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RoBatt: Battery Sorting Robot using Epson VT6 and YOLO v8

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ABSTRACT – This project explores the differentiation of AA, D, and 9V batteries using RoBatt, an Epson VT6 robot integrated with YOLOv8, a state-of-the-art object detection model. The robotic arm is controlled to detect and sort batteries using parameters modeled by the YOLO v8. The use of YOLO v8 allows such detection and classification to occur instantly without compromising the efficiency of the sorting process. Additionally, to improve its operational capabilities, RoBatt is equipped with electromagnetic gripper for the purpose of attracting batteries. The result of the study shows viability to use deep learning and robotics for sorting batteries, and it can be done for commercial or recycling purposes. This integration presents a novel concept for battery waste management and recycling system.

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Introduction

Due to the increasing popularity of battery utilization in industries, there has been a surge in the demand for battery sorting automation. Manual sorting procedures in comparison to battery sorting are slow, ineffective, and require a lot of workers to perform as shown in Figure 1. However, as robots and machine learning develop, these solutions can be addressed with autonomous systems. This project aims at combining industrial manipulator robot, a USB camera and an electromagnetic gripper for battery sorting. To do so, YOLOv8 object detection model is utilized for battery sorting and battery type recognition objectives.

Batteries power many products, but disposing of them is environmentally harmful. In 2004, Canada disposed of 347 million batteries, out of which 12 percent were sorted properly, overloading recycling plants [1]. Proper sorting is necessary for material recovery and environmental conservation but is still inefficient, imprecise, and hazardous when manually performed.

Related Works

There has been intensive research on recycling, yet sorting batteries is underexplored and has room for improvement towards enhanced sustainability. The variation in battery size and type makes typical e-waste sorting laborious and requires unique procedures, particularly for poisonous lithium batteries.

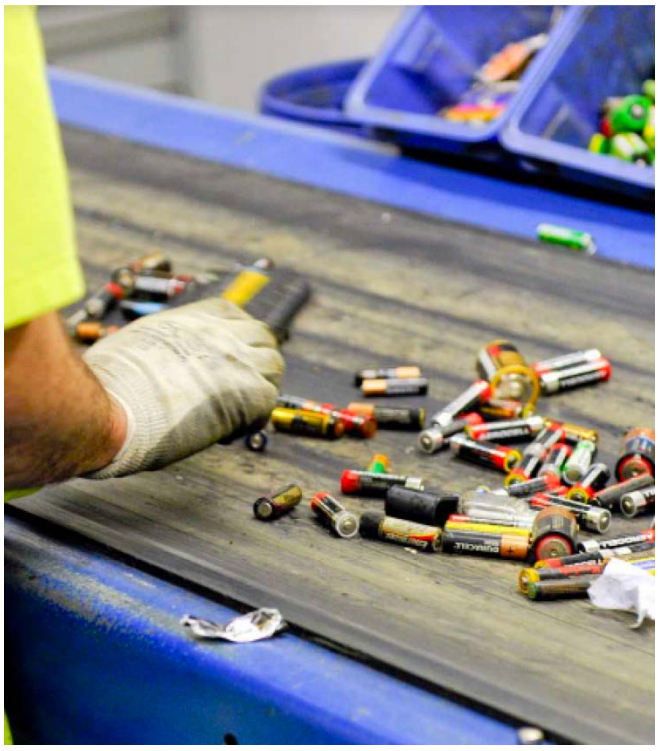

Figure 1. Manual sorting of batteries

In this related work [2], a vision-equipped industrial robot and depth sensors are used to automatically disassemble batteries using few-shot learning to lower dependency on big data. However, depth sensors are expensive and relatively difficult to implement.

The use of IGUS robots with electromagnetic and pneumatic grippers for pick-and-place operations is discussed in [3].

Another research [4] is using three deep architectures of strict convolutional, image splitting, and deep scaling networks all achieve above 80 percent accuracy at 1+ cycle per second in battery sorting.

Method

A. Selecting training model

The popularity of YOLO in computer vision has led to continuous updates, and several high-end versions are now available. On 10th January, 2023, Ultralytics launched YOLOv8, which achieves better speed and accuracy compared to its earlier versions, YOLOv5 and YOLOv7 [5].

YOLOv8 improves detection by adopting an anchorfree strategy, predicting object centers directly instead of using pre-defined anchor boxes. Combined with Non-Maximum Suppression (NMS), this removes duplicate box predictions and improves processing efficiency. It consists of three primary components: the input side, neck network, and backbone network [6]. Improvements such as adaptive image scaling, anchor computation, and mosaic augmentation improve detection performance by reducing redundant computation and improving diversity of data. YOLOv8 replaces YOLOv5's C3 structure with a C2f structure to obtain better gradient flow and feature extraction. The C2F module, as a residual block, adaptively adjusts its depth according to model size for better detection performance.

For improved object localization, YOLOv8 introduces the Task-Aligned Assigner algorithm that more accurately selects positive and negative samples. In NMS, low-confidence anchors are removed and highconfidence anchors are retained, and bounding box accuracy is improved. A novel alignment metric that dynamically scales anchor predictions by combining multiple feature maps is introduced, which improves detection accuracy and stability [7].

YOLOv8 was chosen for battery sorting due to its real-time object detection feature, which allows for effective sorting of AA, D, and 9V batteries. It is among the models capable of detecting more than one object at a time, making it ideal for the work. The model is fast and accurate, with rapid image processing and accurate classification. With a strong established history of object detection tasks, YOLOv8 provides reliable performance for industrial recycling and sorting applications.

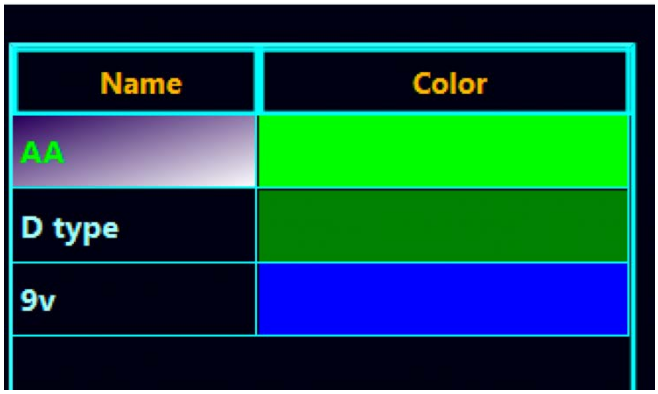

Figure 2. Classification of batteries in YOLO

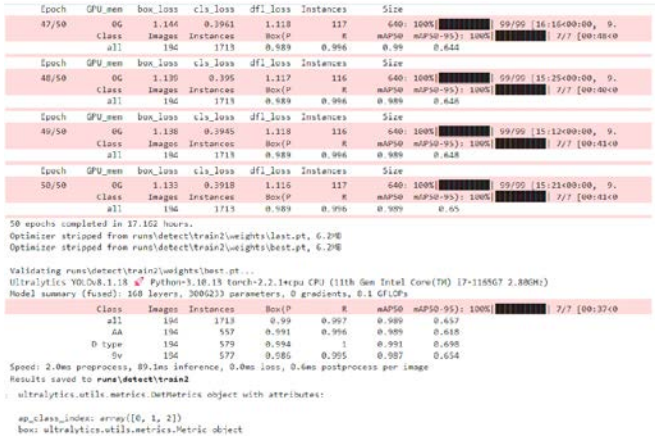

Figure 3. 50 Epochs trained in 17.162 Hours

The training phase continued for 50 epochs (Figure 3) so that the model could learn prominent features without overfitting. Having a GPU-enabled environment was computationally more efficient and enabled the model to possess good generalization properties. Being the most recent version of YOLO, YOLOv8 has quicker detection rates and better accuracy and is thus apt for this robotic sorting system. Furthermore, the model was easily integrated with the robot control system as it was programmed using Python scripts.

YOLOv8 has following advantages

1. Appropriate for applications that require a realtime approach because of the fast detection rates.
2. Few chances of making errors during detection hence high precision.
3. Can be used together with the OpenCV library for photo processing.
4. Multiple targets can be located and identified within one frame making it possible to sort batteries concurrently.

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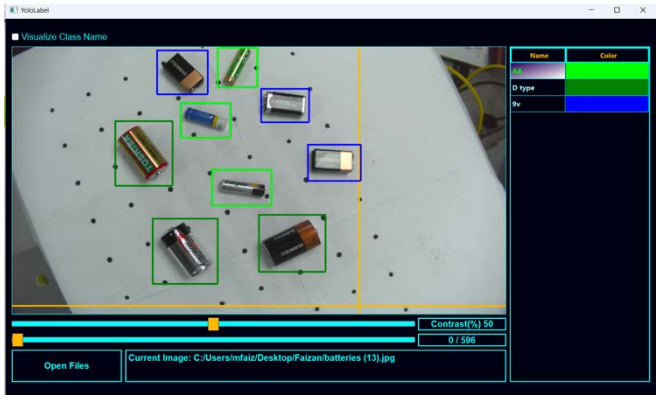

Figure 4. Sample Image for training data

B. Dataset Used

The data set consisted of three battery types from different companies, taken under different orientations and light conditions to mimic real conditions. It was divided into training and validation sets to allow for effective model building and testing.

The training set consists of 1581 images, with up to nine batteries placed at random on a 9×7 grid shown in Figure 4. The validation set was 194 images to evaluate model performance during training.

Furthermore, we assembled an independent test set with 109 entirely new photos that were not included in the training or validation datasets. These photos functioned as a separate assessment to gauge the model's ability to perform well in unfamiliar environments and generalize beyond the training set. For training and validating strong deep learning models specifically designed for battery classification tasks, such a diverse and meticulously organized dataset must be included.

C. Robot Manipulator

A robot manipulator has to locate and orient objects to perform tasks. It consists of revolute joints that provide angular motion. Pick-and-place robots are better with this approach as suggested by [3].

The Epson VT6 robot, is an industrial grade manipulator with built-in controllers, capable of handling a payload of 6 kg, and a reach of 900 mm. Its repeatability of 0.1 mm gives precision motion.

An electromagnetic gripper shown in figure-6 Is used as the end effector. Its magnetic strength cannot be changed by permanent magnets because it can be regulated by varying the electric current or distance. This 12V DC electromagnet used here can hold up to 5 kg [8].

The gripper mechanism switches on the magnetic field when the robot is at the battery, so that it can grasp and release batteries at specific points. The robot programming script provides synchronized movement of the gripper with its movement.



Figure 5. Epson VT6 with electromagnetic gripper



Figure 6. Electromagnetic Gripper

The system works by taking images of the batteries on a fixed surface, using the USB camera. The YOLOv8 model detects the positions and types of batteries from the images. Based on the battery type (AA, 9V, or D), the Python script sends commands to the robot to move to the battery position, activate the gripper, return to a home position, and finally drop the battery in the corresponding bin.



Figure 7. Setup

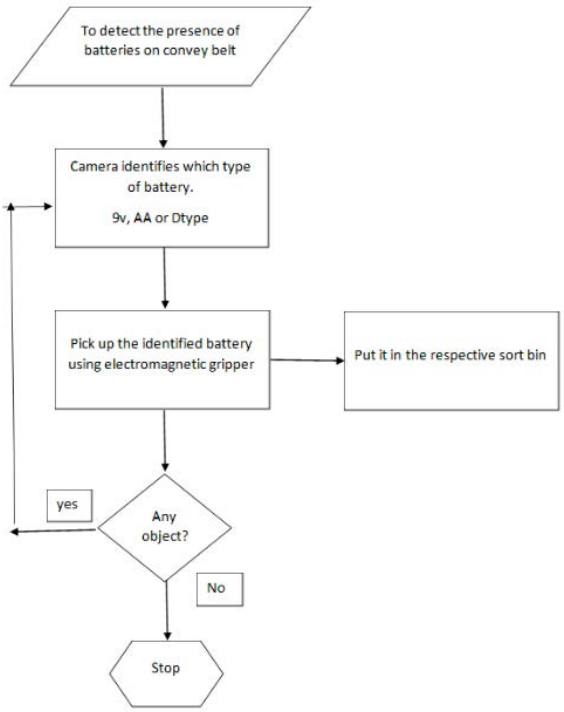

Figure 8. Flow Chart

D. Process Flow

First, batteries are placed within the sorting area as shown in Figure 7 and capture the image of batteries using a USB camera. YOLOv8 analyzes the images captured by the camera and identifies the type of batteries and their location coordinates.

Send movement commands to the robot via Python. The robot then moves to the pickup position coordinates upon detecting a battery. Using Epson RC+, the robot calculates the trajectory to reach the pickup position in an efficient manner.

Activate the electromagnet at the battery pick-up point. Once the robot reaches the pickup position, an electromagnet attached to its gripper activates. The electromagnet secures the battery onto the gripper.

After picking up the battery, the robot moves back to a safe position. The robot then calculates the trajectory to the designated drop-off position based on the battery type and sorting requirements. Once at the drop-off position, the electromagnet is deactivated, releasing the battery. The battery is deposited at the drop-off point as per the sorting criteria.

The robot repeats this process for each detected battery until all batteries have been sorted. Once sorting is complete, the robot waits for the Next command. After spacebar is pressed the camera sends the command to robot about the current camera frame and the process is repeated (Figure 8).

E. Connectivity

The camera is connected to a PC running Python script, while the robot receives movement and action command messages from the Python script over a TCP/IP connection. The messages sent by Python script to the robot are formatted as “X Y Z” coordinates for movement and “PICK” or “DROP” for activating or deactivating the gripper.

Implementation and Results

A. Implementation

(1) Ensure the Epson VT6 is properly configured, then Turn on the robot and confirm that the end-effector (gripper) is firmly attached to the robot arm shown in Figure 5.

(2) For the Electromagnet Attachment, securely attach the 12V electromagnet to the robot’s end-effector using a 3D printed mount. Ensure the electromagnet is centered and secure enough to hold batteries effectively.

(3) Connect the positive terminal of the 12V electromagnet to the power supply with plate number 1. Connect the negative terminal of the electromagnet to the output connector number 8 on the robot.

(4) Install an external camera above the battery sorting table and ensure it has a clear view of the table and batteries. Adjust the camera angle and focus for optimal detection.

(5) Place the battery sorting table in the robot’s working area. Ensure it is stable and level for precise sorting.

(6) Arrange the batteries to be sorted on the battery sorting table. Ensure that they are spaced out and organized neatly.

(7) Establish communication between the robot and the PC running Epson RC+ software. Ensure the PC is connected to the external camera

(8) Configure Epson RC+ software to communicate with the robot and set up programs for battery detection, pickup, and drop-off.

(9) Calibrate the external camera to ensure accurate detection of batteries. Adjust camera settings such as focus, exposure, and resolution.

(10) Calibrate the gripper's movement and grip strength using Epson RC+ software. Teach the pickup and dropoff positions for each battery type shows in Figure 9.

B. Testing

The battery classification system was extensively tested to evaluate its effectiveness. We tested the system under various conditions, including different types of lighting (natural, artificial room light, and yellow light), battery orientations (such as standing or lying down), and various backgrounds. The primary goal was to see how well the system could identify and categorize AA, D, and 9V batteries in real time.

A battery of locations was used in a comprehensive testing procedure to confirm accuracy and efficacy. The robot's ability to identify various battery types, pick them up, and put them in the proper bins was evaluated throughout the testing phase.

We also tested batteries from brands not included in the original training data and used battery orientations that the system hadn't previously encountered. The system performed excellent, in recognizing and classifying all three types of batteries and in identifying new brands.

However, under natural lighting, the system sometimes fails to detect AA batteries. In very rare cases, we encountered a specific issue where the system occasionally confused 9V and D batteries from the same brands. We experimented with placing the camera at different distances from the batteries, but this did not significantly affect the accuracy.

Overall, the system correctly identified the batteries 85 percent of the time, often with high confidence. We also observed that misidentified batteries typically had

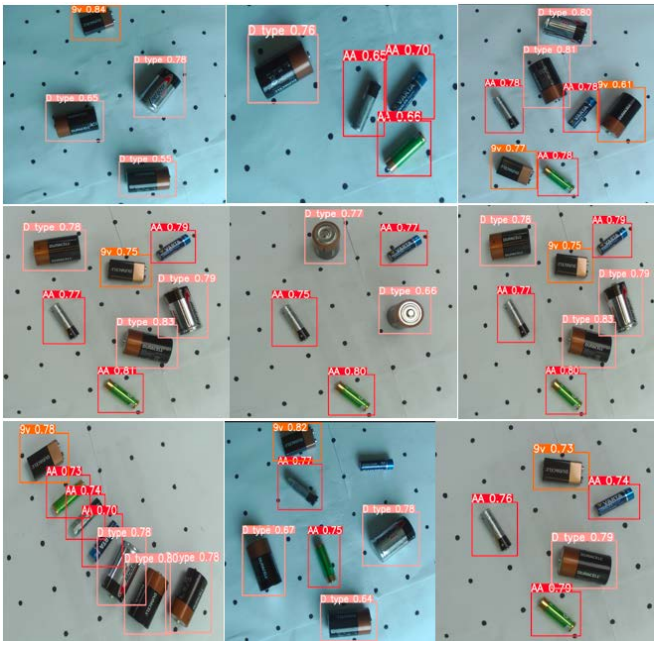

Figure 9. Captured test images

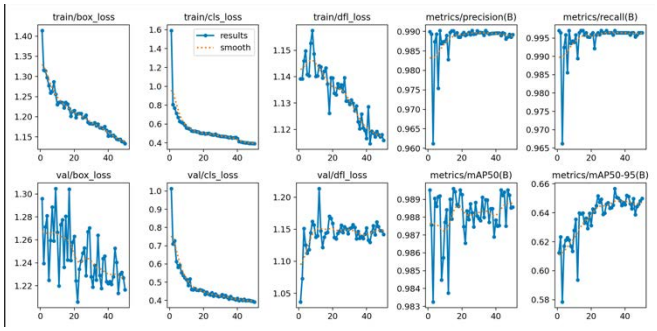

Figure 10. YoloV8 model trained in different conditions

lower confidence scores. To improve accuracy, we could introduce a confidence threshold that would help avoid incorrect classifications. The system demonstrated high accuracy and speed in differentiating between the three battery types, even in challenging scenarios. Testing result confirmed the system's effectiveness for industrial and recycling applications.

Figure 10 illustrates the evolution of different metrics throughout the training and validation processes. These metrics encompass box loss, class loss, as well as post-epoch indicators like accuracy and recall [6].

C. Test scenarios

(1) Tests were carried out in three different lighting scenarios: mixed, artificial, and natural light. With an overall accuracy rating of 85 percent, the system did well.

(2) Battery Orientation: Batteries were stacked, placed flat, and stood upright for the tests. Accurate sorting was ensured by the efficient handling of these cases by the coordinate transformation and camera calibration.

(3) Brands of Batteries: To evaluate the adaptability of the system, several brands that were not used during model training were introduced. While the system successfully identified the batteries, it had some trouble telling apart AA batteries in dimly lit areas.

The summary of testing result is shown on Figure 11. Demonstration video is available online at https://tiny.cc/robatt.

Method:	Placing randomly 3 types of batteries		
Experiment #	Type D	Type 9v	Type AA
1	SUCCESS	SUCCESS	SUCCESS
2	SUCCESS	SUCCESS	SUCCESS
3	SUCCESS	SUCCESS	SUCCESS
4	SUCCESS	SUCCESS	SUCCESS
5	SUCCESS	SUCCESS	FAILED
6	SUCCESS	SUCCESS	SUCCESS
7	SUCCESS	SUCCESS	SUCCESS
8	SUCCESS	SUCCESS	SUCCESS
9	SUCCESS	Failed(detection wrong)	SUCCESS
10	SUCCESS	SUCCESS	FAILED
11	SUCCESS	SUCCESS	
12	SUCCESS	SUCCESS	
13	SUCCESS	SUCCESS	
14	SUCCESS	SUCCESS	
15	SUCCESS	Failed(detection wrong)	
16	SUCCESS	SUCCESS	
17	SUCCESS	SUCCESS	
18	SUCCESS	SUCCESS	
19	SUCCESS	SUCCESS	
20	SUCCESS	SUCCESS	
Total Success	20	18	8
Total Failed	0	2	2

Figure 11. Accuracy of the Task

F. Challenges faced

(1) Battery Positioning: The accuracy of the camera and the model had to be carefully taken into account in order to determine the exact battery position. Any difference in position would lead to inaccurate sorting.

(2) Gripper Activation: It was crucial to make sure the electromagnetic gripper only switched on when it was needed to avoid batteries running out too quickly.

(1) Data augmentation adds object appearances and scene variations to make the model stronger.

(2) Regularization of dropoutout prevents overfitting randomly suppressing neuronsons during training.

(3) Analysis of model complexity improves architecture for improved generalization and performance.

(4) Training data background images help to differentiate batteries from other environments and reduce false positives.

(5) More battery types and sizes (AA, AAA, C, D, etc.) improve system flexibility across various brands and chemistries.

(6) Sophisticated grippers with adjustable magnet power and adaptive calibration enhance handling and reliability, supported by safety features such as anomaly detection and remote monitoring.

Conclusion and Discussion

In conclusion, a viable solution to accurate and efficient battery sorting was achieved by combining the Epson VT6 robot with an electromagnetic gripper and the YOLOv8 object identification model. The system's ability to manage several types of batteries in real time demonstrates how it may enhance industrial and recycling processes. Speed and detection accuracy can be maximized for industrial applications.

Potential future developments could involve optimizing the YOLOv8 model for better generalization and exploring novel approaches to boost the system's adaptability to diverse environmental scenarios. Having the camera attached to the robot would enhance detection quality and flexibility. Parallel processing can accelerate sorting by allowing the detection and sorting of several batteries in parallel.

The system is scalable for industrial recycling, accommodating various battery sizes and types as well as reacting to changing conditions. In addition to battery sorting, the approach can be applied to warehouse automation, delicate goods handling, and component sorting in manufacturing, offering greater AI-based automation potential to other industries.

Acknowledgement

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References

[1] Environment Canada calls for more battery recycling - Waste & Recycling [Internet]. Available from: https://wasterecyclingmag.ca/waste-management/environment-canada-calls-for-more-battery-recycling/1000063260/

[2] Philip Keller, Johannes Mangler, Nicolas Hügel, Marvin Grosse Besselmann, Arne Rönnau, and Rüdiger Dillmann. Robotic sorting of batteries using visual few-shot learning and fusion with depth data. In 2023 3rd International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME), pages 1–7, 2023.

[3] Venkata Siva Bathula, Venkannababu Mendi, Sekhar Chinthamreddy, Arigela Pavan Kumar, and B Chandra Bose. Pick and place operation by collaborating electromagnetic and pneumatic gripper robots. Materials Today: Proceedings, 2023.

[4] Hamidreza Karbasi, Adam Sanderson, Alireza Sharifi, and Cristian Pop. Robotic sorting of used button cell batteries: Utilizing deep learning. In 2018 IEEE Conference on Technologies for Sustainability (SusTech), pages 1–6, 2018.

[5] Gang Wang, Yanfei Chen, Pei An, Hanyu Hong, Jinghu Hu, and Tiange Huang. Uav-yolov8: A small-object-detection model based on improved yolov8 for uav aerial photography scenarios. Sensors, 23(16), 2023.

[6] Tianyong Wu and Youkou Dong. Yolo-se: Improved yolov8 for remote sensing object detection and recognition. Applied Sciences, 13(24), 2023.

[7] Yongjing Zhou, Weigang Zhu, Yonghua He, and Yonggang Li. Yolov8-based spatial target part

recognition. In 2023 IEEE 3rd International Conference on Information Technology, Big Data and Artificial Intelligence (ICIBA), volume 3, pages 1684–1687, 2023.

[8] Abdulkareem Alasli, Levent Çetin, Nail Akçura, Aytaç Kahveci, Fatih Cemal Can, and Özgür Tamer. Electromagnet design for untethered actuation system mounted on robotic manipulator. Sensors and Actuators A: Physical, 285:550–565, 2019.