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AI-Enhanced Detection of Hazardous Materials in Metal Scrap for Safer Industrial Operations

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Abstract: Well-regulated safety is indispensable in scrap-based liquid alloy manufacturing specifically in settings that employ induction furnaces within, in the realm of the metal based scrap industry unit that drives eco-efficient engineering by converting waste into valuable resources strengthening the repurposing of scrap into steel bars reduces dependence on naturally sourced materials enhances resource-efficient energy use and mitigates environmental disruption however the presence of hazardous items such as gas cylinders and pressurized canisters poses significant risks in high-temperature recycling operations To address these challenges we present an automated approach to hazardous substance detection using advanced computer vision techniques our enhanced modern system leverages a custom dataset developed using client-provided and web-sourced images of metal scrap annotated with smart polygon shapes to capture object contours accurately ,where single-shot detector model which is YOLO(You Look Only Once) versions such as yolov9 ,yolov8 and its variants were used and evaluated through extensive data preprocessing and augmentation strategies , yolov9 was selected for deployment due to its superior performance the model achieved a mAP(mean average precision) of 0.86 on test data enabling precise detection and classification of hazardous materials within industrial settings Our solution serves as a safeguard for operational safety, preventing catastrophic events such as chemical reactions, explosions, and toxic emissions that could endanger human lives and disrupt production, as safety becomes important when scraps are melted, as during this process presence of closed substances can cause tremendous effects to environment and workers. Deployed via Streamlit(open-source Python framework), the model provides real-time monitoring of live video feeds, enhancing safety measures and operational efficiency in scrap-based liquid steel production. This automated system not only mitigates risks but also ensures compliance with safety regulations, ultimately improving the integrity and sustainability of industrial processes.

Keywords: *Hazard Management, Scrap-Based Liquid Steel Production, Yolov8(You Only Look Once), Computer Vision, Object Detection, Safety, Induction Furnace.*

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I. INTRODUCTION

To keep induction furnaces used in the production of steel manufacturing environment with safer and effective usage ,it is essential to detect dangerous materials in metal trash items classified as closed containers such as fire extinguishers ,canisters, and shock absorbers ,which can cause significant harm if left in place ,these things can result in dangerous working conditions expensive repairs and furnace malfunctions. Early detection minimizes operating downtime ,safeguards equipment and saves accidents [8], it is a vital step in guaranteeing security and reducing monetary losses in the sector AI provides a dependable way to find dangerous materials in intricate settings it is perfect for this application because of its real-time picture analysis capabilities and high accuracy object identification. AI efficiently manages massive amounts of data and minimizes human error although previous studies have demonstrated the promise of AI in object detection this work particularly uses it to identify hazards in the processing of metal trash The problem lies in identifying hazardous items hidden in mixed piles[10] of metal scrap. Manual checks are prone to error and inefficiency. This paper introduces an AI-based system that detects objects like shock absorbers and canisters during crane operations and in storage. By automating this task, the system enhances safety and operational efficiency.

In a bid to enhance safety in steel-producing processes this study deals with the critical issue of identification of harmful substances in metal scrap these drums are very dangerous when smelted at elevated temperatures in blast furnaces these closed drums pose serious challenges once smelted in blast furnaces at elevated temperatures we give a systematic approach with the aid of state-of-the-art object identification techniques in order to counter this issue our research focuses on improved hazard identification and promoting safer and more effective recycling processes in metal scrap industry utilizing Cross Industry Standard

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Process For Machine Learning with Quality Assurance approach (CRISP-ML(Q)) Fig.1 which gives solid backup for managing machine learning project life cycle with emphasis on quality assurance.

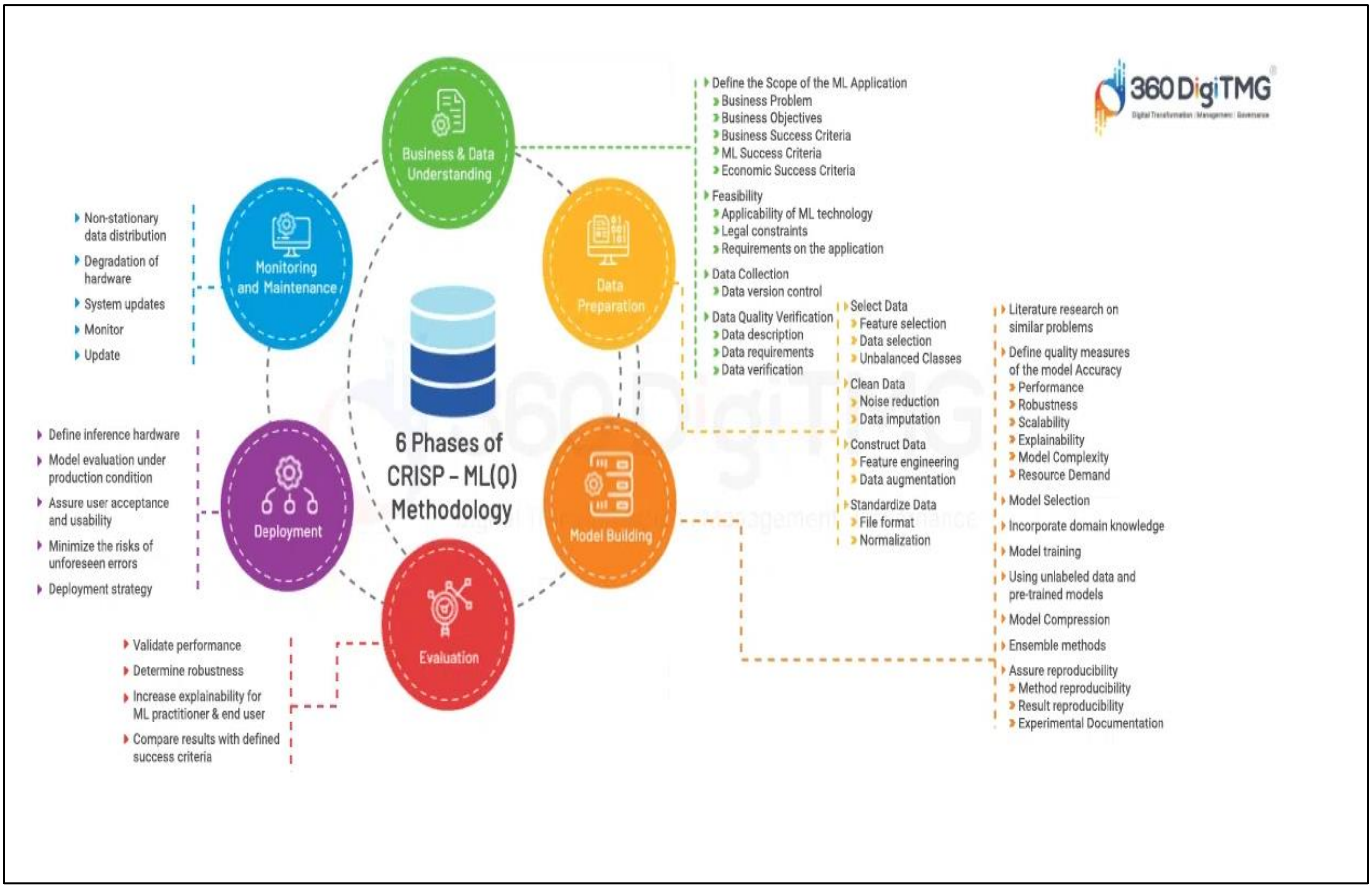

Fig.1 CRISP-ML (Q) Methodological Framework and its procedural steps Source: - Mind Map 360DigiTMG

Images of metal scrap piles are included in the collection emphasizing potentially dangerous items like fire extinguishers and cylinders images guarantee the resilience of the model by capturing a range of lighting conditions and angles because polygon annotations[3] accurately delineate item borders the dataset can be used to train artificial intelligence detection methods YOLOv8[5] and YOLOv9 [4][6]models were used for training on the dataset for this project, Whereby achieving accuracies of 89.5% and 92%, respectively. YOLOv9 showed better precision and recall, with a mean Average Precision(mAP) of 0.91 compared to YOLOv8's 0.87. Both models demonstrated effectiveness in detecting hazardous substances.

II. METHODS AND TECHNOLOGY

➢ *System Requirements:*

The following information comprise the hardware and software specs needed to implement the AI-based object detection solution the necessary infrastructure to guarantee peak performance for deployment and training the Table.1 below outlines the projects needs.

Table.1 Shows Infrastructure configuration (Hardware, and Software Configurations.)

Component	**Specification**
Operating System	Ubuntu 20.04 or Windows 10
Processor	Intel Xeon Family
Clock Speed (GHz)	2.5
CPU Architecture	x86_64
vCPUs	8
Memory (GiB)	32.0
Memory per vCPU (GiB)	4.0
GPU	NVIDIA T4 Tensor Core
Video Memory (GiB)	16
GPU Compute Capability	7.5
Storage	SSD with at least 1 TB
Frameworks and Tools	PyTorch 2.0, YOLOv8, YOLOv9, OpenCV, Roboflow
Software Dependencies	Python 3.9, CUDA Toolkit 11.8, cuDNN, TensorRT

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➢ *Model Architecture:*

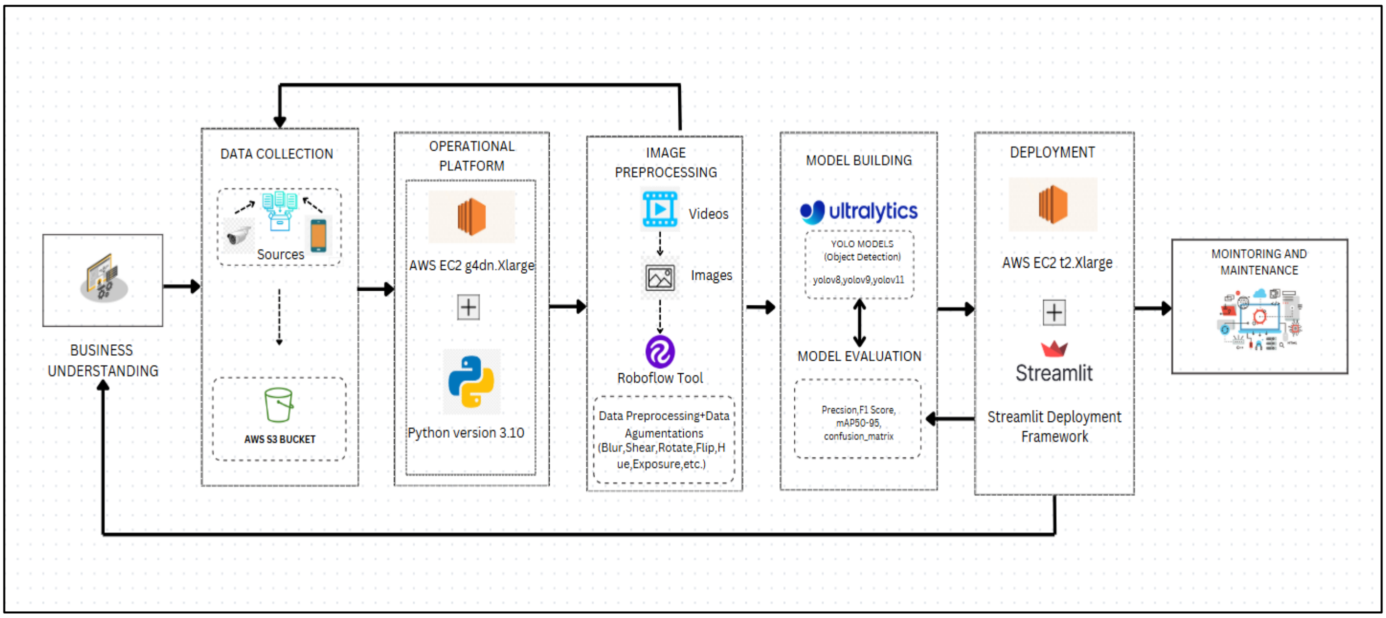

Fig 2 Model Architecture for Identifying the hazardous closed vessel substance in metal scrape.

The model architecture is meticulously designed following the CRISP-ML(Q) Cross Industry Standard Process for Machine Learning with Quality Assurance [1] methodology, ensuring a systematic approach to solving the business challenge. The pipeline begins with understanding the problem and gathering relevant data from various sources. It proceeds through preprocessing and augmenting the data, followed by model building and evaluation using advanced YOLO[4],[5],[6][7] models. Deployment is handled via the Streamlit framework on AWS, providing a scalable and efficient solution. Each stage of the architecture is carefully crafted to achieve optimal performance, and the subsequent sections delve into these components in detail.

Detecting hazardous closed containers within metal scrap is essential to safeguard the operation and longevity of induction furnaces[2]. Containers like compressors, canisters, shock absorbers, fire extinguishers, cylinders, and air tanks, etc. are particularly dangerous due to their sealed nature, which makes them prone to explosions. To train the model effectively, a comprehensive dataset [Table 2],[Table 3] was created by combining high-resolution images captured at the client site with supplementary images from open sources. This approach provides the model with a wide variety of hazardous object shapes, ensuring it can generalize and detect such containers accurately in diverse scenarios.

The data collection process began with recording videos at the client's location, leveraging a fixed camera position to capture consistent footage. Frames were extracted from these videos and complemented by additional images sourced from smartphones and open repositories to enrich the dataset. Each image was meticulously annotated with polygon-based labels[3], accurately delineating the boundaries of hazardous objects. This diverse and precisely labeled dataset ensures the model learns to recognize these objects even in cluttered or complex scenes, mimicking real-world conditions.

After data collection and annotation[3], the dataset was divided into training, validation, and testing sets to support effective model training and evaluation. The training set accounted for the majority of the data to provide the model with ample examples to learn from. Validation and testing sets were reserved to evaluate the model's ability to detect hazardous objects in challenging conditions, such as when objects are partially obscured or overlapping with other materials. This systematic division ensured a balanced and reliable approach to training.

The evaluation phase involved rigorous testing of YOLOv8, YOLOv9,models using key performance metrics such as precision, F1 score, mean Average Precision (mAP50-95)), and confusion matrices. Multiple experiments were conducted to fine-tune the models, testing their ability to detect hazardous items under varying conditions. After comprehensive analysis, the best-performing model was selected based on its accuracy, robustness, and reliability. This model now serves as the foundation for detecting hazardous substances in metal scrap, enabling precise and timely identification.

This pipeline integrates advanced object detection techniques with a robust dataset and evaluation strategy, ensuring a practical and reliable solution to the critical problem of hazardous material detection in industrial environments.

- *Problem Overview and Objective:*

There are several working difficulties in transforming metal waste into steel rods like while melting or re-melting metals a highly critical factor of doing so induction furnaces[2] generate huge amounts of toxic gaseous wastes and create loud noises once they get in touch with sealed or pressurized vessels of any kind other than posing grave risks to employees health and the environment these conditions

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slowly lessen the furnaces lifespan as exposure to such extreme heat for extended periods results in structural loss inefficiencies as well as higher maintenance costs there is a need to ensure that all hazardous materials have been evacuated from the scrap prior to treatment

- *Gathering and Comprehending Data:*

Collecting data in a polluted and dusty environment such as a metal recycling plant is inherently challenging the cameras used for capturing videos often lack clarity further complicating the task of obtaining high-quality images additionally the irregular shapes of scrap metals make identifying specific hazardous components like shock absorbers and cylinders [Fig.3] difficult ,some components are rare and infrequent adding to the difficulty in maintaining class balance within the dataset furthermore accurately annotating and labeling the data requires significant effort as the irregular and overlapping shapes increase the complexity of the task.

Fig.3 Sample Dataset of closed vessels in metal scrape storage unit

Table 2 Shows Complex Challenging Scenarios of collecting the dataset from dusty and more spacious storage unit.

Challenges in Data Collection	Description
Camera Quality	Limited resolution and clarity hinder the extraction of detailed images.
Environment	Dust and pollution obscure image quality and visibility.
Irregular Shapes of Scrap Metals	Inconsistent and overlapping shapes complicated hazardous substance identification.
Rare Components	Substances like compressors and air tanks are infrequent, creating data imbalance.
Annotation and Labeling Complexity	The variability and overlap of shapes make precise annotations time-consuming and challenging.

- *Dataset Overview*

The dataset collected for this study comprises images extracted from videos and mobile devices, focusing on hazardous objects within metal scrap piles[Table 3]. The details are outlined below:

Table 3 Shows the distribution of data collected from plant location

Category	Details
Total Images	2,000
Video Sources	4 videos, each 20 minutes long, captured at the client location
Camera Height	Fixed at 15 feet
Video Resolution	CCTV: 4px; Mobile: 16px
Annotation Type	Polygon annotations for precise object boundaries
Hazardous Object Types	Shock absorbers, canisters, cylinders, fire extinguishers, and other closed containers as defined by the client
Lighting Conditions	Varying (daylight and artificial light)

This project is trained on a high-performance system equipped with an Intel Xeon processor and NVIDIA T4 Tensor Core GPU [Table 1] , to meet the computational demands of training YOLOv8 and YOLOv9 models where Ultralytics is prominent enough to train on a CPU we used GPU powered computation for ease of training and reduce training time. With 8 vCPUs, 32 GB of memory, and 16 GB of video memory, the system ensures efficient processing for real-time object detection.

The dataset includes 2,000 images, extracted from 4 videos (each 20 minutes long) captured at the client site,

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along with additional images from smartphones. The CCTV videos had a resolution of 4px, while the mobile images were of higher quality at 16px resolution. The camera's fixed position at a height of 15 feet introduced slight challenges in clarity, but polygon annotations helped ensure precise labeling. The dataset focuses on detecting closed containers—such as shock absorbers, canisters, and fire extinguishers—that pose potential safety risks due to their sealed nature. Data was split into training, validation and testing [Fig.4] sets for effective model evaluation.

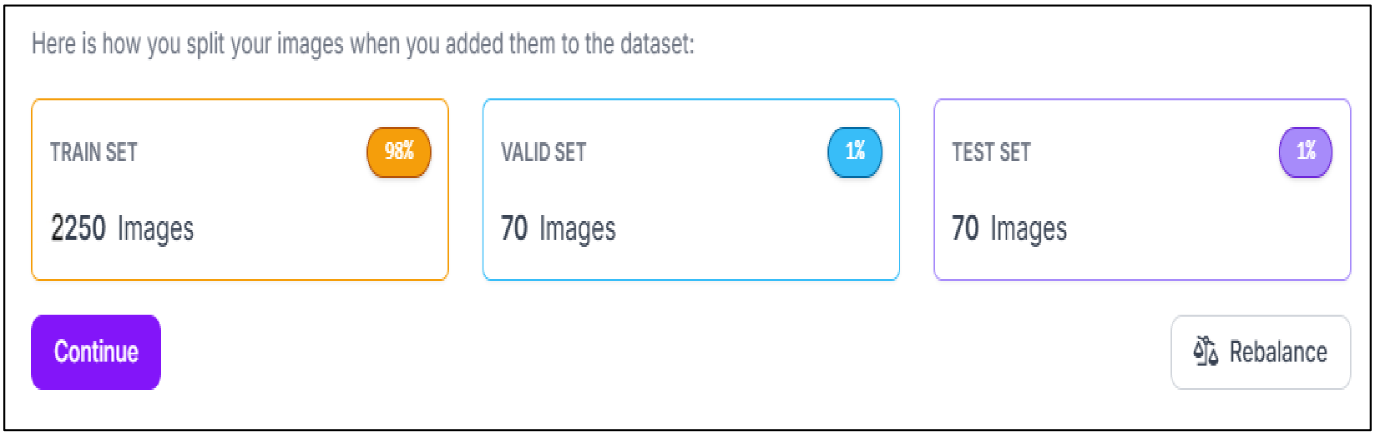

Fig 4: Shows the balance of dataset used for training

- Source: Roboflow Annotation Tool With the aid of this robust dataset and state-of-the-art technology, the issue of identifying hazardous substances in metal waste can be resolved.

- *Data Preprocessing.*

The preprocessing stage involved extracting frames from four videos captured at the client's site. The manufacturing plant features multiple storage areas of varied heights and widths, leading to frequent occlusions [10] and inconsistent image clarity. The preprocessed dataset consisted of 2,000+ images, many of which contained multiple instances of hazardous substances within a single frame, ranging from 20 to 25 instances per image. Due to the limited number of original images, data augmentation techniques were applied to enrich the dataset, ensuring a balanced distribution across classes.

The target variables include canisters, cylinders, compressors, air tanks, fire extinguishers, oxygen cylinders, and shock absorbers. Initially, different classes were created for variations in components like shock aborbers, gas cylinders were of more varieties hence took each substance into single class. However, this approach led to severe class imbalance[3] , prompting a shift to a simpler strategy with only five primary classes: canister, cylinder, fire extinguisher, compressor, and shock absorber. Components with significantly small proportions, like air tanks and oxygen cylinders, were excluded. To address occlusion[10] issues, the model focused on detecting hazardous substances with clear visibility and texture, ignoring items buried beneath other materials.

- *Augmentation Techniques*

Roboflow Tool [3], which is easier to annotate and has a better user interface, is used for this project.

➢ *Data Annotation with Roboflow:*

- Blur: Softens pixel transitions to lessen image sharpness. It helps the model generalize better by simulating real-world situations with low clarity for this project. An image is distorted along the X or Y axis by shear. which mimics the different viewpoints and angles of potentially dangerous objects.
- Rotate: Makes the picture rotate by a certain amount. guarantees that the model picks up object detection regardless of orientation.
- Flip: Flips the image either vertically or horizontally. increases the dataset's diversity by taking into consideration objects' varying orientations.
- Grayscale: Transforms the picture into various grayscale tones. eliminates color dependencies so that the model can concentrate on texture and shape.
- Brightness: Modifies the image's degree of brightness. aids in the model's ability to adjust to changing ambient lighting.
- Random fluctuations are added to pixel values by noise. enhances model resilience by simulating image distortions brought on by dust or camera artifacts.

➢ *Data Dimensions and Class Distribution*

- Image Formats: JPEG, JPG, PNG
- Number of Classes: 5 (canister, cylinder, fire extinguisher, compressor, shock absorber)
- Total Original Images: 700
- Augmented Images: Approximately 2,000 per class
- Instances Per Image: 20 to 25

These preprocessing steps, coupled with augmentation, created a robust and well-balanced dataset capable of effectively training the model to detect hazardous substances under challenging conditions.

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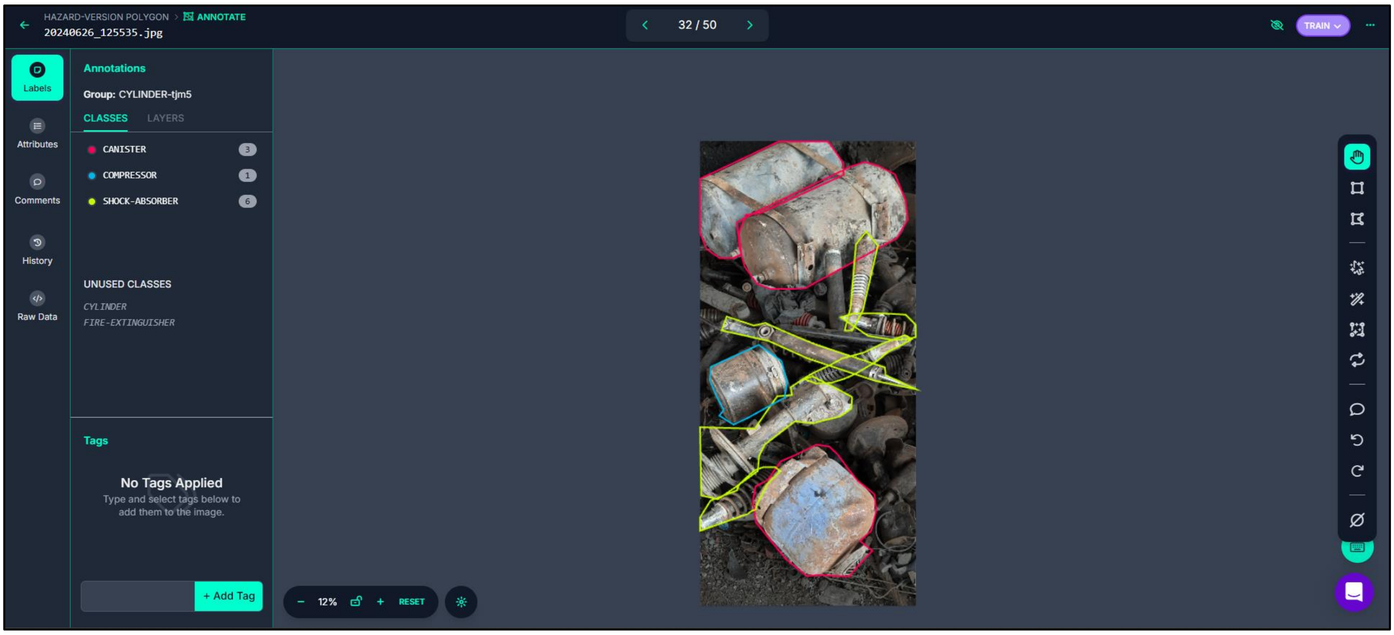

Fig 5 Shows the Annotation Applied on Canister, Compressor and Shock Absorber

In this project, Roboflow [3] was employed for image annotation as part of a comprehensive hazardous substance detection system. The tool was chosen for its advanced computer vision capabilities, making it highly suitable for detecting and localizing hazardous materials. Instead of using bounding boxes, polygon annotations were utilized to achieve more precise and detailed labeling of hazardous substances. Roboflow offered both manual polygon annotation and a smart polygon feature. The smart polygon tool was particularly beneficial, as it accurately captured the exact shape of substances, significantly reducing the annotation workload and improving efficiency.

Additionally, the platform provided a user-friendly zoom-in and zoom-out functionality, which was invaluable for enhancing the clarity of annotations, especially for substances with intricate details. To ensure accuracy and consistency, detailed annotation guidelines were implemented. These guidelines outlined clear instructions for annotating hazardous substances across various scenarios, ensuring standardized and high-quality annotations throughout the dataset. This meticulous approach contributed to building a reliable and efficient detection system.

- *Model Building:*

YOLOv9[4][6] being one of the extremely intricate object detection models has been used in this work because it includes an independent gelan-based structure the modularity in gelan allows it to draw more features and thus is ideal to parse dangerous content having overlapping shapes in various forms it can carry out advanced real-time scenarios with unparalleled accuracy performance efficacy and quicker inference without conceding precision.

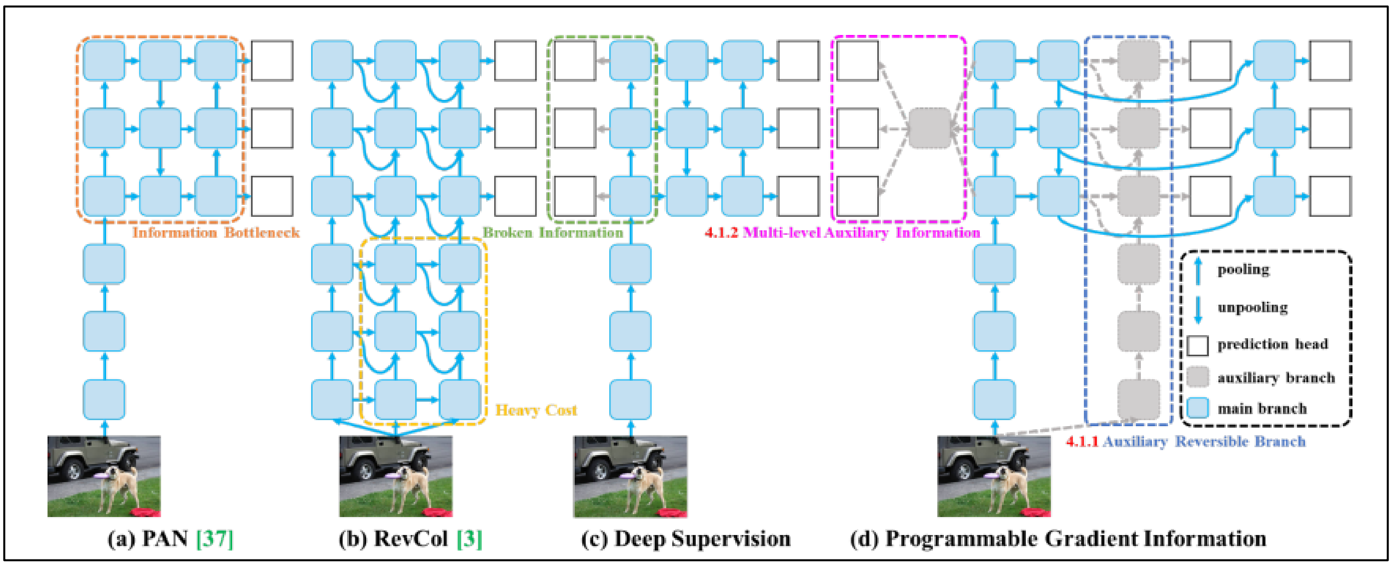

Fig.6 Comparison of network designs showcasing (a) PAN, (b) RevCol, (c) Deep Supervision, and (d) Programmable Gradient Information with Auxiliary Reversible Branches. This highlights the modular and efficient design evolution of YOLOv9 for enhanced feature aggregation and optimization.

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- Source: (YOLOv9 Learning What You Want to Learn Using Programmable Gradient Information) https://arxiv.org/abs/2402.13616

Variants of YOLOv9, such as YOLOv9c and YOLOv9e, were employed to optimize detection for this specific use case. These variants facilitated fine-tuning of critical parameters, including anchor boxes, input size, and confidence thresholds, addressing challenges like occluded objects[10] and the variability of hazardous material shapes.

The YOLOv9 architecture integrates a backbone for feature extraction with detection heads designed to predict bounding boxes, confidence scores, and classifications efficiently. Additionally, its hierarchical feature aggregation mechanism enables better information flow, improving detection performance under adverse conditions such as low clarity, overlapping materials, and challenging industrial environments. The GELAN backbone[Fig.6] , which dynamically adjusts feature granularity**,** plays a pivotal role in handling diverse object sizes and shapes.

To address the issue of data imbalance[11] and rare hazardous component detection, augmentation techniques [3] such as rotation, flipping, scaling, and brightness adjustments were applied to diversify the dataset. These preprocessing strategies enhanced the model's ability to generalize across a variety of real-world scenarios. The resulting model effectively detected components like shock absorbers, compressors, and sealed cylinders, ensuring high accuracy even under constrained conditions.

The project dataset consisted of 700 original images which were extracted into frames from video footage recorded at the client's metal recycling facility. These frames captured hazardous items, such as canisters, cylinders, compressors, fire extinguishers, and shock absorbers, in diverse industrial conditions which in turn is diversified with Roboflow[3] to maximize the data by 2000 images . The GELAN-enhanced YOLOv9 [7],[4] model demonstrated robustness by accurately detecting such materials in real-time, ensuring compliance with industrial safety standards.

To further enhance reliability**,** programmable gradient information was utilized during training, optimizing the model's adaptability to challenging detection environments. This novel technique, a cornerstone of the YOLOv9 framework, allows greater control over feature prioritization and ensures optimal learning rates for diverse detection tasks.

Validation and testing confirmed the model's reliability, with YOLOv9 [6] and its variants achieving superior performance compared to traditional methods. The model's modular yet unified structure streamlines the hazardous material detection process, reducing risks associated with processing unsafe scrap and ensuring operational safety in industrial facilities.

By exclusively leveraging YOLOv9 and its advanced features, this project achieves a robust, efficient, and scalable solution for real-time hazardous material detection. The model not only streamlines identification processes but also enhances safety and productivity in the client's operations.

- *Model Evaluation*

Comparative Analysis of YOLOv8 Variants and Hyperparameters To enhance system performance, YOLO model variants yolov8 and yolov9 variants[6] were trained and rigorously evaluated against critical performance metrics such as training loss, precision, recall, and mean Average Precision (mAP). These models underwent multiple iterations to ensure stability, consistency, and improvements in detection accuracy. To overcome challenges such as data imbalance and rare component detection, the dataset was enriched through advanced augmentation techniques, including flipping, rotation, and brightness adjustments, ensuring a more diverse and representative training set.

Across experiments, the YOLOv8 [5] ,[6]models were trained for 30 epochs with balanced datasets, yielding consistent and stable detection outcomes. While YOLOv8 proved highly efficient in terms of speed and inference time, it exhibited a limitation—multiple bounding boxes were often assigned to the same object, resulting in redundant detections. This issue was effectively addressed in the YOLOv9 model, which demonstrated superior bounding box precision and reduced false positives.

A comparative analysis revealed that the YOLOv9e[Table 4] variant, as shown in [Fig. 7], achieved an optimal balance between detection accuracy and speed. It consistently delivered higher mAP (mean Average Precision) scores while maintaining low inference times, making it a standout choice for applications requiring both real-time processing and high detection accuracy. On the other hand, although YOLOv8 outperformed in terms of processing speed, its lower precision and recall metrics rendered it less suitable for scenarios demanding exceptional accuracy.

The evaluation highlights the significant advancements in YOLOv9e, which not only resolved the challenges observed in YOLOv8 but also provided a robust and reliable framework for detecting complex and overlapping objects in challenging environments. This makes YOLOv9e a highly effective solution for real-world detection tasks requiring precision and efficiency.

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Table 4: Shows the Models used and its Performance with 30 Epochs (Small Dataset)

Models	Layers	Epochs Size	Map(50-95)
YOLOv8n	225	30	79%
YOLOv8s	225	30	82%
YOLOv8m	295	30	81%
YOLOv9c	618	30	80%
YOLOv9e	1,225	30	86%

We were able to achieve a better accuracy of 86% on the potential hazardous subtances which is displayed above.

III. RESULTS AND DISCUSSION

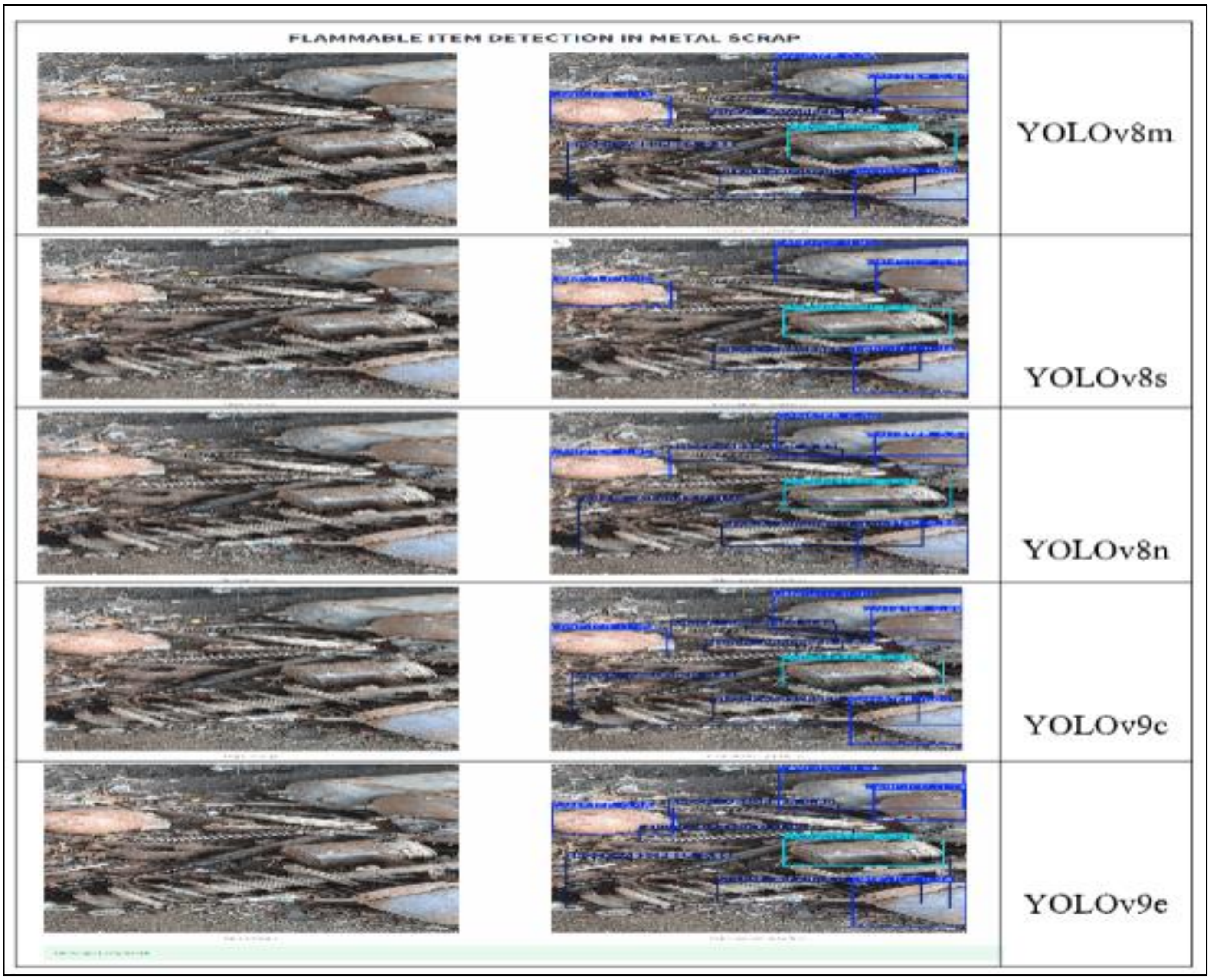

Fig 7 UI Interface to Detect Hazardous Substance in Metal Scrape.

After identifying the most accurate model, a user-friendly interface (UI) was developed to facilitate seamless detection of hazardous substances. This interface allows users to upload images captured directly from the storage unit, enabling the system to automatically identify items such as fire extinguishers, canisters, cylinders, and other closed vessels that could pose potential risks. The system operates without the need for manual intervention, streamlining the detection process and ensuring accurate results.

The UI is fully integrated with the trained detection model, providing real-time insights into hazardous material presence. Users simply upload an image, and the system processes it to identify, locate, and classify potential threats, displaying the results in an intuitive and easy-to-understand format. This automation not only accelerates the detection process but also enhances reliability by eliminating human error, even in challenging conditions such as dim lighting, object occlusion[10], or cluttered storage environments.

The automation of this detection system makes it scalable and highly effective for industrial applications. It can process large volumes of data and images, making it particularly suitable for environments with high operational throughput. By significantly reducing the time and effort required for manual inspections, this solution ensures faster decision-making, better compliance with safety protocols, and a safer operational environment for facilities managing metal scrap or other potentially hazardous materials.

This advanced detection framework combines cutting-edge object recognition with a user-focused design, enabling organizations to enhance safety standards, improve efficiency, and reduce risks associated with hazardous substance handling. It represents a transformative step toward fully automated safety[8] and operational monitoring in industrial settings.

IV. CONCLUSION

In conclusion, this study emphasizes the critical role of enhancing object detection accuracy for industrial safety applications. The research focused on automating the detection of hazardous materials in complex environments, addressing challenges such as overlapping objects, limited datasets, and achieving precision in real-time scenarios. Through systematic improvements, including optimized data splitting and the evaluation of advanced model architectures, significant progress was made in overcoming initial issues like overfitting and enhancing detection performance.

The YOLOv9e model emerged as the most effective solution, achieving an impressive accuracy of 86%. Its advanced architecture demonstrated superior performance in balancing detection precision and speed, making it well-suited for real-time industrial applications. Additionally, the integration of user-friendly platforms, such as those built using the Streamlit framework, enhanced the system's usability and accessibility, providing a seamless experience for end-users. This interface allows for the efficient processing of images and provides actionable insights, thereby streamlining safety protocols in environments like metal recycling and storage facilities.

This research not only advances the field of object detection but also underscores the importance of iterative optimization, robust data processing, and user-centric design. By addressing key challenges and leveraging the YOLOv9e framework, the project offers a scalable, accurate, and efficient solution for improving safety standards and operational workflows in industrial settings. These findings highlight the transformative potential of AI-powered systems in mitigating hazards and enhancing productivity across a variety of applications.

ACKNOWLEDGMENTS

We acknowledge that with the consent from 360DigiTMG, we have used the CRISP-ML(Q) which are available is open-source in the official website of 360DigiTMG methodology.

FUTURE SCOPE

To further enhance the system, several areas can be explored. The integration of alert mechanisms, such as sending real-time signals or notifications when cranes lift and transport metal scrap, can add a proactive layer of safety. employing digital signaling systems for immediate hazard detection and response can mitigate risks significantly. Moreover, training the model on a more diverse dataset that includes images captured from varied storage unit environments, lighting conditions, and angles will enhance detection accuracy.

optimizing detection performance may require using higher-resolution cameras and better camera placement and location camera placement that maximizes coverage and minimizes blind areas would improve overall storage facility observation these technologies have the ability to increase the accuracy of detections as well as broaden the systems use to other industrial safety scenarios By tackling current issues and integrating possible enhancements like growing training datasets with a variety of scenarios, our research lays a solid basis for creating AI-powered safety solutions designed for industrial settings. The system can be further improved by incorporating cutting-edge signaling systems for real-time hazard alerts and refining hardware configurations like camera positioning and resolution. These improvements will not only increase detection accuracy but also expand the system's application to a range of industrial safety contexts with further development. This approach has the potential to develop into a powerful, scalable, and extremely effective instrument for improving operational effectiveness and worker safety in a variety of industries.

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