Responses were coded using a binary scale, assigning 1 to Yes and 0 to No.

TABLE III. USABILITY QUESTIONNAIRE ITEMS (INSTRUMENT FORMAT)

Dimension: Perceived Efficiency		YES	NO
Indicator 1: Usability Grade	Did you clearly understand the functions of the computer vision system from the first use?	-	-
	Did you find it easy to interact with the computer vision system interface?	-	-
	Were you able to perform all tasks without assistance?	-	-
	Do you feel that the system responded appropriately to your actions?	-	-
	Were you able to use the computer vision system without difficulty from the first attempt?	-	-

Complementarily, Fig. 15 summarizes the usability evaluation results, showing consistently positive responses across all assessed items. The highest scores in system responsiveness and functional understanding indicate that operators adapted quickly to the interface and experienced smooth interaction during task execution. Slightly lower, yet still favorable, values in ease-of-use items suggest a brief familiarization period rather than structural usability issues. Overall, the results indicate that the system design supports efficient and autonomous use under real operational conditions.

In addition, this section presents the post-test results related to the system acceptance rate, corresponding to Indicator II of the perceived effectiveness evaluation of the computer vision system. A structured 5 items dichotomous questionnaire (P6–P10) was administered to the same group of 60 operators. Table IV presents the questionnaire format used during data collection as a reference for the evaluation instrument, displaying the response options applied for system acceptance assessment.

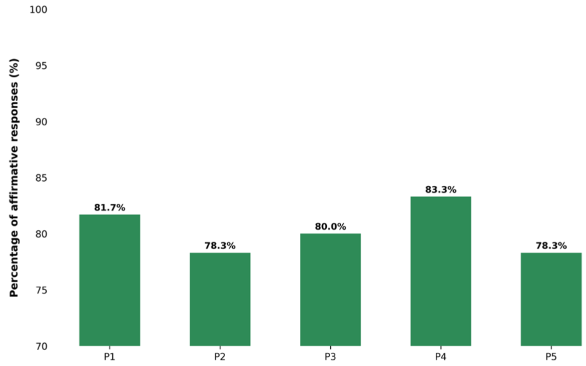

Fig. 15. Percentage distribution of operator responses for usability items.

TABLE IV. SYSTEM ACCEPTANCE QUESTIONNAIRE ITEMS (INSTRUMENT FORMAT)

Dimension: Perceived Efficiency		YES	NO
Indicator 2: System Acceptance Rate	Do you consider the implementation of this computer vision system appropriate for your work?	-	-
	Would you recommend the use of the computer vision system to other operators?	-	-
	Do you believe that this computer vision system improves the traditional sorting process?	-	-
	Do you agree with incorporating this computer vision system as a permanent part of the sorting process?	-	-
	Does the computer vision system help optimize time and reduce errors?	-	-

Fig. 16 shows a consistently high level of system acceptance across all evaluated items. The highest scores in items P9 and P6 suggest that operators clearly perceived improvements compared to traditional classification methods and considered the system suitable for routine use. Uniformly positive responses in aspects related to recommendation, permanent integration, and efficiency-related items indicate that acceptance was driven not only by usability, but also by the operators' perception of system support during the classification process.

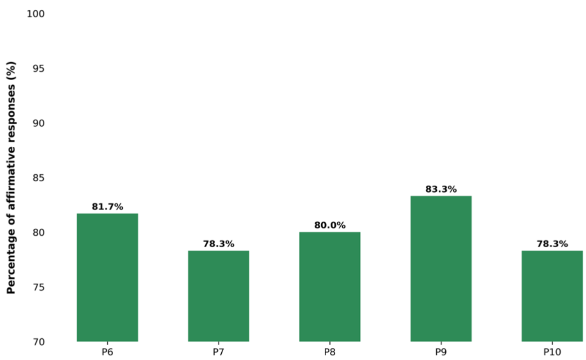

Fig. 16. Percentage distribution of operator responses for the system acceptance item.

V. DISCUSSIONS

This chapter analyzes the research findings by synthesizing the main results and contrasting them with relevant background studies and theoretical frameworks in order to identify similarities and differences. The discussion is coherently structured around the general objective of the study, which was to determine how an OpenCV-based computer vision system influences improvements in solid waste classification in the city of Piura. To achieve this, the analysis follows the 4 specific objectives that guide the discussion, beginning with the measurement of classification time and processing efficiency, followed by the accuracy evaluation, category-specific performance, and finally operator acceptance.

Regarding the first specific objective, which focused on measuring the average classification time for solid waste before and after system implementation, the evaluation concentrated on the classification speed dimension, which is directly related to operational efficiency in waste processing. Improvements in this capability are grounded in Computer Vision Theory. As noted by Kavade *et al.* [18], automated classification systems supported by OpenCV enable the efficient and sustainable segregation of waste types including organics, plastics, metals, and inorganics, demonstrating that real-time processing capabilities significantly enhance operational workflows. In the present study, the system functioned as an automated assistant, allowing operators to process waste items more rapidly while receiving real-time classification recommendations. The results related to classification speed revealed a substantial improvement. During the pre-test phase, the average classification rate was 8.27 items per minute; however, in the post-test phase, this value increased considerably to 14.90 items per minute, representing an 80% increase in the number of items classified per minute. This difference was statistically significant, as confirmed by the Wilcoxon signed-rank test, which yielded a p-value lower than 0.001, leading to the acceptance of the alternative hypothesis. These findings align with studies such as Nahiduzzaman *et al.* [23], who reported a reduction in the average segregation time from 890 s to 520 s per batch, representing a 41.5% improvement in temporal performance. This trend aligns with the 46.8% reduction observed in this study, where the average processing time per batch decreased from 1089.00 s to 579.19 s. Although both studies demonstrate similar performance improvements, the present investigation's results showed a more pronounced increase in items classified per minute. This outcome is logically consistent with the implementation of real-time detection rather than post-processing classification. This improvement is directly associated with the system's ability to provide immediate visual feedback, a feature that effectively addresses the processing bottlenecks inherent in manual sorting, where operators can maintain continuous workflow without pausing for decision-making. Therefore, the results suggest that the proposed computer vision solution is associated with improved classification performance within the evaluated waste management operations. Moreover, these findings demonstrate that adopting methodologies proven effective in comparable contexts lead to positive and replicable outcomes.

Continuing with the second specific objective, which aimed to evaluate the system's accuracy in classifying solid waste, this evaluation is theoretically grounded in Deep Learning Theory. As explained by Lu and Chen [16], classification systems based on computer vision transform waste detection solutions by enabling identification of material types in real conditions, where system accuracy is considered a relevant factor for subsequent waste treatment and recycling processes.

Regarding accuracy results, a significant level of consistency was observed. Over 5 consecutive observation days, the system maintained average accuracy levels of 82.02%, 81.54%, 81.37%, 81.23%, and 81.16% respectively, with an overall mean accuracy of 81.39% across all sessions and operators. This value exceeds the minimum threshold of 75% defined in the research hypothesis. This performance was statistically validated through consistent results with minimal variation, leading to the acceptance of the hypothesis that the system achieved adequate accuracy levels.

This marked consistency aligns with the conclusions of García-Navarrete *et al.* [24], who achieved an average overall accuracy of 78% through calibration techniques and data augmentation, highlighting class balance and threshold optimization as key factors for improving model reliability. While the present study reported higher accuracy values of 81.39%, this difference may be related to the use of a more extensive and balanced training dataset of 7000 images distributed across seven categories, along with rigorous validation through confusion matrix analysis during the training phase. Similarly, Castro-Bello *et al.* [12] confirms this trend, demonstrating considerable reduction in classification error margins through computer vision systems. In this context, the observed precision is fundamentally explained by the combination of robust model architecture using YOLOV11 and extensive training across 100 epochs.

The system's ability to maintain consistent performance under varying operational conditions suggests its potential applicability in similar real-world environments, aligning with the principles of adaptive learning systems that adjust to real-world variability while maintaining accuracy standards. Although the overall classification accuracy of 81.39% demonstrates the robustness of the system, a detailed analysis of misclassification patterns reveals opportunities for optimization. Errors concentrate in material categories with high visual variability. The plastic category (72.5% accuracy) exhibited primary confusion with paper (18% of errors) and glass (12% of errors), particularly when items were translucent or contaminated. The paper category (76% accuracy) was frequently confused with cardboard when items were wet or contaminated, conditions that approximate cardboard's fiber structure. Medical and electronic waste showed lower error rates; however, misclassifications occurred mainly with small items that lacked sufficient visual distinction for reliable detection. These patterns align with visual heterogeneity research. Alsubae *et al.* [25] demonstrated that YOLO-based models show performance degradation proportional to intra-class visual diversity, consistent with the present observations, where plastic (highly variable in color, texture, transparency) shows lowest accuracy while glass and metal (consistent optical properties) demonstrate highest accuracy.

From an operational perspective, confusion between plastic and glass represents a high-impact error due to their differing recycling streams, whereas confusion between paper and cardboard is less critical. This analysis suggests that strategic improvements should focus on high-impact error patterns through the incorporation of depth-sensing features or hierarchical classification approaches.

Regarding the third specific objective, which evaluated the system's accuracy according to the type of waste, the results can be interpreted within the framework of the CNN theory. As described by Echevarry and López [10], and Yogamadhavan and Mannayee [26], category-level performance is a crucial indicator of a model's ability to discriminate between visually similar materials in real-world operating environments.

In this study, all 7 waste categories exceeded the minimum acceptable accuracy threshold of 70%, indicating consistent performance across all evaluated waste categories. Higher accuracy levels were observed for materials such as metal and glass, reaching approximately 85% and 82%, respectively. This performance is attributed to their relatively consistent visual properties, such as regularity of shape, reflective surfaces, and low intraclass variability.

In contrast, categories such as plastic, paper, and electronic waste exhibited accuracy values closer to the acceptance threshold. This near-threshold performance is primarily associated with high intra-category diversity, as these materials exhibit substantial variation in color, texture, transparency, deformation, and contamination levels under real-world classification conditions. These findings are consistent with those reported by Alsubae *et al.* [25], who emphasized that object detection performance in YOLO-based models is strongly influenced by visual heterogeneity and detailed feature representation. Similarly, Cruz *et al.* [15] demonstrated that OpenCV-based systems achieve higher reliability when classifying materials with stable visual characteristics, while performance decreases for categories with greater visual ambiguity. Kavade *et al.* [18] also reported similar trends, highlighting that plastic and mixed materials pose greater classification challenges due to their non-uniform appearance.

Despite these challenges, even the lowest-performing categories in this study remained within operationally acceptable accuracy ranges, supporting the suitability of the proposed YOLOv11-based system for municipal solid waste segregation tasks. Overall, the observed variation among waste types reflects realistic operational constraints rather than model deficiencies and underscores the system's behavior under the evaluated real-world classification conditions. Profundizing in the analysis of accuracy variations, the YOLOv11 architecture demonstrates differentiated feature extraction effectiveness depending on material visual complexity. According to CNN theory, hierarchical feature extraction—from edges and textures in initial layers to complex shapes in deeper layers—is particularly effective for materials with well-defined visual patterns. Glass benefits from consistent optical properties (reflectivity and transparency) and low intra-class variability, whereas plastic exhibits extreme variability in color, texture, and degradation states, which complicates discrimination.

This observation aligns with the findings of Cruz *et al.* [15], who demonstrated that OpenCV-based system reliability is inversely proportional to the visual diversity of the target category. Early network layers capture gross morphological differences effectively; however, deeper layers, which are required for the subtle discrimination of material properties, experience greater confusion when variability exceeds optimal levels. This behavior explains the observed accuracy difference between plastic 72.5% and glass 88%. Although lower-performing categories—plastic 72.5%, paper 76%—approach the minimum acceptable threshold (70%), they remain operationally acceptable when complemented by manual verification. This outcome validates the "automated assistance" rather than a "complete automation" approach.

Addressing the fourth specific objective, which aimed to determine how operators perceived the system's effectiveness, this aspect is fundamental, as perceived efficiency encompasses both usability and acceptance dimensions that directly influence technology adoption in operational environments. The results indicate a highly positive operator perception, where usability level achieved an overall average of 80.66% across the 5 evaluated items, while system acceptance reached 79.46% across the corresponding 5 items. Statistical analysis confirmed that these perceptions reflected genuine satisfaction with the system's practical utility. These findings are consistent with previous studies that have examined user acceptance of AI-based systems in operational contexts. For instance, Vorobeva *et al.* [27] demonstrated that perceived usefulness and ease of use directly influence the acceptance of AI-based technologies, achieving 98% system acceptance in their study. This reinforces the notion that simplicity of interaction and perceived utility are essential components to ensure successful adoption of systems in work environments. Similarly, the high acceptance observed in the present study parallels findings from technology acceptance research in waste management contexts, where operator feedback indicated such systems successfully reduced workload while improving classification accuracy, successful technology adoption in comparable operational studies. Therefore, the fundamental reason for the high level of operator acceptance observed in this study lies in the transition from skepticism toward automated systems to confidence based on tangible performance improvements. Operators directly experienced reduced physical effort, faster processing times, and improved classification accuracy. These outcomes align with human-centered design principles that prioritize user experience alongside technical performance [28], supporting the system's perceived usefulness as an operational support tool that enhances—rather than replaces—human judgment in waste classification tasks.

A. Comparisons with Existing Systems

To contextualize this contribution within the existing literature on waste classification systems, a comparative analysis with related studies reveals several distinguishing characteristics. Echeverry and López [10] developed AUTORECYCLER, which classifies only 4 waste categories (plastic, glass, cardboard, and metal), providing more limited categorical coverage than the seven categories addressed in this study. Similarly, Malik *et al.* [13] focused on binary distinction between biodegradable and non-biodegradable materials, lacking the categorical specificity required for comprehensive municipal waste segregation. Castro-Bello *et al.* [12] addressed municipal waste classification but conducted validation under controlled experimental conditions rather than in operational waste segregation plants. In contrast, the present study validates the system with 60 operators across multiple evaluation sessions under real municipal operating conditions, providing empirical evidence of performance under real operational constraints. Furthermore, Aarthi and Rishma [11] achieved 86% accuracy in multiclass classification in experimental robotic contexts, requiring specialized hardware and limit applicability in resource-constrained municipalities. The present research distinguishes by 3 key aspects: first, evaluation of 7 waste categories, enabling comprehensive municipal segregation; second, validation in real operational environments with human operators rather than controlled laboratory settings; third, inclusion of user-centered evaluation dimensions (usability and system acceptance) beyond technical accuracy metrics alone. The YOLOv11 model achieved an mAP@0.5 of 83.2% during training and demonstrated an average accuracy of 81.39% during operational validation with 60 operators under real segregation conditions, with all 7 waste categories exceeding the minimum acceptable accuracy threshold of 70%. This balanced approach between technical robustness and operational viability positions the proposed YOLOv11-based system as a viable contribution to waste management automation in developing regions.

B. Scalability Considerations

The modular architecture of the proposed system enables its deployment in other municipal waste management contexts without requiring structural redesign. For municipalities considering adoption, key requirements include preliminary audit of the waste composition at the target facility to identify locally prevalent materials, dataset acquisition of 1000–2000 representative images per category from the local detection fine-tuning, and the recalibration of detection confidence thresholds to reflect local waste characteristics. The required hardware infrastructure includes a fixed Red, Green, Blue (RGB) camera (minimum 1920×1080 resolution, 30 fps) positioned above sorting workstations and a local server with Python-OpenCV environment. Operator training requires approximately 4–8 h per operator group, with periodic refresher sessions. This iterative adaptation approach, rather than direct model transfer, represents best practice for deployment in heterogeneous urban contexts. Critical contextual factors affecting viability include reliable electrical infrastructure with voltage stabilization, network connectivity between camera and processing server, a standardized classification setup with consistent camera positioning, and staff receptiveness to automation. These implementation considerations enable replication of this system across comparable municipal waste management facilities in Latin America, directly contributing the scalability of computer vision-based waste segregation solutions in resource-constrained environments.

C. Limitations

Although the results indicate consistent improvements in classification efficiency and accuracy, several limitations directly arising from the study design and operational context must be acknowledged.

First, the study employed a pre-experimental single-group pre-test/post-test design without a control group. This limitation resulted from the operational constraints of the municipal segregation plant, where all operators were required to use the system once deployed, making parallel control conditions infeasible. Consequently, the improvements observed in post-test measurements cannot be attributed exclusively to the computer vision system, as temporal effects or increased task familiarity may have partially influenced performance.

Second, the use of non-probabilistic convenience sampling limits the external validity of the findings. This sampling approach was necessary to ensure participant availability and completion of all evaluation phases; however, it restricts the generalization of results to other municipalities or waste management contexts with different operational dynamics, workforce characteristics, or infrastructure conditions.

Third, the observed near-threshold accuracy in certain waste categories, particularly plastic and paper—may be associated with their high intra-class visual variability. These materials exhibit significant differences in color, transparency, deformation, and degradation state, which increases classification ambiguity under real operational conditions. This limitation is commonly observed in visual-based classification systems and reflects dataset complexity rather than system instability.

Finally, system performance was evaluated under controlled camera positioning and stable illumination conditions to ensure measurement consistency. While this supports internal validity, it limits the extent to which conclusions can be drawn regarding performance under variable illuminated environments commonly found in open or semi-covered waste facilities. Variations in shadows, reflections, or ambient light intensity may affect detection confidence and were not systematically analyzed in this study.

VI. Conclusion

Regarding the general objective, which was to develop a computer vision system based on OpenCV for solid waste classification in the city of Piura, the results demonstrated that the proposed system is a viable solution for supporting municipal waste segregation under real operational conditions. The main contribution of this study is the validation of an integrated framework that combines real-time waste classification, operational performance evaluation, and operator-centered assessment within a municipal recycling facility. However, these findings should be interpreted considering that the study was conducted in a single facility using a pre-experimental design without a control group, which may limit the generalizability of the results. With respect to the first specific objective, which measured the average solid waste classification time before and after system implementation, the results demonstrated improvements in operational efficiency during the waste segregation process, reflected in shorter processing times and higher classification rates after system deployment. These findings support the feasibility of applying computer vision technologies to optimize municipal waste classification operations. However, because the evaluation was conducted using a pre-experimental design without a control group, the observed improvements cannot be attributed exclusively to the implemented system.

Regarding the second specific objective, which aimed to evaluate the system's overall classification accuracy, the results demonstrated that the proposed computer vision system achieved a reliable level of performance for solid waste classification under real operational conditions. These findings support the feasibility of using YOLOv11-based computer vision models as a tool for municipal waste segregation, maintaining consistent classification performance across the evaluated sessions. However, the accuracy assessment was conducted under controlled camera positioning and stable illumination conditions; therefore, further validation is required to confirm system performance in more variable operational environments. Concerning the third specific objective, which assessed classification accuracy by waste type, the results demonstrated that the proposed system was capable of maintaining acceptable classification performance across all evaluated waste categories, supporting its applicability in municipal waste segregation processes involving diverse materials. These findings highlight the ability of the YOLOv11-based model to differentiate multiple waste types under real operational conditions. However, the lower performance observed in visually heterogeneous categories suggests that classification accuracy remains influenced by variations in material appearance, representing an area for future improvement and validation.In relation to the fourth specific objective, the results demonstrated positive levels of usability and system acceptance among the evaluated operators, indicating that the proposed system was perceived as a practical and supportive tool for solid waste segregation activities. These findings highlight the importance of incorporating user-centered evaluation alongside technical performance measures when assessing computer vision solutions in operational environments. However, because operator perceptions were collected through convenience sampling within a single municipal facility, the findings may not fully represent user acceptance in other waste management contexts.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Matias Garcia-Olivares conceived the study, developed the machine vision system, collected the data, supervised the research, contributed to the methodology design, and performed the data analysis. Yeran Carmen-Livia reviewed the results and proofread the manuscript. All authors reviewed and approved the final version of the manuscript.

Acknowledgment

The authors would like to thank the operators of the "Piura Recicla" segregation program for their participation and support during the experimental phase. Special thanks are extended to Dr. Oscar Jhan Marcos Peña Cáceres for his guidance and supervision throughout this research.

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