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Addressing Environmental Sustainability: Detecting Waste Contamination with Cutting-Edge Technology

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Abstract:- Detecting and dealing with waste contamination is a big problem in things like managing the environment, getting rid of waste, and recycling. Right now, people have to check waste by hand, which takes a lot of time and can sometimes make mistakes. Our idea is to use computers to help with this. We've come up with a way to quickly and accurately find out if waste is contaminated or not, which can make managing waste much better.

Here's how it works: First, we clean up pictures of waste to make them clearer. Then, we use fancy computer programs to look at the waste and figure out if there's anything bad in it. These programs use special learning techniques to get good at spotting different kinds of contamination in the waste.

We tested our method to see how well it works. It turns out that it's pretty good at finding and dealing with waste contamination, no matter what the environment is like or what kind of waste we're dealing with.

By using this method, we can save a lot of time and effort because we don't need people to check waste by hand anymore. Plus, we can keep an eye on waste in real-time, so if there's any contamination, we can deal with it quickly.

In the end, our idea is a big step forward in managing waste better and protecting the environment.

Keywords:- *Waste Management, Biodegradable, Non-Biodegradable, Contamination, YOLO, Detectron, Roboflow*

I. INTRODUCTION

The waste issue is a major concern these days. Inadequate waste handling and inefficient sorting cause disposal issues and contamination. Every year, an estimated 11.2 billion tons of solid waste are collected worldwide. we are unable to properly manage our current waste collection because of a lack of effective sorting, resulting in mixed biodegradable and non-biodegradable waste, which is causing disposal issues and impacting environmental sustainability. Our main objective is to minimize contamination while maximizing the effective utilization of allocated waste management tools and materials.

In our research on waste contamination, our main aim is to make sure we sort waste properly. We want to separate it into two main types: material that can break down naturally and material that can't This includes things like consumable scraps paper and leaves, which can all rot away over time thanks to tiny living things like bacteria and fungi This rotting turns into compost, which is great for helping plants grow stuff that can't break down easily This includes things such as polymer bottles glass jars and metal cans They stick around for ages and don't disappear like the other stuff.

➤ *Why is Sorting Waste Like this Important?*

First off, it keeps our surroundings clean and safe. The stuff that can break down makes good food for plants and is made into new stuff, but if it is mixed up with other rubbish, it is left lying around. Second, sorting waste makes it easier to recycle things like plastic and glass, which can be melted down and made into new stuff, but if they are mixed up with other rubbish, it is much harder to do. Last but not least, sorting waste helps us use things wisely. When we recycle, we don't need to dig up as many new materials from the ground; this saves energy and helps protect the environment.

Our aim is to calculate the contamination percentage of an image. If it is less than 5%, that is okay, but if it is greater than 5%, that is what we declare contaminated waste.

To overcome this challenge, one viable solution is to automate the process using computer vision technology. Computer vision technology will extract the information from the images and videos for real-time projects such as classification and reorganizing. When it comes to classification, a model can be trained to identify and categorize an object or an object's physical characteristics in an image. The reliability of the dataset used for training determines the performance of a model when it encounters an image it hasn't seen before.

To manage this process effectively we employed CRISP-ML(Q) methodology [Fig.1]. This methodology provides a structured approach for machine learning projects. It ensures all the project related steps are followed right from business understanding to monitoring and maintenance. This enhances the reliability and effectiveness of a computer vision. This study follows:

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➢ *Preparing the Data Set, Which Consists of Images of Waste Bins. We Made Two Classes*

- Top View Waste
- Contaminated Waste, For Annotation

➢ *The dataset had 7,000 Images before Augmentation.*

- As the next step, the gathered data will be uploaded to Roboflow, where it undergoes thorough preprocessing to ensure it's optimized for your machine learning tasks.
- Build multi-class classification models based on convolutional neural network (CNN) models such as YOLOv8, YOLOv5, R-CNN, Mask R-CNN Detectron2, and Segformer. These models calculate the contamination percentage over the image.
- Upon completion of model construction, the next essential phase involves evaluating the models using diverse metrics. This step is pivotal within the machine learning or deep neural learning workflow as it allows for the assessment of performance and identification of the most effective algorithm tailored to the task at hand.

II. METHOD AND METHODOLOGY

In this section, we'll outline the approach we're taking for our waste classification research. To provide a clear understanding, we'll utilize three diagrams that serve as guiding frameworks for our methodology. The first diagram, the Research Workflow Diagram.

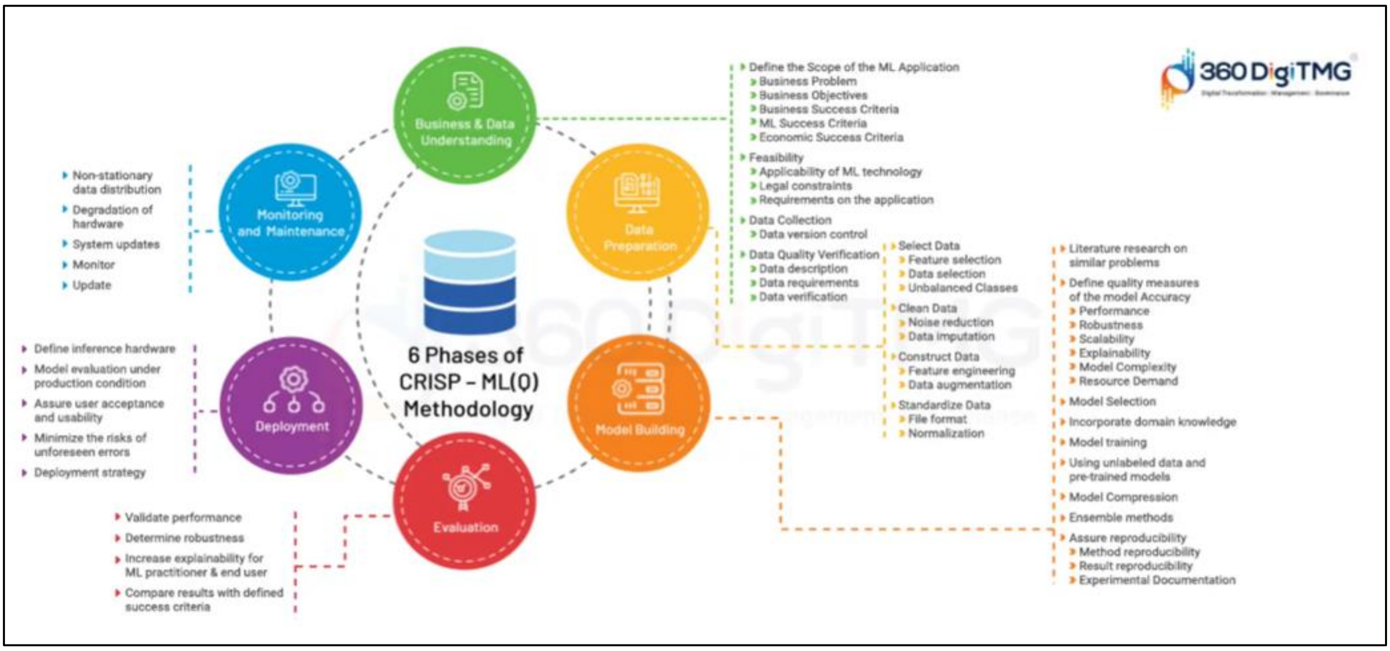

Fig.1: CRISP-ML(Q) Methodological Framework: A Visual Roadmap
(Source: Mind Map - 360DigiTMG)

[Fig.2], illustrates the sequential steps involved in our project, ranging from data collection to model deployment. This diagram serves as a roadmap, helping us stay organized and ensuring a structured approach throughout the project.

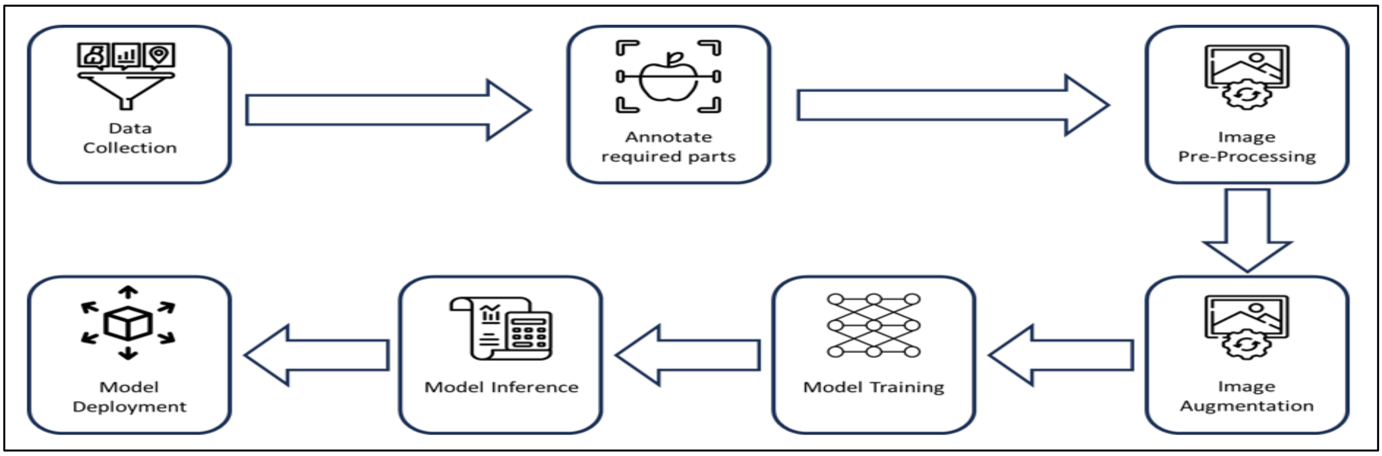

Fig 2: AI-Driven Waste Classification: A Guided Workflow

Following the Research Workflow Diagram, we'll present the Architecture Diagram [Fig.3], which offers a visual representation of the system components and their interactions within our project. This diagram helps us comprehend the underlying infrastructure supporting data processing, model development, and deployment. It provides insights into the hardware and software elements involved, aiding in understanding the technology stack utilized in our project.

Lastly, we'll introduce the ML Workflow Diagram [Fig.4], outlining the iterative process of machine learning model development tailored for waste classification. This diagram illustrates the steps involved in training our computer program to recognize different types of waste. It helps us understand the methodology behind teaching our model and improving its accuracy over time.

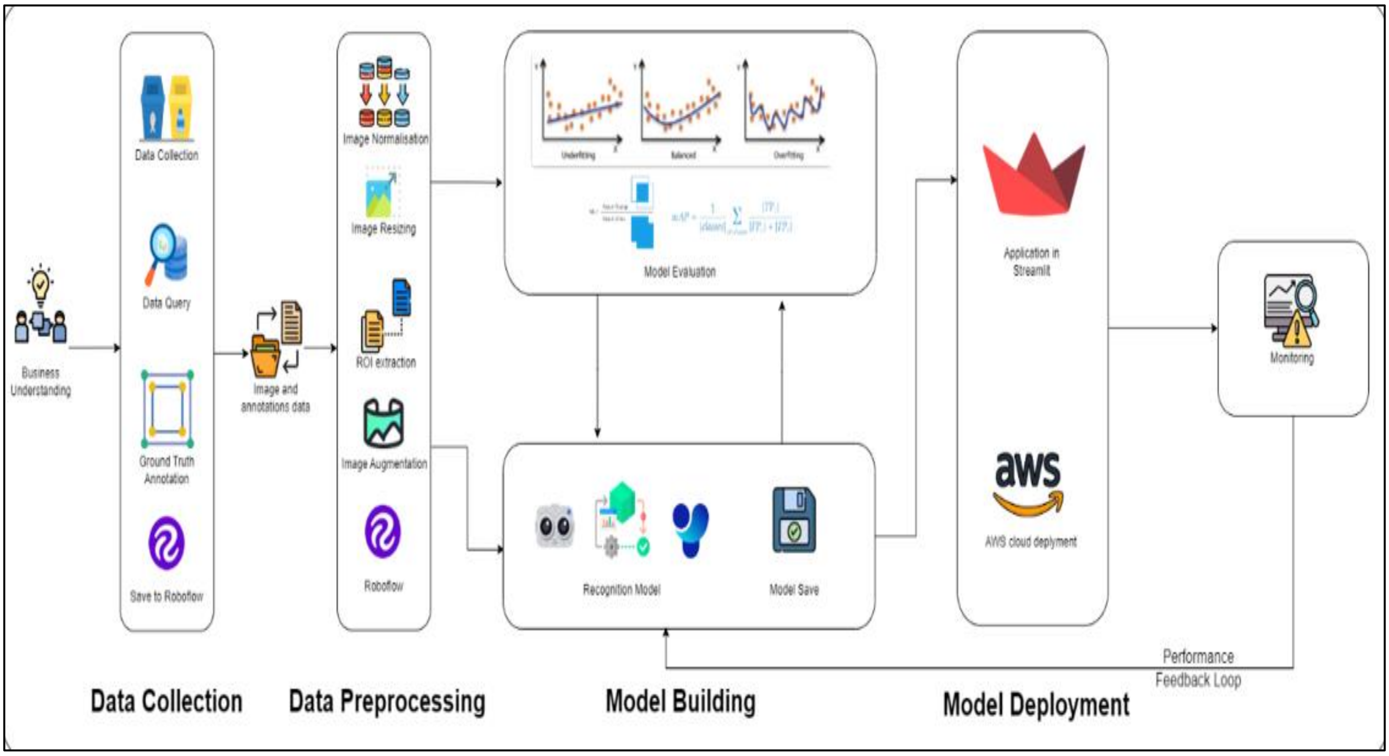

Fig 3: Constructing the Foundation: Architecture of the Waste Classification System

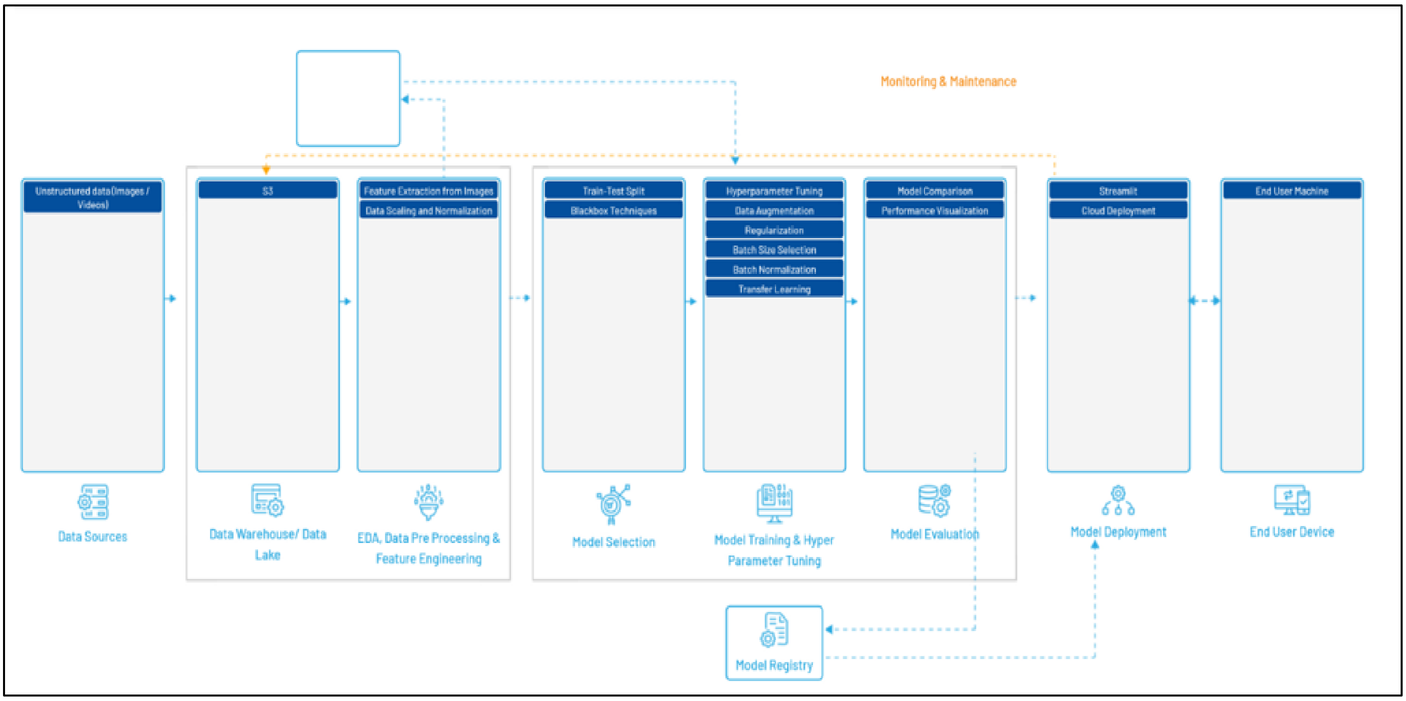

Fig 4: Machine Learning Workflow: From Data Processing to Model Refinement
(Source: ML workflow - 360DigiTMG)

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➢ *Data Understanding*

The data is collected by using a primary data source and a secondary data source. In the primary data source, the data is collected in an experimental setup. The waste bin images are collected from the society waste bins and municipal waste bins for the test sample. The waste bin picture is taken from three different smartphone back cameras, and the images are formatted in '.jpg' format. For every image, five to ten images were captured, varying the background, lighting, camera distance (depth), and side of the waste visible to the camera. The dataset was prepared based on the top view of the bin and on the physical attributes we considered two classes.

- *Biodegradable*
- Non-biodegradable wastes.

The total visible waste excluding bin is top view waste and any non-biodegradable material portion tagged as a contaminated waste portion. That is how we collected data physically.

The secondary data source, we collated data from web-portals. From the secondary data sources, the irrelevant data were removed manually to meet the relevant requirements. The total images collected from primary and secondary were 7200. All images we uploaded in the Roboflow for further processing. [Fig.5]

➢ *Data Preparation:*

Fig 5: Image Samples: A Glimpse into the Waste Classification Dataset

After collecting datasets from both primary and secondary sources, the data is seamlessly uploaded to Roboflow, a comprehensive platform designed to streamline the management of image and video datasets. Roboflow simplifies the process by allowing users to consolidate and organize their datasets efficiently in one centralized location, even when dealing with large volumes of images and lengthy videos.

Moreover, Roboflow offers robust annotation tools, such as bounding boxes and polygons, enabling users to label objects of interest within images effectively. These annotations are crucial for enhancing the performance of machine learning (ML) algorithms and deep neural learning models.

Additionally, Roboflow facilitates dataset annotation and augmentation, offering features like color manipulation, flipping, scaling, and rotation. These augmentation techniques are instrumental in improving ML and deep neural learning model performance by exposing them to a wider array of variables and scenarios.

Furthermore, Roboflow seamlessly integrates with popular frameworks like TensorFlow, PyTorch, and YOLO [6], allowing users to directly train and deploy custom computer vision models using their annotated datasets.

The uploaded image data into Roboflow underwent manual annotation by polygon annotation to identify specific regions / features. In this study we assigned two different labels to classify waste.

- Top view of the trash bin: the whole image, visible waste excluding waste bin.
- Non-biodegradable wastes: the non-biodegradable waste region in the whole image that is assigned to contaminated waste.

After annotation we created versions in Roboflow there is option to apply all the preprocessing steps and augmentation performed on one click.

➢ *Preprocessing Steps Used:*

- *Auto Orient:*

✓ Importance: Ensures consistent image orientation, reducing variability in the dataset.
✓ Significance: Prevents the model from learning spurious correlations based on image orientation, enhancing its adaptability to various datasets.

- *Resize:*

✓ Importance: Standardizes image dimensions for uniform processing.
✓ Significance: Facilitates model training and inference across diverse hardware and software environments by ensuring a consistent input size.

- *Auto Adjust Contrast:*

✓ Importance: Enhances image details through adaptive equalization.
✓ Significance: Maximizes information available to the model, improving its capability to discern subtle distinctions in the dataset.

- *Filter Null:*

✓ Importance: Ensures all images have annotations, preventing data inconsistencies.
✓ Significance: Maintains data integrity and prevents the model from learning from incomplete or inaccurate information, contributing to more reliable predictions.

➢ *Augmentation Steps Used:*

- *Flip (Horizontal):*

✓ Importance: Expands the dataset by creating mirror images.
✓ Significance: Introduces variations in object orientation, enhancing the model's ability to generalize to images with different spatial arrangements.[1]

- *90° Rotate:*

✓ Importance: Introduces rotational invariance, improving generalization.
✓ Significance: Helps the model become less sensitive to the specific orientation of objects, making it more adaptable to diverse real-world scenarios [1].

- *Grayscale:*

✓ Importance: Adds diversity by converting a portion of images to grayscale.
✓ Significance: Introduces variations in color representation, enhancing the model's ability to handle images with different color characteristics.

- *Brightness and Exposure:*

✓ Importance: Introduces controlled variations, enhancing model resilience to different lighting conditions.
✓ Significance: Prepares the model to handle images captured under varying levels of brightness and exposure, improving its performance in real world scenarios.[1]

- *Noise:*

✓ Importance: Simulates real world imperfections, improving model robustness to noisy environments.
✓ Significance: Helps the model learn to ignore irrelevant details and focus on essential features, making it more reliable in challenging conditions.

III. MODEL BUILDING

Our approach towards the problem statement is to first detect the image, segment them in defined classes. For that we have a bundle of deep learning algorithms. We decide to go with task specific models.in initial phase we tried many models to get desired accuracy. We tried best state oof the art YOLO series models, CNN based architecture, transformer-based architecture. Such as YOLOv5, YOLOv8, faster R-CNN, seg-former, detectron-2 architecture.

➢ *This Model has a Capacity to Give Good Accuracy as Per our Problem Statement.*

- YOLO: YOLO is a state-of-the-art architecture in computer vision tasks their amazing speed and accuracy. YOLO is a single stage detection method so it is faster than any other models. [1][6]
- Segformer: Segformer [5] is a deep learning framework by Facebook AI Research. This is specially designed for semantic segmentation and instance segmentation tasks. It is a transformer architecture.it is an encoder and decoder architecture. it takes input image pixels as tokens and embedded on to the high dimension vectors. the transformer core has multiple encoders, every encoder has a self-attention mechanism, which allows to model to capture global dependencies across the input. In short it captures the most important feature. Decoder takes intermediate features and up sample the features.
- Detectron 2: Detectron 2[Fig.6] is also developed by Facebook AI Research. It has a backbone of Resnet [2][3][4]and Resnext to extract input features from the image. After extracting features, it builds feature pyramid network (FPN) from the backbone. Once feature pyramid is built Region proposed networks (RPN) generates bounding boxes to show the objectness score to the proposals after that Region of interest polling performed. That is how Detectron 2 algorithm works. [2][3][4]

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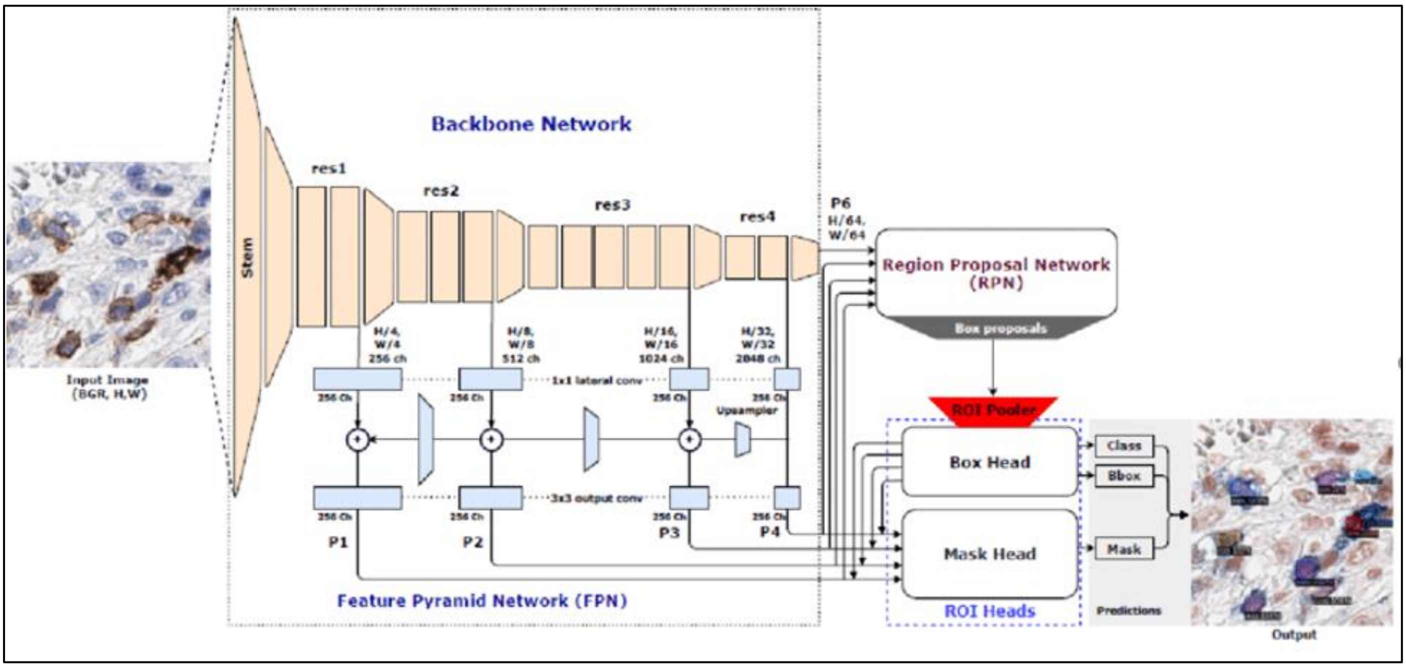

Fig 6: Architectural Insights: Exploring Detectron 2

➢ *Model Selection*

Our project focuses on waste contamination detection using four different deep learning architectures: YOLOv5[6], YOLOv8[1], Segformer [5], and Detectron 2[2][3][4]. Among these, Detectron 2, utilizing pretrained Mask R-CNN weights, stands out with a high accuracy map score of 92%. This score indicates superior performance in detecting and segmenting waste instances within images compared to the other architectures.

Choosing the Detectron 2 model, particularly with pretrained Mask R-CNN [1] weights, was likely a strategic decision based on its superior performance. The high accuracy map score of 92% suggests that the model is proficient in accurately detecting and segmenting waste instances within images. This level of precision is crucial for waste contamination detection tasks, where the reliable identification and segmentation of waste materials are paramount.

Additionally, leveraging pretrained weights allows the model to benefit from knowledge learned from a large dataset, resulting in improved performance on the specific task of waste contamination detection. Overall, the decision to use Detectron 2 aligns with the project's objective of achieving accurate and efficient waste contamination detection.

➢ *Model Evaluation:*

In model evaluation, we mainly focus on the mAP [1][6] score. To gain a deeper assessment of the model's performance, we turn two key parameters recall and precision, which reflects the percentage of bins flagged as contaminated that are truly dirty in essence, it assumes the model’s ability to minimize false alarms clean bins identified as contaminated recall evaluates how effectively the model captures all contaminated bins, ensuring it doesn't miss crucial cases contaminated bins identified as clean.

➢ *Mean Average Precision (Map):*

mAP is most used in object detection tasks, including waste contamination detection. It calculates the average precision across all classes, providing a consolidated measure of the model's detection accuracy. It provides the consolidated measure of accuracy of the model's detection.

Analyzing the patterns in false positives and false negatives throughout the assessment process yields important information about the effectiveness of the model. the efficacy in detecting waste contamination is increased by increases in its recall and accuracy as seen by a declining trend in both measures

➢ *Accuracy Matrix Table:*

Table 1: mAP Evaluation: Comparing Model Performance

MODELS	mAP (SCORE)
YOLOv8	87%
YOLOv5	82%
Detectron 2	92%
Seg former	89%

After conducting a comprehensive evaluation of various object detection models, including YOLOv8, YOLOv5, Detectron 2, and SegFormer, [Table 1] we observed varying mean Average Precision (mAP) scores for each model. YOLOv8 achieved an mAP of 87%, YOLOv5 attained 82%, Detectron 2 demonstrated a superior performance with an mAP of 92%, while SegFormer achieved an mAP of 89%. Upon thorough analysis, we determined that Detectron 2, particularly with its Mask R-CNN variant, exhibited the highest accuracy and robustness in identifying and classifying objects within the waste images[Fig.7]. Hence, based on these results, we concluded that Detectron 2 with Mask R-CNN is

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the most suitable model for our waste classification project. The hyperparameters of Detectron 2 are as follows:

➢ *Hyper Parameters*

In Detectron-2 used parameters are as below:

- ARCHITECTURE = "mask_R-CNN_R_101_FPN_3x"
- MAX_ITER = 9000
- EVAL_PERIOD = 200
- BASE_LR = 0.001
- NUM_CLASSES = 3

➢ *Model Deployment:*

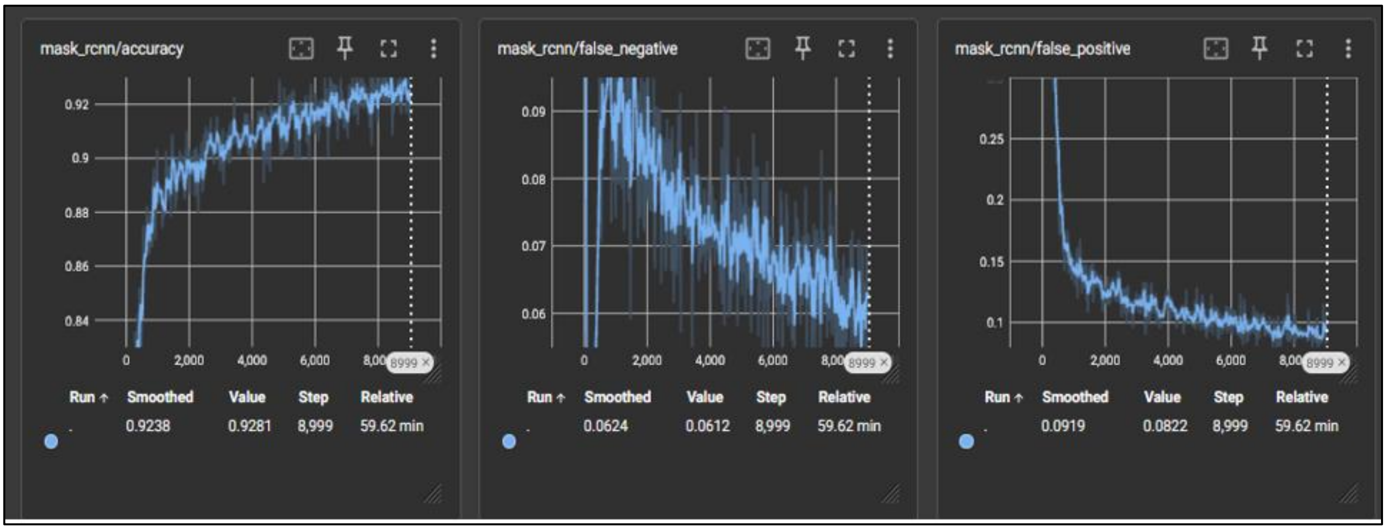

Fig 7: Detectron 2 (Mask R-CNN) Performance: Visual Results

Model deployment is an important phase in the machine learning lifecycle. In this step we deployed our model in the Streamlit. In this section, we discuss the deployment of the waste contamination detection model using Streamlit, a powerful framework for building interactive web applications. In the deployment we take the outputs such as accuracy, contamination percentage around the object as a bounding box it will show up.

➢ *Model Weights and Configuration:*

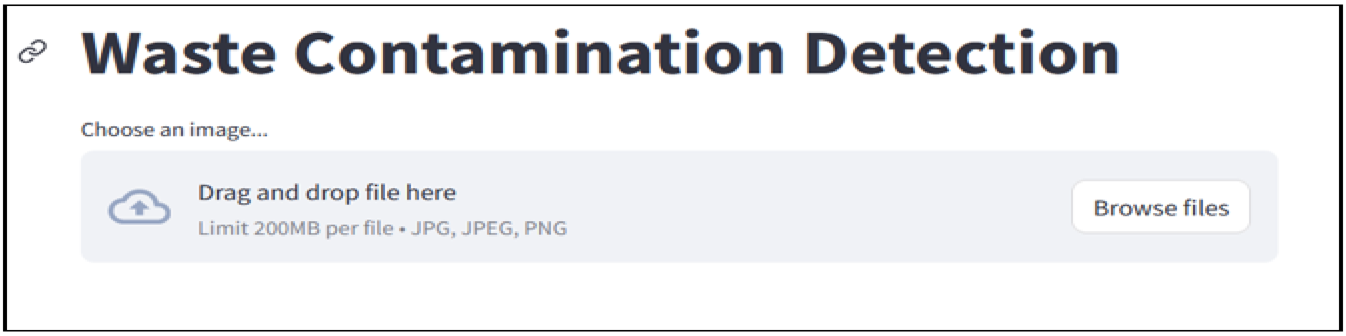

Fig 8: Home Page Interface: Streamlit Deployment

The paths to the saved model weights and configuration files play a crucial role in the deployment process. These files, are best.pt and config.yaml file located at the specified paths, contain the trained parameters and architecture configuration, respectively. They are essential for initializing the model during inference, ensuring that the deployed system maintains consistency with the trained instance.

➢ *Integration with Streamlit:*

Streamlit was selected as the deployment tool for its simplicity, flexibility, and interactive capabilities. Streamlit enables rapid development of data-driven web applications with Python, making it an ideal choice for showcasing model predictions and interacting with users in real-time. Its ease of use and for machine learning models. Real-time updates allow for agile development practices, fostering innovation and creativity. It supports hosting on various platforms, including Streamlit Share, Heroku, and AWS, ensuring easy access for users.

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➢ *Visualization and Interpretation:*

During inference, the deployed system generates visualizations of the detected waste contamination within the uploaded images. Additionally, metrics such as the total area of the bin and non-biodegradable (NBD) waste, along with the contamination percentage, are computed and displayed to provide valuable insights to stakeholders.

- **Visualization:** The input image and the corresponding detection results are displayed side by side, enabling users to visually assess the contamination status.
- **Contamination Metrics:** Key contamination metrics, including the total bin area, NBD area, and contamination percentage, are computed and presented to users. These metrics facilitate informed decision-making regarding waste management practices.

➢ *Class-Specific Information:*

Total Bin Area: 75778

Total NBD Area: 6725

Contaminated percentage: 8.874607405843385

Contaminated Bin

Class Explanations:

- Bin: Top view of the trash bin
- NBD: Non - biodegradable wastes

Fig 9: Quantifying Waste and Contamination: Area Calculation and Percentage Assessment

The system also provides class-specific explanations to aid use rs in understanding the detected objects and their significance in waste contamination detection. These explanations offer insights into the nature of the detected classes, enhancing the overall interpretability of the deployed system.

- **Class Colors:** Classes are visually distinguished using specific colors. For instance, the "Bin" class is represented in green, while the "NBD" (Non-Biodegradable) class is depicted in red.
- **Class Explanations:** Detailed explanations of each class, such as "Top view of the trash bin" for the "Bin" class and "non-biodegradable wastes" for the "NBD" class, are provided to enhance user understanding.

IV. MONITORING AND MAINTENANCE

Fig 10: Image Comparison - Input vs. Masked Output, Illustrating Waste Classification

➢ *Importance of Monitoring and Maintenance*

Effective maintenance and frequent observation are required for keeping up the ongoing reliability of our waste contamination detection system.

➢ *Key Conditions Include:*

- Regular Performance Monitoring: Continuous checks are essential to verify the accuracy of waste image classification models. Managing regularly will prevent keeping up for edge computing devices.

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- Data Quality Confidence: Continuous observation of data quality is necessary to maintain model integrity.
- Anomaly data: Surveillance for anomalous data points or outliers that may bias model training.
- Model Updating and Retraining: Updates and periodically retraining the ensured models remain effective amidst changes in waste managing practices.
- The field of waste management is dynamic.
- Maintenance: Regular maintenance prevents system failures and enhances security.
- User Feedback Integration: Incorporating user feedback helps identify areas for improvement. User feedback is a valuable source of information for improvement.

By following these comprehensive observation and maintenance practices, we can ensure that waste contamination detection system remains accurate, reliable, and adaptable in the ever-evolving waste management landscape.

V. RESULTS AND DISCUSSION

➢ *Assumptions and Achievements*

Beyond accuracy: Our success goes beyond achieving high accuracy with Detectron2.We also explored other CNN architectures such as YOLOv5, YOLOv8, R-CNN, etc.

Comparing their performance for different types of waste helps determining the optimal model for specific situations.

Additionally, we have investigated techniques such as transfer learning to leverage pre-trained models and accelerate the development of new waste streams.

Our aim was to develop accurate waste classification models using CNN architectures, which we successfully achieved through thorough data preprocessing, augmentation, and model training. Notably, our Detectron2 model demonstrated high accuracy (nearly 93%) in identifying contaminated waste images.

➢ *Scalability*

Our successful approach indicates scalability, with potential deployment across various waste management facilities and public premises. We have piloted our system in a controlled waste management facility with promising results.

VI. CONCLUSION

Our primary goal of minimizing pollution while maximizing waste separation efficiency is the guiding principle throughout this project. By harnessing the power of computer vision technology, we are embarking on a transformational path towards a cleaner, more sustainable future. Through the integration of an advanced CNN architecture and a powerful dataset, we have developed a set of classification models capable of accurately distinguishing between top-view waste and waste polluted that is into Degradable and Non-Biodegradable. By leveraging platforms like Roboflow app, we processed and augmented our datasets seamlessly, ensuring optimal performance and generalizability of our models across a wide range of scenarios.

This study tells the importance of technology in addressing environmental challenges. By automating waste contamination detection, we improve waste management efficiency while minimizing environmental impact. Collaboration and further research are key to scaling this solution for a cleaner, healthier future.

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