Artificial Intelligence Based System for Sorting and Detection of Organic and Inorganic Waste

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***Abstract*—Solid waste management has become a global challenge today due to its constant increase in waste and inadequate classification, which leads to serious environmental problems. The research objective is to develop a system based on artificial intelligence (AI) for the classification and detection of organic and inorganic waste. In terms of its approach, it is quantitative with a pre-experimental and applied design. The population was made up of 1,298 images as a data collection technique for observation. Furthermore, the implementation of this system has shown significant improvements in its key indicators: precision, detection speed, and reduction of errors in the tests carried out, obtaining an increase in precision of 11.52%, 23.61% in detection speed and a reduction in 24.13% error rate. Finally, this research highlights the importance of AI in environmental sustainability by promoting much more efficient waste management and thus promoting ecological awareness in educational environments and for students to value the importance of recycling and sustainability. Finally, this research concludes that AI-based systems are a viable and scalable solution to address all the challenges associated with waste management.**

***Keywords*—Artificial intelligence (AI); environmental sustainability; waste classification; organic waste; inorganic waste**

I. Introduction

Nowadays, the proper management of waste represents a growing challenge due to the constant increase in waste generation. This problem aggravates environmental pollution and makes recycling more difficult, affecting progress towards a circular economy. However, emerging technologies such as artificial intelligence (AI) offer an opportunity to improve waste sorting efficiency. In this context, this research proposes an innovative solution: an AI-based intelligent system that optimizes solid waste sorting and promotes more sustainable management.

In recent years, waste production has grown significantly; in 2016, for example, the World Bank estimated that the total solid waste generated in the world reached 2.01 billion tons. It is estimated that by 2030 and 2050, the amount of waste generated in the world could reach 2.01 billion and 3.40 billion tons, respectively [1]. Also, because of their versatility and cost-effectiveness, plastics have become indispensable materials in many sectors of industry. However, inappropriate disposal and management of plastic waste have led to significant problems, including pollution, habitat degradation and the impact on wildlife species [2].

On the other hand, errors in waste management can have disastrous consequences in almost any environment. In addition, the acceleration of technological development has led to increased consumption of resources and an increase in the accumulation of waste. Furthermore, the growing population and the process of urbanization contribute significantly to the accumulation of this type of waste [3]. Also, advances on the Internet of Things (IoT) and AI have enabled smart sensors to be integrated into waste management systems to track in real time and allow for better waste management [4]. Although, robots have become fundamental in society because they can take the place of humans in jobs that are both routine and dangerous. To better understand, robots equipped with vision technology have become essential in various industrial areas because they can move effectively in varied environments thanks to the information provided by their vision sensors [1]. In addition, AI has enormous potential to improve recycling processes, and also, it can be used to sort plastics and improve recycling processes by integrating computer vision. [5]. As mentioned above, the proposed automated classification and detection of solid waste using advanced technologies such as AI and machine learning is transforming the way in which waste is handled, allowing greater efficiency and accuracy in its identification and classification. This technology can facilitate its subsequent management and treatment, thus contributing to the construction of cleaner, healthier and sustainable cities [6]. To be more specific, AI has huge potential to improve recycling processes, how it can also be used to sort plastics and improve recycling processes, by integrating computer vision, and how it can be used to improve the quality of plastics recycling [5]. Therefore, software is proposed to be able to sort and detect solid waste in a more efficient way, taking advantage of advanced technologies such as AI [7].

The rationale for this work is based on the imperative need to reduce the environmental impact generated by the accumulation and inefficient treatment of waste. With the support of advanced technologies such as AI, it is hoped to achieve a more accurate and efficient classification of waste, which would facilitate better management and encourage the development of environmentally sustainable technologies. From a societal perspective, this initiative responds to the problem of the growing volume of waste and the complexity of waste sorting in contexts where good management could significantly reduce human-caused environmental damage.

The objective is to develop a system based on artificial intelligence to improve the classification and detection of organic and inorganic waste.

II. Related Works

For [8], who indicated that solid waste recycling is an essential step in creating a pure and sustainable environment. Additionally, in their work, they propose a cloud-based algorithm for sorting in automatic machines in waste recycling plants, and it was implemented in Python programming language using the Tensor Flow library with the cooperation of different modules. To train an efficient model that can classify five different types of waste, the output can be realized in real time on the cloud server. Several methods have been described and applied to increase the separation accuracy, such as increasing data in hyper parameter setting. That is why experimental results show that the solution can achieve excellent performance with up to 96.57 % accuracy using cloud servers. Moreover.

In [9], the author emphasizes that, in recent times, the massive amount of waste has increased considerably with the increase in population. In turn, the proposed model mainly derives an object detection module to identify the existence of waste objects in the images, to refine the classification accuracy, the model parameters are adjusted using the Adagrad optimizer. Therefore, to ensure the unanticipated results of the AIEWO-WMC technique, extensive experimentation is performed on a standard dataset, and the obtained values indicate the supremacy of the AIEWO-WMC model over the other techniques with an increased accuracy of 99.15%. 2023 Global NEST Printed in Greece.

According to [10] emphasize that waste or garbage management is receiving more and more attention with the aim of smart and sustainable development, especially in evolved countries and nations undergoing transformation. As for a waste management system, it consists of a series of interrelated processes that perform various complex functions. That is why, their study investigated different models for detecting objects and classifying images and their application in waste detection and classification tasks, providing waste analysis, detection and classification methods with accurate and organized presentation and collection of more than 20 reference garbage data sets.

In [6], the authors addresses how the increase of urban solid waste is currently the biggest challenge, first because the amount and composition of waste increases and changes under the influence of new consumption styles (reduction of organic, paper and glass designs and increase of plastic designs), and second, because it is a social problem, product of the growth of the economy, the state of contemporary neoliberal models. Therefore, the estimated affected population is 46,010 people, of which 46% come from landfills in flooded areas and 32.45% come from landfills in disadvantaged communities. Moreover, in this sense, their identification and characteristics, as well as the size of the population and affected areas, will guide possible mitigation and elimination actions within the framework of global spatial planning.

On the other hand, [11] presented the design and implementation of an automated waste management procedure using the You Only Look Once (YOLO) algorithm and computer vision techniques to sort waste efficiently. Using YOLO's computer vision and object detection capabilities, their system accurately identifies and sorts different types of waste in real time.

In addition, [12] discusses how waste pollution is one of the world's most serious environmental obstacles. He presents a tethered object detector for solid pollutant detection in aerial imagery (SWDet). Thus, he constructed a deep asymmetric aggregation (ADA) network with structurally varied parameters of asymmetric blocks to recover junk objects with discrete shapes.

On the other hand, [13] highlight that, in recent days, with the increase in population, the amount of huge waste has increased significantly, thus, proper waste management has become necessary to reduce environmental deterioration and prosper in welfare in smart homes. In addition, proper waste sorting requires the development of automated waste sorting models based on AI and computer vision (CV) approaches.

III. Methodology

A quantitative, applied approach was adopted, and the research design was experimental, specifically pre-experimental, which is characterized by handling an independent variable to establish cause-and-effect links [14]. The population consisted of 1298 images extracted from the free repositories Kaggle and ImageNet, of which 1278 images were considered for training and validation of the model. Of these, 285 were related to metals, 305 to organic materials, 138 to paper and cardboard, 334 to plastics and 216 to glass. Observation was used as the data collection technique. The study variable was the classification and detection of organic and inorganic waste [6], and the dimensions were: percentage accuracy [15], detection speed [16] and error rate [17].

A. Case Study

In this case study, the waterfall methodology was applied for the implementation of the project. The waterfall methodology is a sequential approach to software development, where each phase must be completed before moving on to the next. The phases of this methodology as applied to the project are described below:

1) Phase 1: Requirements analysis

a) Scope definition: Development of desktop software with a simple graphical interface that allows real-time image capture and automatic object classification through a pre-trained YOLO model, with historical record of detections.

Prerequisites:

- A processor with real-time image processing capability.
- Compatibility with Windows or Linux operating systems.
- Access to OpenCV compatible cameras.
- Object detection model trained in YOLO.

Table I details the essential functional requirements for the development and successful implementation of the automated waste classification and detection system using artificial intelligence.

TABLE I. TABLE OF FUNCTIONAL REQUIREMENTS

Code	Requirement	Description
RF001	Waste Classification	The system must be able to sort waste into specific categories such as organics, plastics, metals, glass, and paper or cardboard, as detected through the camera.
RF002	Automated Residue Detection	The system should automatically identify the type of waste as it approaches the camera, displaying the corresponding category on the system interface.
RF003	Intuitive User Interface	The interface must be easy to use, clearly showing the waste category detected so that the user can deposit the waste in the correct container.
RF004	Response Time	The system should process and display the waste category in an optimal time, allowing for a smooth and efficient user experience.
RF005	Error Handling	The system must correctly handle false positives and negatives, providing feedback to the user in case of classification error.
RF006	Device Compatibility	The system must be compatible with the cameras and processing devices used at the school in the San Juan de Lurigancho district.
RF007	Data Registration	The system must record and store data on the classifications performed, including response time, type of waste detected, and possible errors, for later analysis.
RF008	Database Update	The system should allow the database to be updated with new waste categories or improvements in the classification algorithms.

2) Phase 2: System design

a) Definition of the software architecture:

Technologies:

- Python (Tkinter for the graphical interface)
- OpenCV (image processing)
- YOLO (object detection)
- Pandas (for history management and export to Excel)

b) System components:

- Graphic interface (Tkinter): Allows the visualization of the camera in real time and action buttons (start, history, exit).
- Detection module (YOLO): In charge of processing the captured images and performing object detection.
- History module: Recording and storage of detected objects along with date and time, allowing their export to Excel.
- An intuitive and user-friendly user interface should be designed for automated waste classification and detection.

Fig. 1 shows the final design of the glass sensing interface.

Fig. 1. Final design of the system when detecting glass.

c) Methodological architecture for training: The dataset is organized and stored, allowing correct management and access during the model training process. For the development of the system, the PyCharm programming environment is used, and a neural network model is trained, specifically YOLO V8 (You Only Look Once, version 8), which specializes in the detection and classification of objects in real time.

Once trained, the model is implemented in an artificial intelligence-based system, which analyzes the debris images, detecting and classifying each type of debris.

Fig. 2 shows the methodological architecture of the system training.

Fig. 2. Methodological architecture of the system training.

Fig. 3 shows the technological architecture for the development of the system. PyCharm was used as the integrated development environment (IDE), with the integration of the YOLO V8 framework for the detection and classification of organic and inorganic waste. Model training and tuning were performed using PyTorch, an efficient and flexible framework for deep learning. The user interface was implemented in Python, using the Tkinter library to provide an interactive and accessible experience. In addition, a 4K Full HD camera with autofocus was used to capture images of the waste, which were then processed and classified by the system. All development and testing of the system were carried out on a Windows 11 computer.

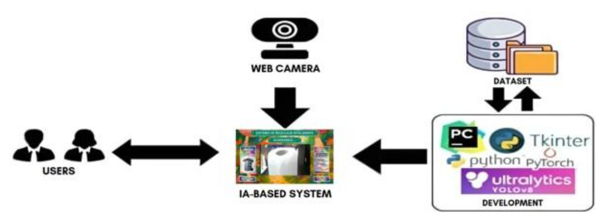

Fig. 3. Technological architecture for system development.

3) Phase 3: Implementation

- Development of the graphical interface:
- A startup window was implemented that gives access to object scanning and visualization of detection history.
- Integration of the YOLO model:
- The YOLO detection model was integrated to process real-time images captured by the camera.
- History logging:
- A system for recording detections was implemented, allowing the information to be stored in a downloadable Excel file.

a) Training: A data set classified into five categories was considered: plastic, organic, glass, metal, and paper or cardboard. Finally, the pre-trained model is fitted to the new classes with optimized parameters; while observing metrics such as loss (loss) and accuracy (mAP) across epochs. The process involves the use of hardware acceleration (AMP) to improve efficiency.

4) Phase 4: Testing: In this section, we carefully checked if the system complies with the indicators defined in the methodology. Basically, we validated that each of these points is being met as planned. See Table II.

5) Phase 5: Maintenance: In this stage, errors identified during testing were fixed, and adjustments were made to optimize both the accuracy and speed of the detection system. In addition, work was done to improve the user experience in the graphical interface. Everything necessary was documented in the system.

TABLE II. STATUS OF SYSTEM TESTING AGAINST FUNCTIONAL REQUIREMENTS

Code	Functional requirement	Status
RF001	The system must be able to sort waste into specific categories such as organics, plastics, metals, glass, and paper or cardboard, as detected through the camera.	Meets the requirement
RF002	The system should automatically identify the type of waste as it approaches the camera, displaying the corresponding category on the system interface.	Meets the requirement
RF003	The interface must be easy to use, clearly showing the waste category detected so that the user can deposit the waste in the correct container.	Meets the requirement
RF004	The system should process and display the waste category in an optimal time, allowing for a smooth and efficient user experience.	Meets the requirement
RF005	The system must correctly handle false positives and negatives, providing feedback to the user in case of classification error.	Meets the requirement
RF006	The system must be compatible with the cameras and processing devices used at the school in the San Juan de Lurigancho district.	Meets the requirement
RF007	The system must record and store data on the classifications performed, including response time, type of waste detected, and possible errors, for later analysis.	Meets the requirement
RF008	The system should allow the database to be updated with new waste categories or improvements in the classification algorithms.	Meets the requirement

IV. RESULTS

A. Hypothesis Testing of Specific Hypothesis 1

To evaluate whether the implementation of the AI-based system significantly improves the percentage of accuracy in the classification and detection of residues, the t-test was performed. The results indicated a significant increase in accuracy after implementation of the system, as shown in Table III.

The effect size analysis for the accuracy indicator (%) shows that the implementation of the AI-based system had a significant impact on improving the classification and detection of organic and inorganic waste. Three main metrics were calculated: Cohen's d, which yielded an effect size of 2.585, indicating a substantial improvement; Hedges' correction, which adjusts Cohen's d for small samples and resulted in a value of 2.534, confirming the robustness of the effect; and Glass' delta, which uses only the standard deviation of the control group and presented a value of 2.783. These effect sizes, all greater than 2, reflect a considerable difference between pretest and posttest, supporting that the intervention is not only statistically significant, but also relevant in practical terms. Furthermore, the 95% confidence intervals for these metrics reinforce the stability of the results, with ranges varying between 1.728 and 3.845. This confirms that the system significantly improved the accuracy of the classification, highlighting the effectiveness of the applied technology, as shown in Table IV.

B. Test of Specific Hypothesis 2

To assess whether the AI-based system improves detection speed, the t-test was used because the data followed a normal distribution.

TABLE III. T-TEST FOR INDICATOR 1

		t-test for equality of means						
		t	gl	Sig. (bilateral)	Difference in averages	Standard error difference	95% confidence interval of the difference	
							Inferior	Superior
Accuracy (%)	Equal variances are assumed	8.175	38	0.000	0.09950	0.01217	0.07486	0.12414
	Equal variances are not assumed	8.175	37.301	0.000	0.09950	0.01217	0.07484	0.12416

TABLE IV. EFFECT SIZES OF INDEPENDENT SAMPLES - ACCURACY

		Standardizer[a]	Estimated points	95% confidence interval	
				Inferior	Superior
Accuracy (%)	Cohen's d	0.03849	2.585	1.728	3.424
	Hedges correction	0.03927	2.534	1.693	3.356
	Glass delta	0.03576	2.783	1.695	3.845

Although the posttest data show an improvement in detection speed (23.61%), the t-test results did not reveal statistically significant differences between the pretest and posttest means, as detailed in Table V. This may be due to the low variability between samples or the small sample size, which decreases the statistical power of the test.

The effect size analysis for the detection speed indicator shows low values, indicating that the difference between pretest and posttest in this indicator was not significant in practical terms. Three metrics were used to calculate the effect size: Cohen's d, which had a value of -0.392, indicating a slight negative effect; Hedges' correction, which adjusts Cohen's d for small samples, with a value of -0.384; and Glass' delta, which uses exclusively the standard deviation of the control group, with a value of -0.405. The 95% confidence intervals for these metrics, ranging from -1.033 to 0.237, include zero, reinforcing the conclusion that there was no significant change in detection speed after the intervention. This suggests that, although the AI-based system shows improvement in speed, their magnitude is not large enough to be considered relevant in practical terms under the study conditions, presented in Table VI.

C. Hypothesis Testing of Specific Hypothesis 3

The t-test was applied to evaluate whether the error rate decreased significantly after the implementation of the system. The results, presented in Table VII, show that the reduction in error rate was significant ($p < 0.001$). This supports the effectiveness of the system in reducing errors in waste classification and detection.

TABLE V. T-TEST FOR INDICATOR 2

		t-test for equality of means						
		t	gl	Sig. (bilateral)	Difference in averages	Standard error difference	95% confidence interval of the difference	
							Inferior	Superior
Speed (s)	Equal variances are assumed	-1.239	38	0.223	-0.00500	0.00404	-0.01317	0.00317
	Equal variances are not assumed	-1.239	37.842	0.223	-0.00500	0.00404	-0.01317	0.00317

TABLE VI. EFFECT SIZES OF INDEPENDENT SAMPLES -SPEED

		Standardizer[a]	Estimated points	95% confidence interval	
				Inferior	Superior
Speed (s)	Cohen's d	0.01276	-0.392	-1.015	0.237
	Hedges correction	0.01302	-0.384	-0.995	0.232
	Glass delta	0.01234	-0.405	-1.033	0.233

TABLE VII. T-TEST FOR INDICATOR 3

		t-test for equality of means						
		t	gl	Sig. (bilateral)	Difference in averages	Standard error difference	95% confidence interval of the difference	
							Inferior	Superior
Error Rate (%)	Equal variances are assumed	-9.129	38	0.000	-0.10450	0.01145	-0.12767	-0.08133
	Equal variances are not assumed	-9.129	37.978	0.000	-0.10450	0.01145	-0.12767	-0.08133

The effect size analysis for the error rate indicator shows a significant decrease in classification and detection errors after implementation of the AI-based system. Three metrics were calculated to assess the magnitude of this reduction: Cohen's d, which obtained a value of -2.887, indicating a very large effect; Hedges' correction, with a value of -2.829, which adjusts the effect size for small samples, confirming the consistency of the results; and Glass' delta, which uses exclusively the standard deviation of the control group, with a value of -2.922. The 95% confidence intervals for these metrics (ranging from -4.021 to -1.799) do not include zero, reinforcing the practical and statistical significance of the reduction in the error rate. These results reflect that the system not only achieved a reduction in errors, but that this improvement is sufficiently relevant in practical terms to support the effectiveness of the implemented model. See Table VIII.

TABLE VIII. EFFECT SIZES OF INDEPENDENT SAMPLES – ERROR RATE

		Standardizer[a]	Point estimations	95% confidence interval	
				Inferior	Superior
Error Rate (%)	Cohen's d	0.03620	-2.887	-3.773	-1.982
	Hedges correction	0.03693	-2.829	-3.698	-1.942
	Glass delta	0.03576	-2.922	-4.021	-1.799

D. Testing the General Hypothesis

Since the conditions of specific hypotheses one, two and three were accepted, the general hypothesis was accepted: "The implementation of an AI-based system significantly improves the classification and detection of organic and inorganic waste". This shows that the proposed system had a positive and significant impact on the three indicators evaluated: percentage accuracy, detection speed and error rate.

V. DISCUSSION

The first specific objective was to evaluate the ability of the proposed system to improve the accuracy in the classification and detection of organic and inorganic waste. This objective was aligned with studies such as that of [8], who highlighted those systems based on advanced algorithms, such as TensorFlow, can achieve accuracies higher than 95%. In this case, the results showed a significant increase in accuracy, going from an average of 78.95% in the pretest to 88.05% in the posttest, representing an increase of 11.52%. This finding confirms the effectiveness of the developed model to improve waste classification. Also, despite the progress, slight limitations were detected in the classification of certain specific wastes, such as organics and glass, due to factors such as lighting and perspective of the images used, these limitations highlight the need to optimize the model, implementing additional techniques such as data augmentation and hyperparameter adjustment, compared to previous research, such as those of [18], which achieved accuracies of 75%, the results obtained exceed those standards, which could be attributed to the quality of the images used and the use of convolutional neural networks in training. Therefore, this objective demonstrates that the use of artificial intelligence is an effective tool to improve recycling processes through a more accurate and automated waste classification.

On the other hand, it was proposed to evaluate the ability of the system to optimize the time required to identify all the waste. Furthermore, in this study, the results showed that the system throughput increased by 23.61% and significantly reduced the response time, a finding that supports AI-based systems that can overcome the limitations of traditional manual classification optimization with studies such as [18], who highlighted that networks such as EfficientDet-D2 achieve reduced response times when implementing computer vision-based systems. However, it is very important to mention that, although substantial improvements in speed were observed, some factors, such as the size of the images and their model complexity, could have influenced the variability of the results, to further optimize this indicator, it would be advisable to explore advanced architectures such as YOLOv5, which offer us a balance between speed and accuracy. In conclusion, this objective demonstrated that the incorporation of artificial intelligence techniques not only improves classification speed but also establishes an efficient framework for handling large volumes of data in recycling systems.

In addition, we sought to reduce the error rate in the classification of waste, since this is one of the main challenges in automated systems. According to the results, the implemented system managed to reduce the error rate by 24.13%, going from an average of 15.75% in the pretest to 11.95% in the posttest. Furthermore, this progress reflects a significant improvement in the system's ability to minimize false positives and negatives, compared to previous studies, such as that of [18], which reported higher error margins, this system stands out for its effectiveness, some errors persisted in specific residuals, suggesting that factors such as dataset quality and lighting conditions affect the model's performance. To address these limitations, it is proposed to incorporate more diversified datasets and image preprocessing techniques that improve the system's ability to generalize across different scenarios. Implementing additional metrics, such as sensitivity and specificity analysis, could provide a more detailed assessment of model performance. In conclusion, this objective evidenced that the AI-based system is not only effective in reducing errors but also sets a higher standard in the reliability of automated waste sorting processes. This research highlights how digital technologies, by improving the management of organic and inorganic waste, not only optimize economic resources but also strengthen commitment to the environment and to safer and more efficient working conditions [19].

VI. CONCLUSION

In relation to the general objective, the implementation of a system based on artificial intelligence for the classification and detection of organic and inorganic waste has proven to be an effective and sustainable solution, the results confirm that the system can significantly improve the accuracy, speed of detection and error reduction, this will not only facilitate the classification and management of waste, but it will also promote more environmentally responsible practices, this technological advance supports the integration of automated systems in recycling processes, allowing the optimization of resources, reducing the ecological footprint and promoting environmental sustainability in various applications, especially in educational institutions. Firstly, the accuracy of the system reached an average of 88.05% in the post-intervention stage, representing an increase of 11.52%. This result validates the effectiveness of the applied computer vision algorithms, as well as the relevance of having well-labelled databases. Secondly, the 23.61% improvement in detection speed confirms that the system can operate in real time, which is particularly useful in environments such as educational institutions, where waste generation is constant and varied. Finally, a 24.13% reduction in the error rate was achieved, which reinforces the reliability of the model in practical scenarios, reducing human errors in sorting and optimizing the overall waste management process. These results not only demonstrate the effectiveness of the developed system but also open new possibilities for its application in real-life contexts. The automation of the waste sorting process not only optimizes resources and reduces the ecological footprint but also fosters a culture of recycling and sustainability, especially when implemented in educational spaces. Furthermore, this work confirms the potential of artificial intelligence as a key tool in the transformation of traditional environmental processes, enabling more efficient and responsible waste management.

Based on the results obtained, several lines of research are identified that can be explored in subsequent studies to broaden and strengthen the scope of the proposed system. Although the developed system has achieved relevant advances in waste classification through artificial intelligence, there are still substantial gaps between the current achievements and the technological potential that can be reached. This gap is manifested, for example, in the use of basic deep learning architectures, as opposed to more advanced models such as YOLO or EfficientNet, which could significantly improve the accuracy and efficiency of the system. Similarly, the implemented approach is limited to static images and controlled environments, while it is proposed to evolve towards solutions that integrate artificial intelligence with IoT sensors, capable of operating in real time and adapting to varying conditions, particularly in resource-constrained contexts. A significant gap is also identified between the data availability used in this study and that required for robust training; therefore, future research should explore the use of synthetic data and data augmentation techniques. Finally, the current system lacks mobility and autonomy, so the development of applications on mobile or robotic platforms is proposed as a line of research. Recognizing and addressing these differences will allow us to better focus research efforts and move towards more complete, scalable and applicable solutions in a variety of real-world scenarios.

It is important to note that, as in any area of applied research, the study of the use of artificial intelligence for solid waste classification presents certain limitations that must be considered when analyzing the results and their projection. Firstly, the diversity of organic and inorganic waste, in terms of shape, size, color and condition, represents a constant challenge for automated systems, which require highly adap models trained on a wide variety of data. In addition, the scarcity of public and standardized databases makes it difficult to compare research and develop generalizable solutions. The implementation of such technologies in real-world settings is also subject to factors such as access to technological infrastructure, changing environmental conditions and limited resources, especially in rural or educational contexts. On the other hand, the rapid evolution of artificial intelligence models means that current solutions can be quickly outdated, requiring a constant updating of the technical approach. These limitations do not detract from the progress made, but they do reflect the complexity of the field and the need to continue to develop innovative and scalable strategies.

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