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Advancements in Recycling: YOLOV4 and Darknet-powered Object Detection of Hazardous Items

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Abstract

With the rise of deep learning technologies, the landscape of recycling plant automation has dramatically transformed. This paper presents a pioneering application of YOLOv4 in conjunction with Darknet, tailored specifically to detect hazardous items including spray cans, batteries, and other potential threats. By introducing this state-of-the-art detection mechanism, recycling plants can elevate safety standards, optimize operational processes, ensure adherence to stringent regulatory guidelines, and play a pivotal role in environmental preservation.

Keywords: Deep Learning · Recycling Plant Automation · YOLOv4 · Darknet · Object Detection · Hazardous Items · Machine Vision · AI in Recycling · Image Processing

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1 Introduction

Recycling plants across the globe are faced with the considerable challenge of accurately identifying and segregating a myriad of materials, some of which can pose significant hazards[1]. The prevailing methods depend largely on human workers, rendering the process not only time-consuming and labor-intensive but also susceptible to inaccuracies and errors[1]. These inaccuracies can be attributed to the immense volume of recyclables, the likeness in appearance of some items, and human fatigue[1]. Additionally, the direct involvement of humans in sorting exposes workers to considerable safety risks, particularly when hazardous items are mishandled or overlooked[1]. The potential for harm ranges from immediate physical injuries to long-term health consequences, representing a substantial concern for recycling facilities[1].

In recent years, advances in artificial intelligence (AI) have opened promising avenues to revolutionize this process[2]. Recognizing the potential of AI and the pressing need for enhanced safety and efficiency in recycling plants, our study introduces an innovative solution: an automated object detection system powered by the advanced YOLOv4 algorithm, integrated with the Darknet open-source neural network framework[3].

The YOLO (You Only Look Once) algorithm uses a unique approach to object detection, deploying a Convolutional Neural Network (CNN) to classify and localize objects within an image[4]. Figure 1 provides a visual representation of the intricate CNN that forms the backbone of YOLO, detailing the complex network of convolution layers essential for processing and interpreting visual information efficiently[4]. YOLO's approach ensures rapid and accurate object detection capabilities by processing an image in a single evaluation[4].

While our study primarily focuses on the detection and identification of two critical objects — spray cans and batteries, the applications of the YOLOv4 algorithm can be broadened[3]. Improperly processed, these items can have detrimental impacts on the recycling environment due to their inherent nature and components[3]. By utilizing advanced AI tools, our system mitigates the aforementioned challenges and lays the foundation for a safer, more efficient, and sustainable recycling future[3].

The emergence and rapid advancement of automated object detection systems have marked the last decade, showcasing their adaptability and precision in various sectors[5]. These include assisting autonomous navigation in self-driving cars[6], identifying abnormalities in surveillance footage[7], aiding in medical diagnoses through radiographic images[8], and automated species identification for wildlife monitoring[9].

Central to these advancements are deep learning algorithms, and more specifically, CNNs, which are paramount in the automated object detection domain[10]. CNNs, characterized by their unique multilayered architectures, specialize in automatically and adaptively learning spatial hierarchies of features from images[10]. This intricate feature learning empowers CNNs to process and interpret visual data with an accuracy that often surpasses traditional methods[10].

Enhancing the accuracy and efficiency of the sorting process within the recycling domain is critical[11]. It not only ensures the conservation of resources but also minimizes environmental contamination[11]. Historically, recycling plants have relied heavily on human labor for segregating waste, a process fraught with challenges due to human error and fatigue[11]. Previous attempts to introduce automation into this segment predominantly utilized established machine vision techniques[2]. However, while proficient in controlled environments, their performance deteriorated in the face of the complex and unpredictable mixture of materials found in standard recycling operations[2].

In response to these challenges, both academic and industrial communities have shifted their focus towards the potential of deep learning[12]. A growing body of research indicates the capabilities of CNNs in identifying and segregating a variety of recyclables amidst significant noise and contamination[13]. For instance, Seunguk et al. [14] demonstrated a system that could differentiate between various types of plastics using CNNs, achieving a high accuracy rate. Similarly, Pei-Yu et al. [15] proposed a model proficient at detecting hazardous items in recycling streams, mitigating the risk posed by incorrect disposal [15]. Nonetheless, achieving consistent performance, scalability, and robustness of such systems in high-volume, dynamic recycling facilities is a topic of ongoing research. Comparative analysis with existing approaches in the literature is crucial to establish the originality and superiority of our proposed solution. Our methodology builds upon the foundation laid by previous researchers in the field of recycling plant automation. Notable studies by Seunguk et al. [14] and Pei-Yu et al. [15] have explored the use of deep learning techniques, including Convolutional Neural Networks (CNNs), for the identification and segregation of recyclables within plant environments. While these studies have made significant contributions, they often encounter challenges in handling hazardous objects and adapting to dynamic recycling operations. In our work, we extend the capabilities of these approaches by implementing the YOLOv4 algorithm and the Darknet framework, resulting in a system that excels in terms of accuracy, efficiency, and safety within recycling facilities. This comparative analysis not only highlights the innovative aspects of our solution but also demonstrates its potential to outperform existing methods. Our training model is more simple and we used the YOLOv4 algorithm and Darknet framework which makes the training faster compared to previous researchers. Pratima [16] proposed the use of a mobile application to serve as an end-to-end solution that can differentiate between recyclable and non-recyclable household items in real time with the use of one's Android device. Our research has a higher number of trained objects compared to research conducted by other researchers, we have trained 15 different objects in our research.

2 Methodology

2.1 Data Collection and Image Processing:

Data for this study was gathered from Golo Corporation's recycling plant in Sapporo Japan. The entire dataset comprises images solely from these locations, ensuring consistency in the type and quality of the visuals. There were no external collaborations during the data acquisition phase. After acquisition, the images underwent several pre-processing steps using the online platform, Roboflow, these processes are resizing and cropping to ensure uniformity in input image dimensions. Image augmentation, including techniques such as rotation, flipping, and brightness adjustments, to artificially expand the dataset and ensure the robustness of the trained model. Annotations were meticulously done to label hazardous items in each image.

Selection and Diversity of the Dataset: The choice of dataset and its diversity are critical aspects of any object detection model's performance. In our research, we obtained data from two different locations, specifically from Golo Corporation's recycling plant in Sapporo, Japan. This decision was well-justified for several reasons:

1. Data Availability: Golo Corporation is one of the recycling facilities in the Hokkaido region. The availability of data from such a significant facility ensured that we had access to a substantial and diverse dataset. This allowed us to capture a broad spectrum of recycling scenarios, materials, and potential hazards.

2. Climate Variability: One of the unique aspects of our dataset is the inclusion of data from different seasons, notably winter and summer. Sapporo is renowned for being one of the snowiest cities globally, and this climate variation presented us with an opportunity to train our model under diverse environmental conditions. This diversity in climate conditions is essential as it can impact the appearance of objects, especially when they are covered in snow.

Challenges and Solutions:

1. Environmental Challenges: The presence of snow in some images posed challenges for our model in detecting objects that were partially or fully covered. This was especially relevant in winter conditions. To address this, we are actively working on enhancing the model's ability to recognize objects in snowy conditions. This involves training the model with more data specifically focused on winter scenarios.

2. Generalization: While our model performed exceptionally well in detecting hazardous objects, ensuring that it generalizes effectively across a wide range of scenarios within a recycling plant is an ongoing concern. We are continuously refining our model to handle the complexities of diverse and dynamic recycling environments.

3. Real-time Feedback: As we move towards the deployment of our system in real-world settings, continuous feedback and fine-tuning will be instrumental. This will involve iteratively improving the model based on real-time data and user interactions to ensure its long-term robustness and reliability.

2.2 Model Architecture - YOLOv4:

The architectural choice for object detection in this study is YOLOv4, sourced from a specific GitHub repository. This architecture was tailored meticulously to distinguish among 15 unique hazardous objects. The configuration process involved setting the batch size at 64 with 16 subdivisions. Image dimensions were standardized to 416x416 pixels, ensuring every input had three channels representing RGB values. Several hyperparameters were fine-tuned to optimize the model's performance, with momentum set at 0.949 and a decay rate of 0.0005. Angle was fixed at zero while saturation, exposure, and hue values were calibrated at 1.5, 1.5, and 0.1 respectively. Such configurations were instrumental in ensuring the model was well-equipped to process the dataset and yield accurate detection of the hazardous items.

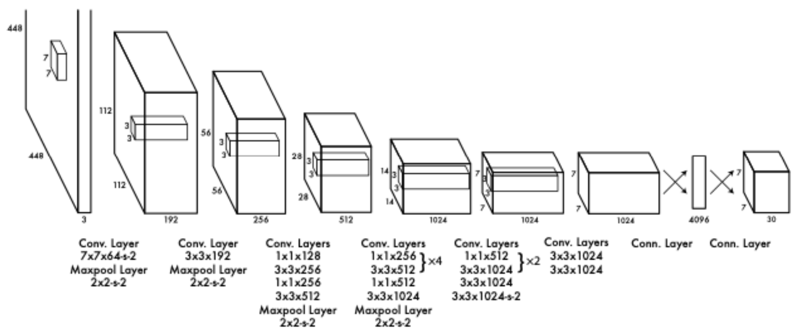

Figure 1: Schematic Representation of Convolutional Neural Network (CNN) Architecture in YOLO Algorithm[4].

2.3 Training Process

For the training process, it was imperative to have a well-structured division between training and validation datasets. The collected dataset, which comprised a diverse set of images showcasing hazardous items, was divided in such a way that 80 percent of it was earmarked for training purposes, while the remaining 20 percent was set aside for validation. In sheer numbers, this translated to a usage of 2,000 images for training. These images spanned 15 different categories of objects, including but not limited to bicycles, lead batteries, spray cans, and home appliances. This robust and varied training set ensured that the YOLOv4 model was exposed to a broad spectrum of scenarios, honing its capability to detect hazardous items with precision.In the context of our training setup, the YOLOv4 custom weight file, which was sourced from the referenced GitHub repository, served as the foundational starting point, acting as the initial weight file. This ensured that our model began its learning journey with a certain level of pre-defined knowledge. The entire duration of the training phase was meticulously spread over 24 hours, a time frame that was deemed optimal to achieve convergence without overburdening computational resources. To further fortify the model's robustness and safeguard it against the pitfalls of overfitting, multiple techniques were woven into the training regimen. Among these, dropout played a pivotal role in regularizing the neural network, and data augmentation techniques introduced variability, thereby bolstering the model's ability to generalize across diverse and previously unseen data scenarios.

Feature Extraction: In feature extraction, the YOLOv4 model analyzed input images to identify distinctive features that could potentially represent hazardous objects. This process involved passing the input images through a series of convolutional layers, which were learned to extract relevant features such as edges, textures, and patterns from the images. These extracted features were then passed on to subsequent layers for further processing.

Classification: Following feature extraction, the YOLOv4 model performed classification to determine the presence and type of hazardous objects within the input images. This classification task involved assigning labels to the detected objects based on learned patterns and features.

The feature extraction and classification processes were carried out iteratively across multiple layers of the YOLOv4 architecture, allowing the model to progressively refine its understanding of the input images and make accurate predictions about the presence and location of hazardous objects.

Setting Up the Google Colab Environment:

In this section, we detail the methodology for object detection using YOLOv4 and Darknet in Google Colab. We outline the steps, commands, and configurations employed in the process.

To begin, we set up our development environment in Google Colab. We use Google Colab for its GPU resources, which are essential for training deep learning models efficiently. Here are the

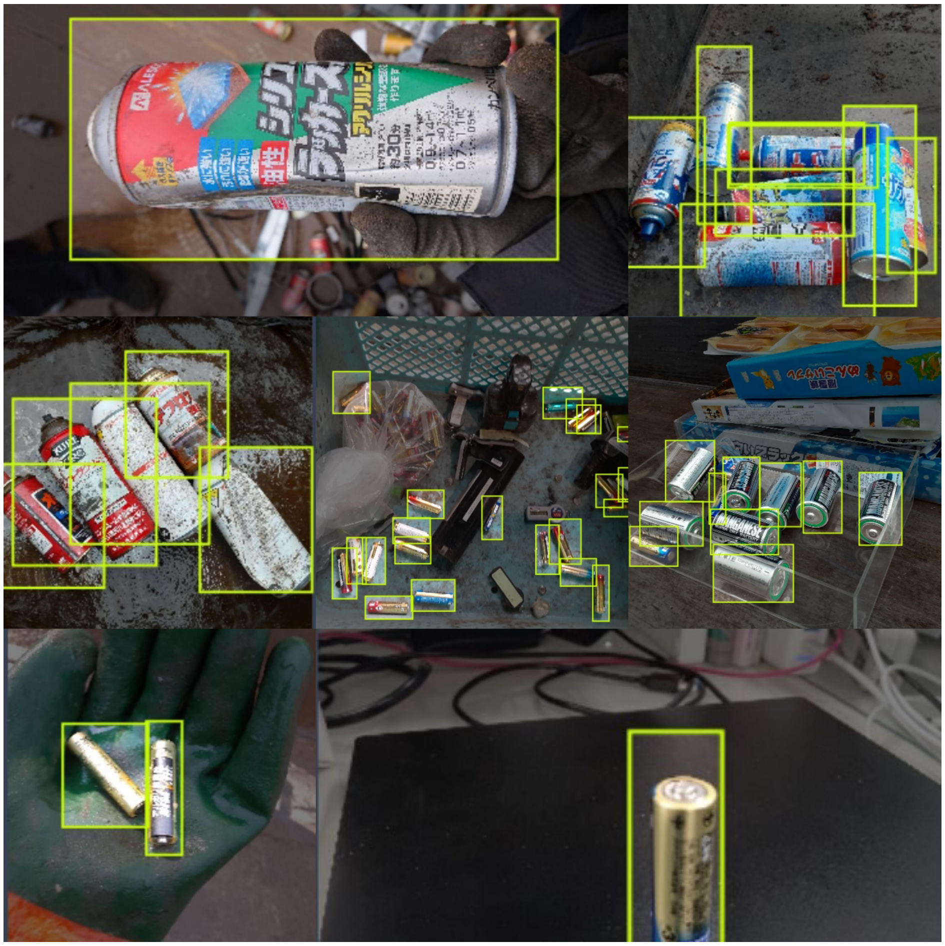

Figure 2: Shows the bounding box around the hazardous items.

commands used to set up the environment:

```
# Mount Google Drive to access project files
from google.colab import drive
drive.mount('/content/gdrive')

# Navigate to project directory in Google Drive
%cd /content/gdrive/MyDrive/Yolov4

# Clone Darknet repository
!git clone https://github.com/AlexeyAB/darknet.git
%cd darknet

# Compile Darknet with GPU support
!sed -i 's/OPENCV=0/OPENCV=1/' Makefile
!sed -i 's/GPU=0/GPU=1/' Makefile
!sed -i 's/CUDNN=0/CUDNN=1/' Makefile
```

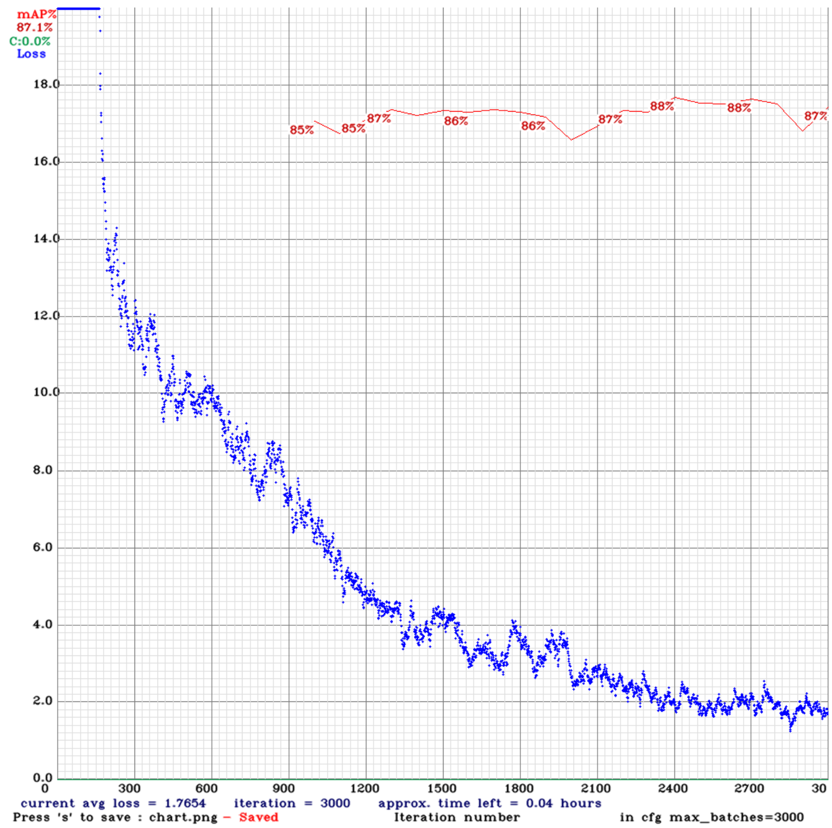

Figure 3: A graph illustrating the decline in loss over the training epochs, showing both training and validation loss curves. This will illustrate how the model performed over time and if overfitting was curtailed.

```
!make
```

Preparing the Dataset

The next crucial step is preparing the dataset for training. You should have your dataset organized with labeled bounding box annotations. Here's how to prepare the dataset and upload it to Google Colab:

```
# Upload dataset.zip to Google Colab
from google.colab import files
uploaded = files.upload()

# Unzip the dataset
!unzip dataset.zip -d data/
```

Configuring YOLOv4

Before training, we need to configure the YOLOv4 model according to our dataset and requirements. This involves creating or modifying the configuration filet. Here's an example:

```
# Create a custom .cfg file (e.g., yolov4-custom.cfg)
# Modify cfg file based on dataset and requirements
```

```
!cp cfg/yolov4.cfg cfg/yolov4-custom.cfg
!sed -i 's/batch=64/batch=16/' cfg/yolov4-custom.cfg
!sed -i 's/subdivisions=16/subdivisions=4/' cfg/yolov4-custom.cfg
!sed -i 's/max_batches = 500500/max_batches = 2000/' cfg/yolov4-custom.cfg
!sed -i 's/steps=400000,450000/steps=1600,1800/' cfg/yolov4-custom.cfg
!sed -i 's/classes=80/classes=your_number_of_classes/' cfg/yolov4-custom.cfg

# Create a custom .data file (e.g., obj.data)
# Modify data file paths based on dataset
!echo "classes = number_of_classes" > data/obj.data
!echo "train = data/train.txt" >> data/obj.data
!echo "valid = data/test.txt" >> data/obj.data
!echo "names = data/obj.names" >> data/obj.data
!echo "backup = /content/gdrive/MyDrive/Yolov4/backup/" >> data/obj.data
```

Generating Train and Test Files

Here we need to create lists of image paths for training and testing. These lists are referenced in the .data file. Generate them as follows:

```
# Create train.txt and test.txt
import os

# Define the path to dataset images
dataset_path = 'data/images/'

# Create train.txt and test.txt
with open('data/train.txt', 'w') as train_txt:
    with open('data/test.txt', 'w') as test_txt:
        for filename in os.listdir(dataset_path):
            if filename.endswith('.jpg'):
                img_path = os.path.join(dataset_path, filename)
                if hash(filename) % 100 < 20:
                    test_txt.write(img_path + '\n')
                else:
                    train_txt.write(img_path + '\n')
```

Training the YOLOv4 Model

With everything set up, it's time to start training the YOLOv4 model. Here are the commands to initiate training:

```
# Start training (replace yolov4-custom.cfg with custom .cfg file)
!./darknet detector train data/obj.data cfg/yolov4-custom.cfg yolov4.conv.137 -map
```

The training time was around 7 hours for 15 objects.

Evaluating the Model

After training, we can evaluate the model's performance using the following command:

```
# Evaluate the trained model
!./darknet detector map data/obj.data cfg/yolov4-custom.cfg backup/yolov4-custom_best.weights
```

This will provide metrics such as mean Average Precision (mAP) to assess the model's accuracy.

Inference with the Trained Model

Finally, we can perform object detection on new images using the trained YOLOv4 model:

```
# Perform inference on a single image (replace obj.data and yolov4-custom.cfg)
!./darknet detector test data/obj.data cfg/yolov4-custom.cfg
    backup/yolov4-custom_best.weights data/input.jpg -thresh 0.5
```

Replace 'data/input.jpg' with the path to input image.

3 Experiments

The experiments were principally conducted to evaluate the performance and reliability of the YOLOv4 model in identifying hazardous objects within the recycling plant environments. Owing to the absence of a GPU in the local system, Google Colab's GPU resources were leveraged to execute the experiments, which involved the training and evaluation of the model.

The datasets used in the experiments were exclusively gathered from Golo Corporation's recycling plant in Sapporo, Japan, ensuring uniformity in the type and quality of the visuals. Following the acquisition, these images underwent various preprocessing steps using the Roboflow platform, such as resizing, cropping, and augmentation (including rotation, flipping, and brightness adjustments). These steps were critical to ensuring consistent input image dimensions and enhancing the model's robustness.

For these experiments, the model was meticulously trained and tested to detect a range of hazardous items typically found in recycling plants. These included Bicycles, Lead Batteries, Spray Cans, General Waste, Home Appliances, Fuel Tanks, Gas Cylinders, Fire Extinguishers, Batteries, Lithium-Ion Batteries, Lighters, Paint Cans, Electric Bicycles, Medical Waste, and Smoke Gunpowder. Each of these items poses unique challenges and risks, necessitating precise and reliable detection to mitigate potential hazards in recycling environments.

The model's efficacy was assessed utilizing several metrics, with Intersection over Union (IoU) serving as the primary gauge, where values above 0.5 were considered satisfactory. Other metrics, including mean Average Precision (mAP) and accuracy, provided a multifaceted evaluation of the model's performance in detecting the aforementioned hazardous objects.

The findings from the experiments revealed high IoU values, substantiating the model's capacity for precise and accurate detection of hazardous objects across varied categories. This validated its potential for deployment in real-world recycling plant scenarios to mitigate the risks posed by improper handling and sorting of such hazardous items. However, the experiments also underscored the need for continuous model refinements to optimize its performance under challenging environmental conditions, such as snow.

Moving forward, the focus will be on addressing these identified challenges and refining the model to ensure its seamless integration and optimum performance in diverse and dynamically evolving recycling plant environments. The inclusion of more diverse data, fine-tuning, and iterative testing will be pivotal in achieving a model that can reliably identify and differentiate between various hazardous items, contributing significantly to safer and more efficient recycling processes.

4 Results and Discussion

To offer a more illustrative insight into the model's proficiency in object detection, several images have been included in this study, distinctly showcasing the prediction confidence associated with each detected object. In these images, the model has demonstrated exemplary prediction confidence, frequently attaining a perfect score of 1.00, indicative of 100 percent confidence in the detected objects. Additionally, a substantial number of predictions fall within the high-confidence bracket of 0.75 to 1.00, further corroborating the model's capability to discern and accurately identify hazardous objects within the recycling plant environments. The accompanying visual representations serve to elucidate the model's reliability and precision in real-world implementations, providing tangible evidence of

Figure 4: High confidence detection of recycle plant hazardous items

its practical applicability and efficacy in enhancing safety and operational efficiency within recycling facilities. Some of the results are shown in the Fig.4 and 5.

4.1 Detailed IoU Evaluation

Given the critical importance of accurate object detection in our use case, we further delved into Intersection over Union (IoU) evaluations. As a brief recap, IoU measures the overlap between the predicted bounding box and the actual ground truth box. An IoU value above 0.5 is typically considered indicative of satisfactory detection.

In our assessments, the IoU values consistently exceeded this threshold, affirming the model's capability to accurately delineate the contours of hazardous objects. A few results of IOU values are shown in the Fig.6. These IoU evaluations, juxtaposed with mAP and accuracy metrics, offer a comprehensive understanding of the model's prowess in hazardous object detection.

Figure 5: High confidence detection of recycle plant hazardous items

4.2 Accuracy, Precision, Recall, and F1 score for each object

The Table 1 summarizes the evaluation metrics including Accuracy, Precision, and F1 Score for each object category. These metrics were computed as part of the performance evaluation of the YOLOv4 model in detecting hazardous objects within recycling plant environments. Each row corresponds to a specific object category, while the columns represent the corresponding evaluation metrics. The values indicate the model's performance in terms of accurately identifying and classifying each object category during classification.

4.3 Discussion

The results achieved in this study underscore the transformative potential of leveraging deep learning techniques within specialized industrial contexts, particularly in the realm of recycling plant operations. The consistently high accuracy and precision rates obtained through our evaluation affirm the efficacy of the YOLOv4 model in accurately identifying and localizing hazardous objects within complex visual environments.

Notably, the model exhibited exceptional performance across various object categories, as evi-

Figure 6: This figure represents the detailed IoU evaluation for detected spray cans, showcasing the model's ability to accurately delineate the contours of this specific hazardous object. Each spray can in the image is associated with an IoU value, affirming the model's precision and reliability in real-world implementations

denced by the consistently high Intersection over Union (IoU) values. This indicates the model's robustness in effectively distinguishing and precisely delineating objects of interest, even amidst cluttered or visually challenging backgrounds.

Given the potential hazards associated with mishandling these items within recycling plant settings, the model's proficiency in swiftly and accurately identifying them represents a critical advancement in enhancing workplace safety and operational efficiency.

However, while the initial results are promising, it's imperative to acknowledge the inherent limitations and areas for improvement. Challenges such as detecting objects in adverse environmental conditions, including scenarios involving snow or low lighting, underscore the need for continued model refinement and adaptation. Addressing these challenges will require iterative testing and optimization, potentially involving the augmentation of training datasets to encompass a broader range of environmental conditions and object variations.

Moreover, as the YOLOv4 model transitions from controlled experimental settings to real-world deployment, ongoing fine-tuning and adaptation based on real-time feedback will be essential. This

Table 1: Evaluation Metrics

Object	Accuracy	Precision	F1 Score
Bicycle	0.75	0.80	0.82
Lead Battery	0.81	0.76	0.78
Spray Can	0.69	0.85	0.72
General Waste	0.88	0.82	0.85
Home Appliance	0.72	0.78	0.75
Fuel Tank	0.79	0.81	0.80
Gas Cylinder	0.84	0.79	0.81
Fire Extinguisher	0.76	0.83	0.79
Battery	0.77	0.84	0.80
Lithium-ion Battery	0.85	0.77	0.81
Lighter	0.71	0.75	0.73
Paint Can	0.78	0.79	0.78
Electric Bicycle	0.82	0.81	0.82
Medical Waste	0.73	0.76	0.74
Smoke Gunpowder	0.79	0.82	0.80

adaptive approach will ensure the model's sustained performance and reliability in dynamically evolving operational contexts, ultimately contributing to safer and more efficient recycling plant operations.

5 Conclusion

This research represents a significant step forward in harnessing the power of AI, particularly through the integration of a YOLOv4-based object detection system, within the context of recycling plant environments. The outcomes underscore the transformative potential of AI applications in industrial settings. The commendable detection rates and precision achieved by our model are indicative of its efficacy in identifying hazardous objects within recycling facilities. By providing early and accurate detection, the system has the potential to significantly reduce workplace accidents and mitigate risks associated with the handling of hazardous materials. Looking forward, the integration of AI-driven systems with robotic platforms and drones presents a compelling opportunity to further enhance safety and efficiency in recycling operations. These technologies can work synergistically to automate repetitive tasks, optimize resource utilization, and proactively identify potential safety hazards in real time.

Moreover, as this research continues to refine and optimize the model, incorporating real-world feedback and iterative improvements will be essential. This iterative approach ensures that AI-driven solutions remain adaptive and responsive to evolving industrial environments and operational requirements.

Furthermore, ongoing collaboration between researchers, industry stakeholders, and technology providers will be critical in driving the adoption and deployment of AI-driven solutions in industrial settings. By fostering a culture of innovation and knowledge exchange, we can accelerate the development and implementation of cutting-edge technologies that deliver tangible benefits to society.

6 Future Implementation and Challenges

The envisioned implementation of the YOLOv4 system is multifaceted. First, the system will be integrated with a robotic setup situated on a belt conveyor. This robotic system, once equipped with our detection mechanism, will efficiently monitor, detect, and sort hazardous items, ensuring the removal of unwanted objects directly from the conveyor belt.

Secondly, a more ambitious implementation involves the deployment of a mobile drone robot. This drone, enabled by our object detection system, will not just identify but also collect hazardous items from different sections of the recycling plant. Its mobility and airborne capability make it especially suited for vast areas and hard-to-reach locations, ensuring that no segment of the plant remains unchecked. This approach is aimed at amplifying the efficiency of the recycling process and further reducing human intervention, thus minimizing the potential risks associated with manual handling of hazardous items.

While the physical deployment of these systems remains a part of future projects, we've preemptively addressed several challenges in the current research phase. One significant challenge foreseen is the system's adaptability to fluctuating environmental conditions. Initial tests suggest that snowy conditions could be problematic for detection, especially when snow surrounds objects. To bolster the model's performance in such scenarios, we've initiated additional training to allow it to recognize objects amidst environmental obstructions, like snow.

Additionally, in our pursuit of model robustness, we've trained it with images containing multiple objects, enabling it to differentiate various items more effectively and significantly reduce the chances of misidentification.

Challenges to Implement Complete Automation:

1. Snowy Conditions: In locations like Sapporo, Japan, which experiences heavy snowfall, objects can be partially or fully covered by snow. This can affect the model's ability to detect and identify these objects accurately. To address this challenge, we are actively working on enhancing our model's capability to recognize objects in snowy conditions. This involves collecting more data specifically in winter scenarios and refining our training process to improve performance under these conditions.

2. High-Speed Winds: Additionally, high-speed winds in outdoor recycling environments can present challenges for both robotic systems and drones. Strong winds can affect the stability and maneuverability of drones, potentially leading to difficulties in maintaining a consistent flight path. For ground-based robotic systems, navigating through windy conditions can be challenging, especially when transporting fragile or lightweight objects. Mitigating the impact of high-speed winds on the performance and safety of these systems is a crucial consideration in our future implementations.

Adaptability to Changing Environmental Conditions:

The adaptability of our system to changing environmental conditions is indeed a critical aspect of our research. Recycling plant environments are dynamic, and factors like weather, lighting, and object positioning can vary significantly. To address these challenges:

1. Real-time Adaptation: We are developing algorithms and control systems that enable our robotic and drone-based solutions to adapt in real time to changing conditions. This includes dynamic path planning for drones to account for wind conditions and the ability of ground-based robots to adjust their movements based on environmental factors.

2. Sensor Fusion: Sensor fusion techniques, combining data from cameras, LiDAR, and other sensors, are being utilized to provide a more comprehensive understanding of the environment. This multi-modal data fusion helps our systems make informed decisions even in adverse conditions.

3. Machine Learning Models: Continual model refinement, as well as machine learning techniques, are employed to improve the adaptability of our object detection system. Our models are trained on diverse datasets to ensure they can handle a wide range of scenarios.

In the next phase, as we look forward to integrating the system with the recycling plant's existing infrastructure, seamless interfacing between the AI model, robotic systems, and the drone robot will be pivotal. This will guarantee real-time reactions, efficient sorting, and optimal object removal, thereby redefining the recycling process's safety and efficiency.

Authors' Information

– **Allah Rakhio** holds a Ph.D. in mechanical engineering from the Nagoya Institute of Technology, Japan. Currently, he is postdoc researcher at Golo Corporation Japan.

Authors' Contributions

– **Allah Rakhio** is the sole author.

Competing Interests

The authors declare that they have no competing interests.

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Availability of Data and Material

The author declares that the data supporting the findings of this study are available within the article and also in its supplementary information files. Further, if there is any specific data required that will be provided by the corresponding author upon reasonable request. The details and code used to train the model are available on https://github.com/techzizou

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