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Woodlog Inventory Optimization using Object Detection and Object Tracking

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Abstract:- In the timber industry, keeping track of wood stacks is crucial to avoid stockpiles that are too large or too small ensuring efficient operations. Traditional methods are often time-consuming and inaccurate, leading to inefficiencies. This research proposes a novel solution for timber yard inventory management using cutting-edge technology.The approach utilizes YOLOv8, a powerful object detection algorithm, to identify wood logs in live video feeds. DeepSORT, a tracking algorithm, then follows these identified logs over time. This automation eliminates the need for manual tracking, minimizes errors, and enforces the "First-In-First-Out" (FIFO) principle for efficient inventory use.The study also compares DeepSORT to other tracking algorithms like OC-SORT and ByteTrack to identify the most effective option for this specific application. The results demonstrate that the proposed method significantly improves detection accuracy and reliability, leading to better inventory management.In essence, this research highlights how integrating advanced detection and tracking technologies can revolutionize timber yard operations. By automating processes and ensuring accurate inventory control, these technologies can significantly reduce costs and boost overall efficiency in the timber sector.

Keywords:- *Woodlogs Inventory, First-in-First-Out (FIFO), Timber Industry, Object Detection, Object Tracking, YOLOv8, DeepSORT, ByteTrack, OC-SORT.*

I. INTRODUCTION

Effective inventory management is vital throughout numerous industries, which include the timber enterprise. Improper control in this region often leads to older wood stacks being used earlier than more recent ones, ensuing in wastage due to decay. This defeats the cause of the usage of clean timber. To prevent this, it's miles critical to have a technique to distinguish older timber from more moderen stacks. The precept of "First-In-First-Out" (FIFO) need to be carried out, making sure that the primary wooden stack that enters is the one used first.

Wooden is an important fabric in production, applied globally for buildings both massive and small. This includes wooden for building homes of six or more storeys, where know-how the biochemistry and chemistry of wooden change can allow even larger structures.[1]

Stock control is crucial for almost each sort of business, whether service or product-orientated. It affects almost each factor of operations, requiring a balance to preserve proper stock with minimal economic impact at the consumer.[2]

FIFO, an acronym for "First-In, First-Out," is a mechanism for stock manage that organizes stack primarily based at the date obtained and sold. The primary batch of merchandise acquired need to be the primary disbursed to customers. In inventory accounting models, FIFO is a perpetual inventory device, ensuring the oldest stack is used first, preserving stock clean. This method improves material utilization and decreases loss due to stack expiration.[3]

Our project goals to revolutionize wooden stack control via assigning a completely unique identifier to each timber stack, making sure strict adherence to the FIFO precept. This approach will decorate raw material usage efficiency and decrease waste within the timber enterprise. The approach to this research study is based at the CRISP-ML(Q) technique available as open-supply at the 360DigiTMG internet site. (ak.1) [Fig. 1]

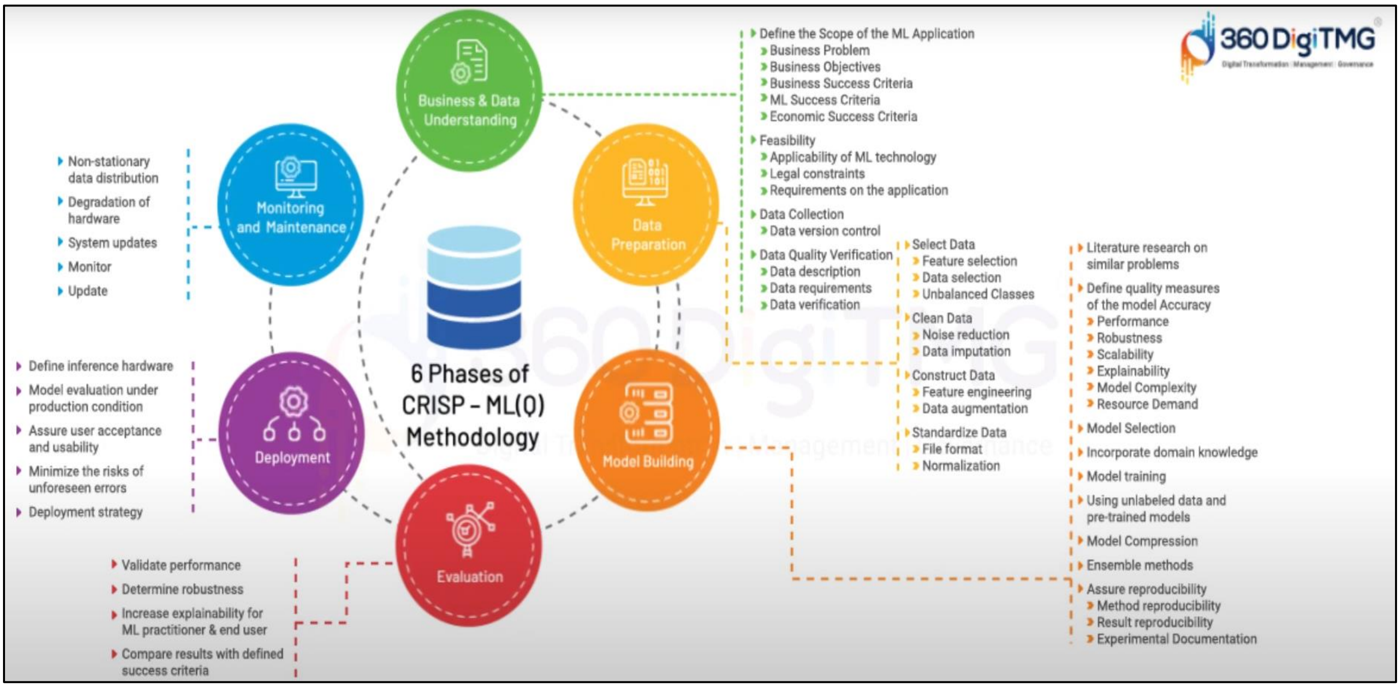

Fig 1 CRISP-ML (Q) Methodological Framework, Outlining its Key Components and Steps Visually.
Source: - Open-Source ML Workflow Tool- 360DigiTMG

II. LITERATURE REVIEW

Inventory management is essential to the success of any business and plays an important role in ensuring profitability. Small and medium-sized enterprises (SMEs), which typically operate on limited budgets, often rely on manual methods of inventory management. While this manual process is common, it can be labor intensive, error prone, and generally inefficient. The use of an inventory management system has been shown to improve the efficiency and accuracy of these methods.[4]

Manual inventory work presents many challenges. These include time-consuming inventory counts, difficulty in tracking inventory levels, increased risk of error, and increased costs associated with over-inventory or excess inventory. Salih et al. (2023) highlighted these problems in their study on adopting automated inventory management systems in SMEs, emphasizing the potential for such systems to streamline operations and improve accuracy in inventory tracking .[4]

In an SQL- and PHP-based program implementation of an automated catalog management system, Mascarenhas et al. (2020) demonstrated the practical advantages of such technologies. Their system was designed to monitor inventory in real time, significantly reducing the manual effort required and minimizing the possibility of error.[5]

Accurate demand forecasting is another important component of effective inventory management. Inaccurate expectations can lead to excess inventories or inventories, both of which are important.Albayrak et al. (2023) reviewed the applications of artificial intelligence in inventory management, noting that AI can enhance the precision of demand forecasts, thereby improving the overall efficiency of inventory management processes .[6]

Object tracking, mainly within the context of inventory management, also benefits from advances in technology. Han et al. (2004) proposed a more than one speculation approach for monitoring multiple objects, which integrates object detection and monitoring to ensure a sturdy and efficient monitoring set of rules . This technique uses a neural network-based totally item detection module to become aware of and tune items, offering real-time updates and feedback for progressed accuracy.[7]

Sun et al. (2021) introduced a Deep Affinity Network (DAN) that learns target object appearances and their affinities in pairs of video frames. This technique enhances item tracking by means of incorporating hierarchical feature gaining knowledge of, which improves the accuracy of tracking over more than one ranges of abstraction .[8]

Behrendt et al. (2017) presented a deep learning approach for real-time searches and tracking with OpenCV. Their pipeline includes steps for detecting, classifying and tracking objects, with applications ranging from traffic light detection to complex situations Similarly, Liu et al. (2018) developed an effective fruit first algorithm that combines deep learning, tracking, and planning from motion (SfM). Their system proved to be highly accurate in fruit counting in image sequences, and demonstrated deep learning in practical observational experiments.[9,10]

In the end, the combination of computerized systems and superior tracking technology can considerably improve the efficiency and accuracy of stock control, especially for SMEs. By decreasing manual effort and minimizing

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mistakes, these technologies allow companies to better manage their sources, forecast demand appropriately, and in the end enhance their general operational efficiency.

III. METHODOLOGY AND TECHNIQUES

A. *Object Detection*

Object detection is a computer vision technique used to identify and locate objects in an image or video. Unlike simple image recognition, which assigns a single label to an entire image, object detection not only labels objects but also draws bounding boxes around them. This provides precise information about the location of objects within a given scene. For instance, while image recognition might label an entire image as containing a "dog," object detection would draw individual bounding boxes around each dog in the image and label each box accordingly. This allows for accurate detection of the location and number of objects present.

To leverage the capabilities of object detection techniques like YOLO (You Only Look Once) [11] and address its limitations, we propose a new workflow that combines YOLO's efficiency with additional methods [12] (ak.2) Fig 2 . This workflow involves a multi-step approach where YOLO's initial detections are refined using sophisticated post-processing algorithms. Through feature-based refinement and context analysis, our proposed workflow aims to improve detection accuracy, particularly for scenarios involving small objects or fine classification. In the following sections, we detail the components of this workflow and present experimental results demonstrating its effectiveness in enhancing object detection performance.

➢ *Overview of YOLO Algorithm:*

YOLOv8 is an advanced version of the YOLO object detection algorithm that uses a deep neural network to analyze entire images, identifying objects with class probabilities and bounding boxes. It is faster, more accurate, and better at detecting small objects compared to traditional methods. YOLOv8 employs a convolutional neural network (CNN) to extract features, predict bounding boxes, and refine these predictions with offsets, calculating confidence by combining class probability and bounding box confidence score.

The YOLO algorithm has significantly impacted computer vision, particularly in real-time object detection, due to its speed and efficiency. It is popular in applications like video surveillance, self-driving cars, and augmented reality. One of its main advantages is the ability to process images quickly, enabling real-time detection with relatively little training data.

However, YOLO also has limitations. It may struggle with accurately detecting small objects and performing fine-grained classification. Despite these challenges, YOLO has advanced object detection and created new opportunities for computer vision research and applications. As the field evolves, improvements to YOLO and other algorithms will likely address these limitations and meet new challenges.

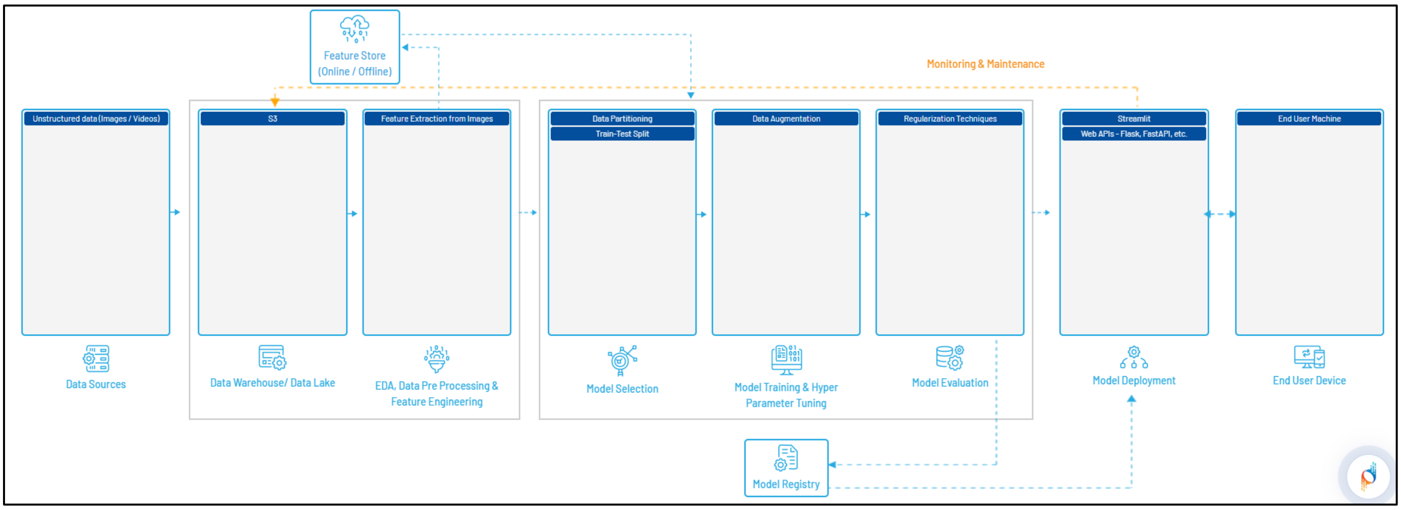

Fig 2 ML Workflow Architecture: A comprehensive overview of the ML pipeline for Wood Logs Inventory Optimization. Source: Open-Source ML Workflow Tool- 360DigiTMG

B. *Object Tracking*

Object tracking involves identifying an object in a video and monitoring its movement over time, with applications in surveillance, robotics, and self-driving cars. This task is particularly challenging in complex environments where objects can become occluded or their appearance can change due to lighting variations. Traditional algorithms often rely on motion models and feature extraction techniques. In contrast, modern methods such as Deep Simple Online and Real-time Tracking (DeepSORT), OC-SORT, and ByteTrack combine deep learning with traditional tracking techniques to achieve state-of-the-art performance.

- *Overview of DeepSORT:*

The Deep Simple Online and Real-time Tracking (DeepSORT) algorithm[13] is an advanced method for tracking multiple objects simultaneously by associating detections across frames. An extension of the SORT (Simple

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Online Real Time Tracking) algorithm, DeepSORT adds a deep learning-based appearance descriptor to reduce identity switches and enhance tracking efficiency. DeepSORT uses the Kalman filter to predict an object's location in the next frame and associates the detection with the predicted location using a combination of the Intersection over Union (IOU) metric and the appearance descriptor. The Kalman filter's state is then updated using the associated detection, and the process is repeated for the subsequent frames. Fig 3 shows the overview of the DeepSORT algorithm.

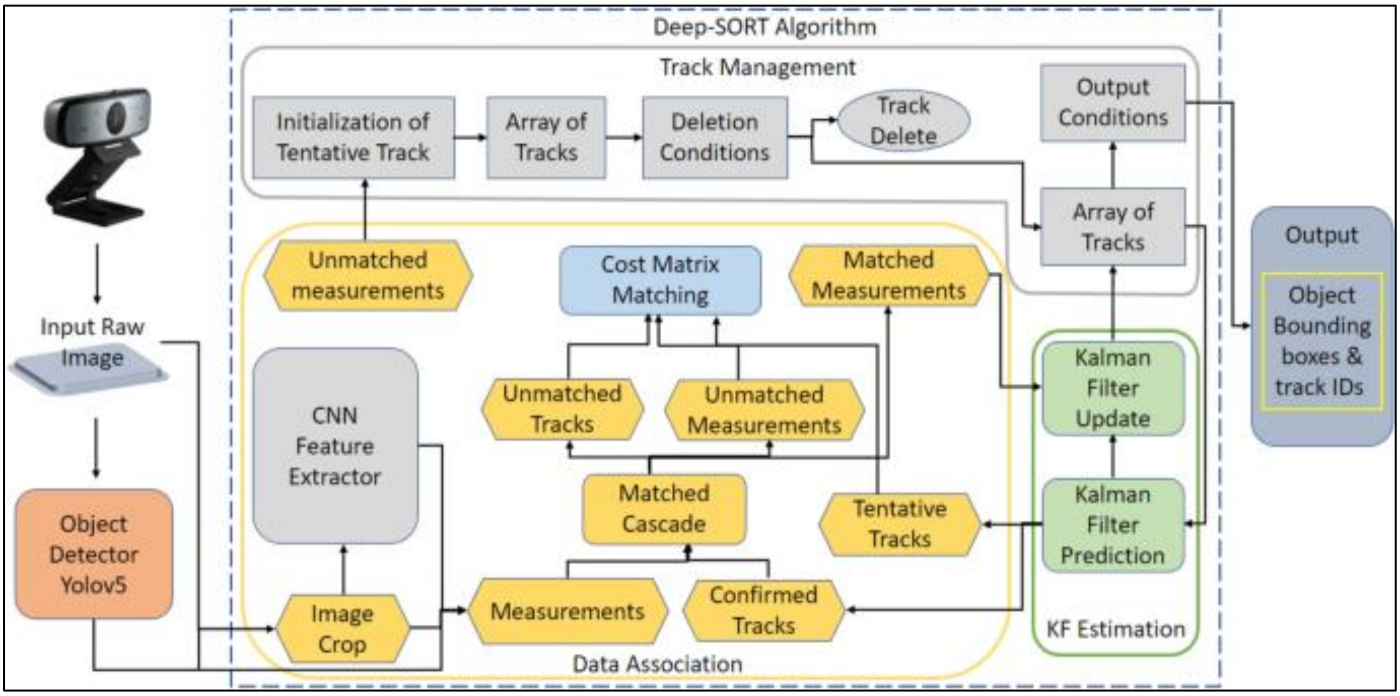

Fig 3 : Overview of the DeepSORT algorithm
Source: ref. [14]

➢ *Overview of ByteTrack:*

ByteTrack[15] represents a significant advancement in multi-object tracking by incorporating all detection boxes, including those with low confidence scores, into the association process. This approach results in more accurate and continuous tracking, particularly in complex and dynamic environments. The algorithm's performance on benchmark datasets underscores its effectiveness and potential for real-world applications.

➢ *Overview of OC-SORT:*

OC-SORT[16] represents a significant evolution of the SORT algorithm by adopting an observation-centric approach that prioritizes accurate data association and robust handling of occlusions and appearance changes. This results in improved multi-object tracking performance, making it highly effective for various real-world scenarios where traditional motion model-based tracking methods may fall short.

C. Proposed Method for Wood Logs Inventory Optimization:

This paper introduces a method for detecting and tracking wood log stacks in a warehouse using the object detection and tracking algorithms. Ref. [Fig 4] for better understanding of the project architecture. Here's how it works:

- Warehouse Inventory: Wood logs are stored and managed based on the FIFO principle.
- Cameras: Multiple cameras capture images or video frames of wood log stacks from various angles in the warehouse.
- Computing Resources: A powerful computer or server is used for training and deploying the Object detection and object tracking model, depending on dataset size and complexity.
- Dataset Collection: A diverse dataset of wood log stack images or frames is collected to train the models, ensuring coverage of different positions, orientations, and lighting conditions.
- Annotation Tools: Tools like Roboflow label the dataset by drawing bounding boxes around stacks and assigning class labels.
- Tracking Algorithm: After training, Object tracking algorithms track wood log stacks in real-time, assigning unique identifiers for accurate inventory management. It uses appearance features and motion information to ensure precise tracking.

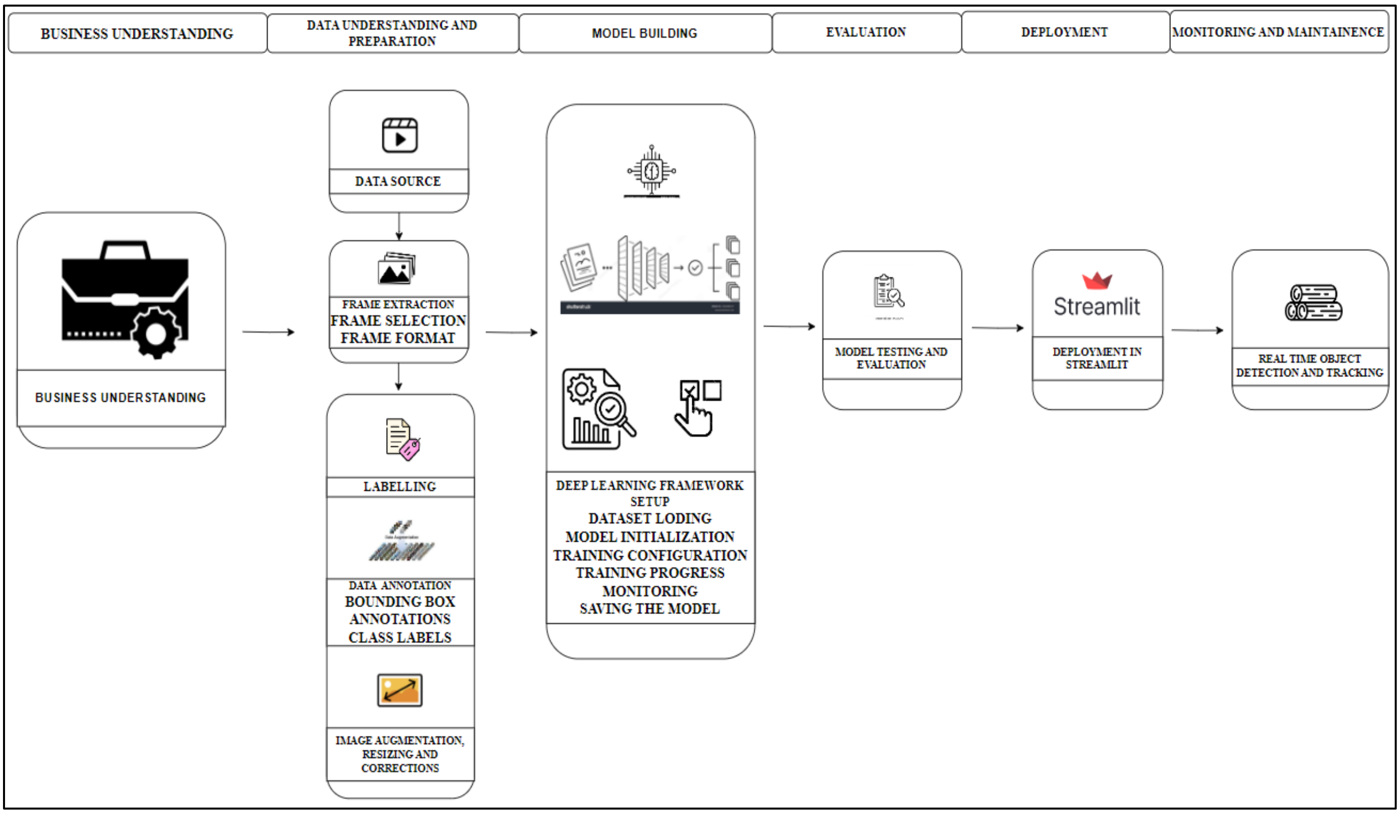

Fig 4 Model Architecture

D. Implementation Steps:

Figure 5 depicts the Project Implementation Roadmap, which will be detailed in the subsequent sections.

- *Extracting Images from Videos :*

The initial step involves extracting frames from video recordings of wood log stacks. This process ensures a diverse and comprehensive dataset capturing various angles and conditions of the wood log stacks.

- *Frame Extraction, Frame Selection, Frame Resolution & Quality*

Once the frames are picked, we carefully select the ones with the desired shape and quality. This selection process ensures that the next step works on the most informative and high-quality images.

- *Reading Frames and Labeling Using Roboflow*

The selected frame is read into our system and then encoded by Roboflow. In this step, each frame is annotated with a bounding box, and class labels are provided to identify the different wooden log stacks.

- *Annotation Tools (Bounding Box Annotation, Class Labels)*

Annotation tools are used to create bounding boxes around each wood-log stack and assign appropriate class labels. This labeled data set is important for training the analytical model.

- *Data Augmentation (Flip, Rotation, Shear, Hue, Saturation, Brightness, Noise)*

Data enhancement techniques such as flipping, rotation, shearing, hue adjustment, saturation, brightness and adding noise are applied to the annotated images to enhance the robustness and generalizability of the model.

- *Train Test Split*

The data set is divided into training and testing subsets. This classification allows the performance of the model to be checked on unseen data, thus improving reliability and accuracy.

- *Loading Dataset to YOLO Model for Training*

A training subset of the annotated dataset is then loaded into the YOLOv8 model. This phase involves configuring the model with appropriate parameters and initializing the training process.

- *Loading the Trained Model for Detection*

Upon completion of the training process, the trained YOLOv8 model is loaded to detect wood log stacks. This step involves testing the model on various scenarios to ensure it can accurately identify and classify the log stacks.

- *Tracking Algorithms (Deep SORT, OC-SORT, Byte Track)*

To facilitate continuous monitoring and tracking of the wood log stacks, the trained detection model is integrated with tracking algorithms such as Deep SORT, OC-SORT, and BYTE TRACK.These algorithms maintain the identity of each log stack over time , even in crowded places.

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➢ *Model Evaluation (MOTA, MOTP, IDF)*

The model's performance is evaluated using metrics such as Multiple Object Tracking Accuracy (MOTA), Multiple Object Tracking Precision (MOTP), and Identity F1 Score (IDF). These metrics assess the model's detection and tracking capabilities, ensuring it meets the required standards.

➢ *Best Model Selected and DeepSORT Tracker Updated with the IDS and Bounding Boxes*

Based on the results of the analysis, the best performing model was selected. The selected model is then merged with the Deep SORT tracker, which updates the IDs and bounding boxes for each known log stack.

➢ *Bounding Boxes Along with Their Classes Shown*

The system displays bounding boxes with their class labels around each detected tree log stack. This visual image helps verify the search and tracking process.

➢ *Desired Output where Stacks are Labeled Based on When They Come into the Frame Obtained*

The system tracks and registers the stacks of logs based on the time they enter the frame, following FIFO (First-In-First-Out) principles. The combination of the YOLOv8 model with Deep SORT ensures that each stack is constantly monitored and accurately identified. As the characters enter the frame, they are assigned unique signals and their positions are updated in real time. This approach ensures that the catalog is maintained, and that old records are processed before new ones are created, so key.

➢ *Deployment*

The fully trained and validated model, integrated with a tracking algorithm, has been successfully deployed on the Streamlit platform for real-time monitoring. This deployment currently focuses on monitoring wood log stacks using an AI-driven camera system. Future work includes extending this deployment to a warehouse environment for broader application.

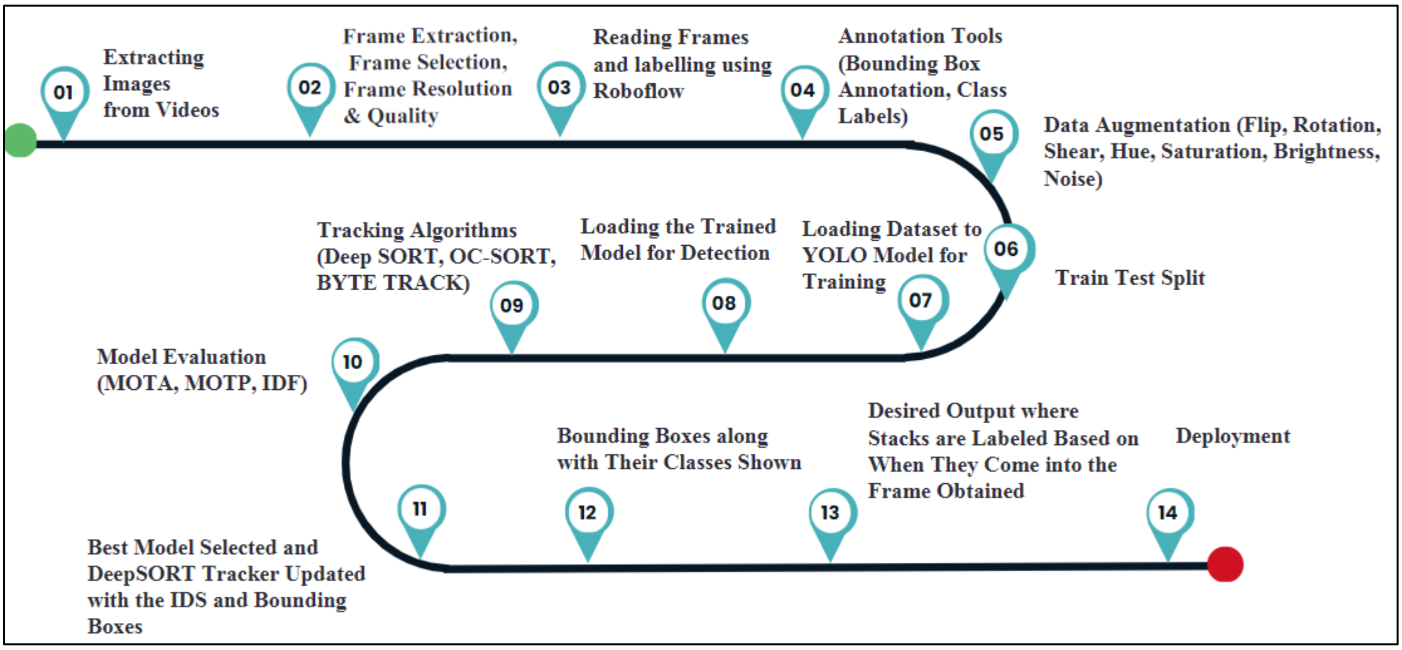

Fig 5 Project Implementation Roadmap

➢ *Data Collection*

For this research project, the dataset consists of 497 images of stacks. These images are used to develop and train a model that identifies and tracks each stack. The model assigns a unique identifier to each stack, enabling accurate tracking and management. When a stack is removed from the frame, the system re-assigns IDs to maintain updated inventory records effectively. By doing this we will get to know which stack should be shipped out next from the inventory.

➢ *Data Preprocessing*

Wood log pile image analysis is crucial for stockpile identification and shipping decisions. Before feeding images into deep learning models, a robust preprocessing pipeline is essential to enhance data quality, reduce noise, and optimize model performance.

➢ *Here's the Process:*

- *Data Extraction and Annotation:*

Frames were extracted from sample videos using Python/Roboflow. Each stack case in a frame was labeled using the Roboflow algorithm, resulting in 497 labeled images. Fig 6 shows the bounding boxes drawn by using roboflow.

- *Annotation Format:*

Each image is accompanied by a .txt file containing bounding box annotations in the format:” *class_id center_x center_y width height* ” [17] Coordinates are normalized from zero to one.

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- *Data Augmentation:*

To increase dataset diversity, data augmentation techniques were applied. These include random transformations like translation, cropping, rotation, and color distortions. Augmentation helps in training robust deep learning models by exposing them to varied scenarios.

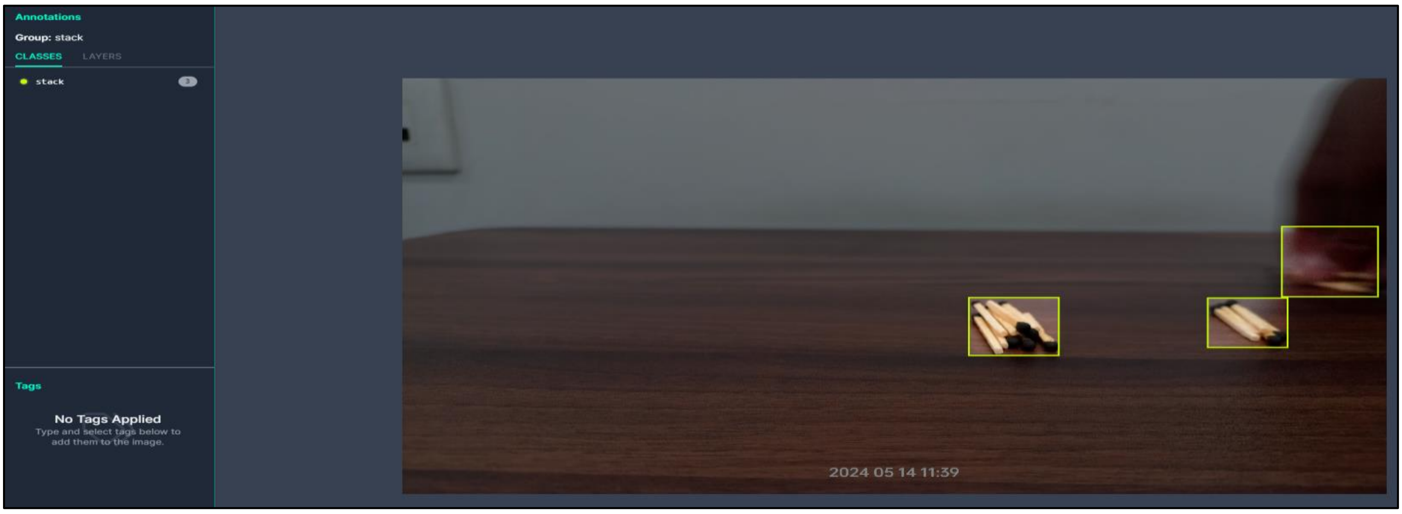

Fig 6 Views of Object Detection Bounding Boxes, Contributing to a Comprehensive Understanding of Detection Accuracy.

Roboflow[17] is a computer vision tool used by developers for various deep learning tasks, including annotation, model building, and deployment. Roboflow Annotate is an online tool for labeling images for object detection, classification, and segmentation. For this project, Roboflow was used for annotation and pre-processing. During the pre-processing stage, we applied auto-orientation, auto-resizing, and automatic contrast adjustment to the images. In the augmentation process, we applied:

- Flip: Horizontal,Vertical
- Rotate: Clockwise, Counter-Clockwise, Upside Down
- Rotation: Between -10° and +10°,
- Shear: ±10° Horizontal, ±10° Vertical,
- Hue: Between -15° and +15°,
- Saturation: Between -25% and +25%,
- Brightness: Between -15% and +15%,
- Noise: Up to 0.1% of pixels,

Ref. [Fig: 7, 8, 9, 10, 11, 12] These figures collectively provide a comprehensive understanding of both the dataset and the model's performance. They cover aspects from data composition and annotation patterns to the model's training progression and final evaluation metrics, offering a holistic view of the entire process from data preparation to model validation and testing.

Fig 7 Dataset's Images, Annotations, and Average Image Sizes, Offering Insight into its Composition and Characteristics

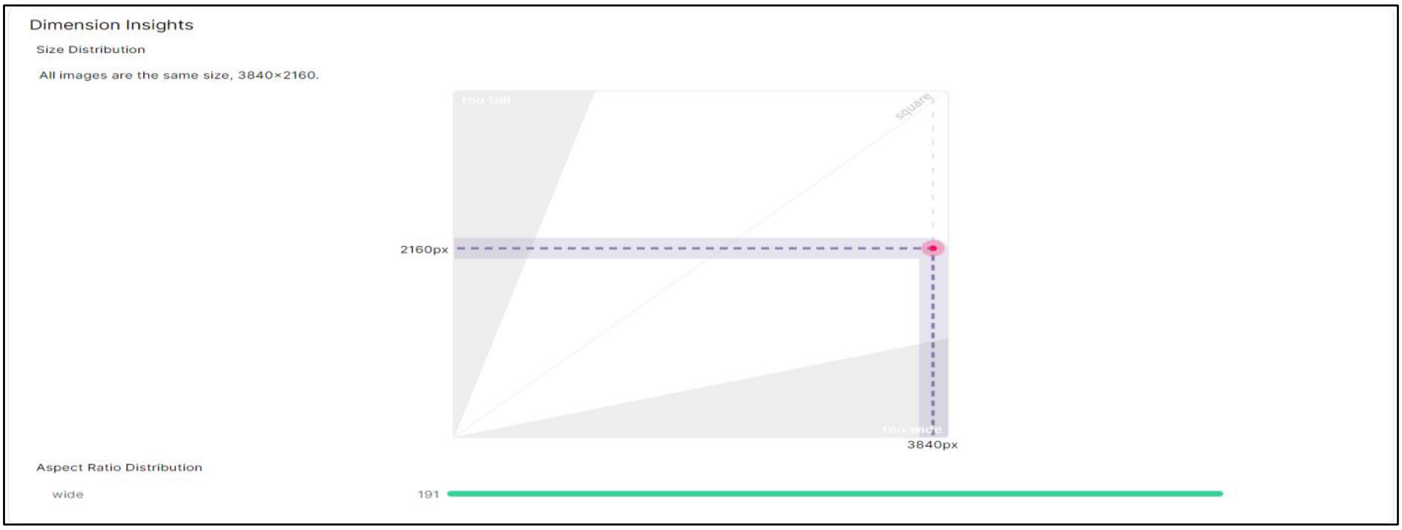

Fig 8 Distribution of Image Sizes within our Dataset, Highlighting Variations in Dimensions Across the Data.

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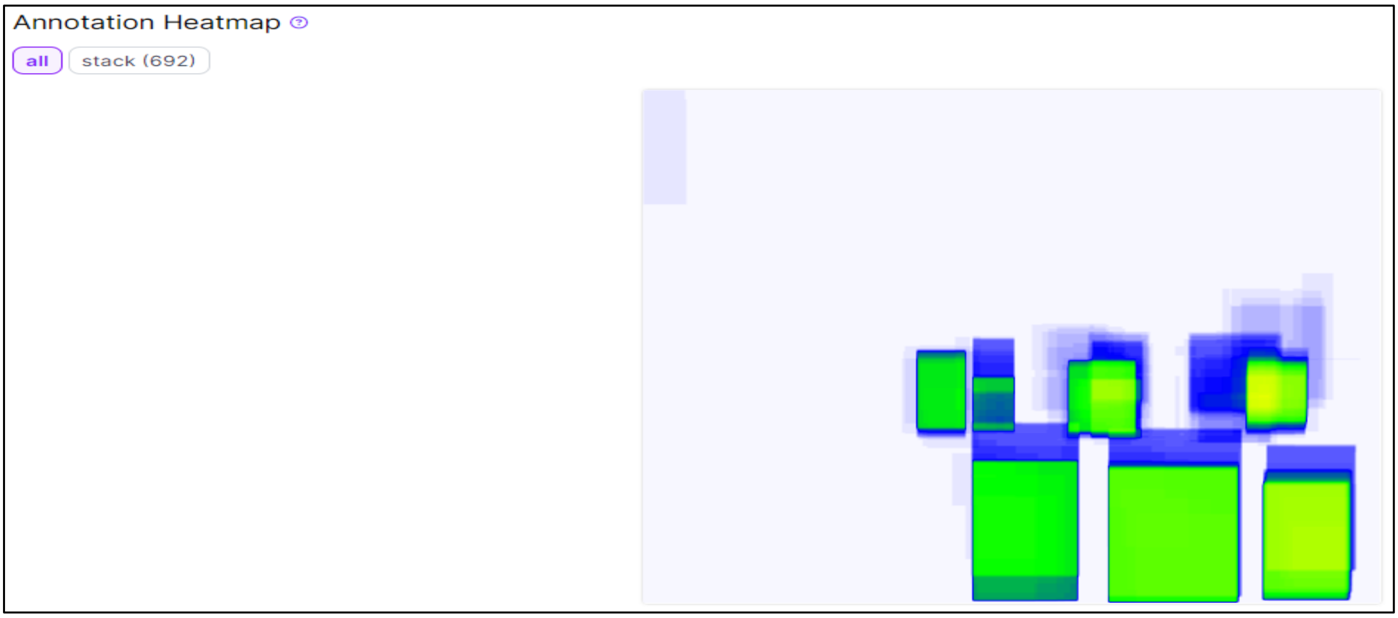

Fig 9 Annotation Heatmap, Providing a Visual Representation of the Density of Object Annotations within Images

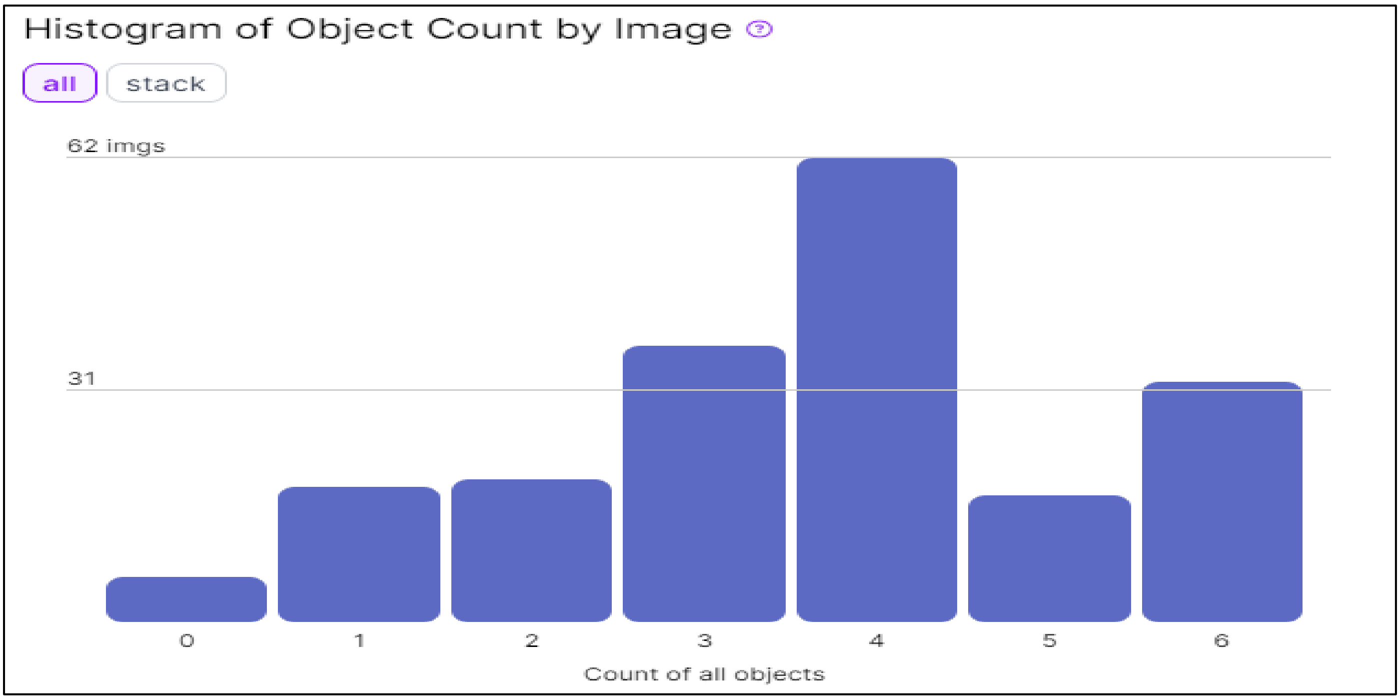

Fig 10 Histogram Illustrating how the Number of Objects per Image is Distributed Across the Dataset

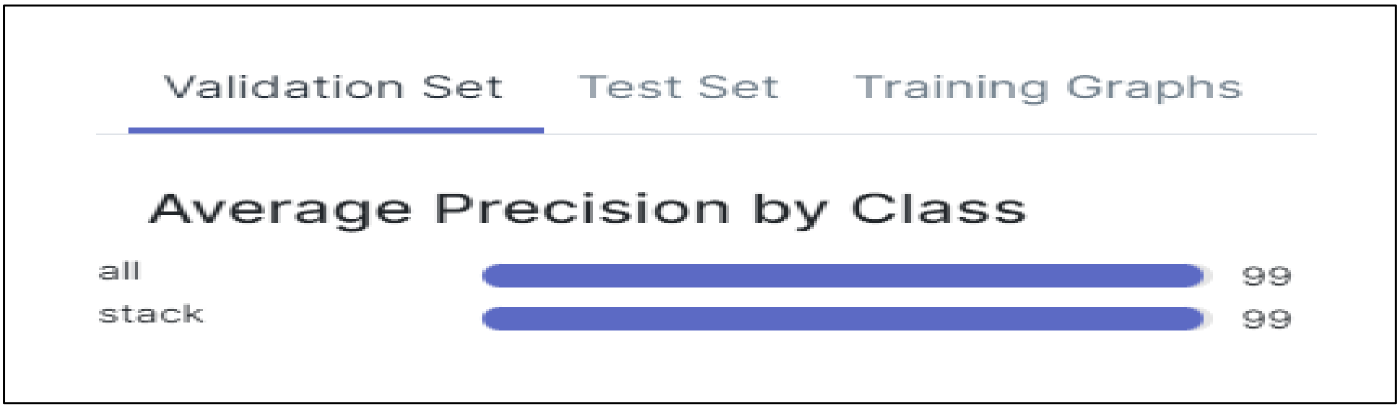

Fig 11 Validation Set Results for Average Precision, Compactly Conveying the Model's Performance.

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Fig 12 Test Set Results for Average Precision are Depicted, Showcasing the Model's Performance.

➢ *Model Selection*

In this project, we explored various object tracking methods, including DeepSORT, OC-SORT, and ByteTrack. Our approach incorporated a combination of advanced post-processing and optimization techniques to address challenges specific to YOLO, as illustrated in Figure 2 of our Machine Learning Workflow Architecture. By evaluating these methods, we aimed to identify the most effective tracking and recognition techniques. Based on the experimental results from these evaluations, we will select the model that delivers the highest performance in terms of detection and tracking accuracy. This approach ensures that we choose the most effective solution for our specific project needs.

➢ *Model Training*

Our project trains, deploys, and tests YOLOv8 with the goal of improving wood log stack recognition and tracking in warehouses. To achieve the best model performance, we started by carefully selecting a wide range of datasets, carefully annotating them, and preprocessing the data. To achieve precise stack identification, YOLOv8 configuration required parameter selection and training process optimization. Before combining YOLOv8 with tracking algorithms for robust object tracking, we verified its performance using metrics like mean Average Precision (mAP) and precision. To make sure our integrated model satisfies strict requirements for warehouse inventory management, it underwent extensive testing in both simulated and real-world settings before being deployed. Keeping an eye on things and making adjustments as needed are crucial to keeping our project running well.

- *YOLO Performance Summary:*

For object detection, we used YOLOv8, achieving the following performance metrics: Ref. Fig [13] and Fig [14].

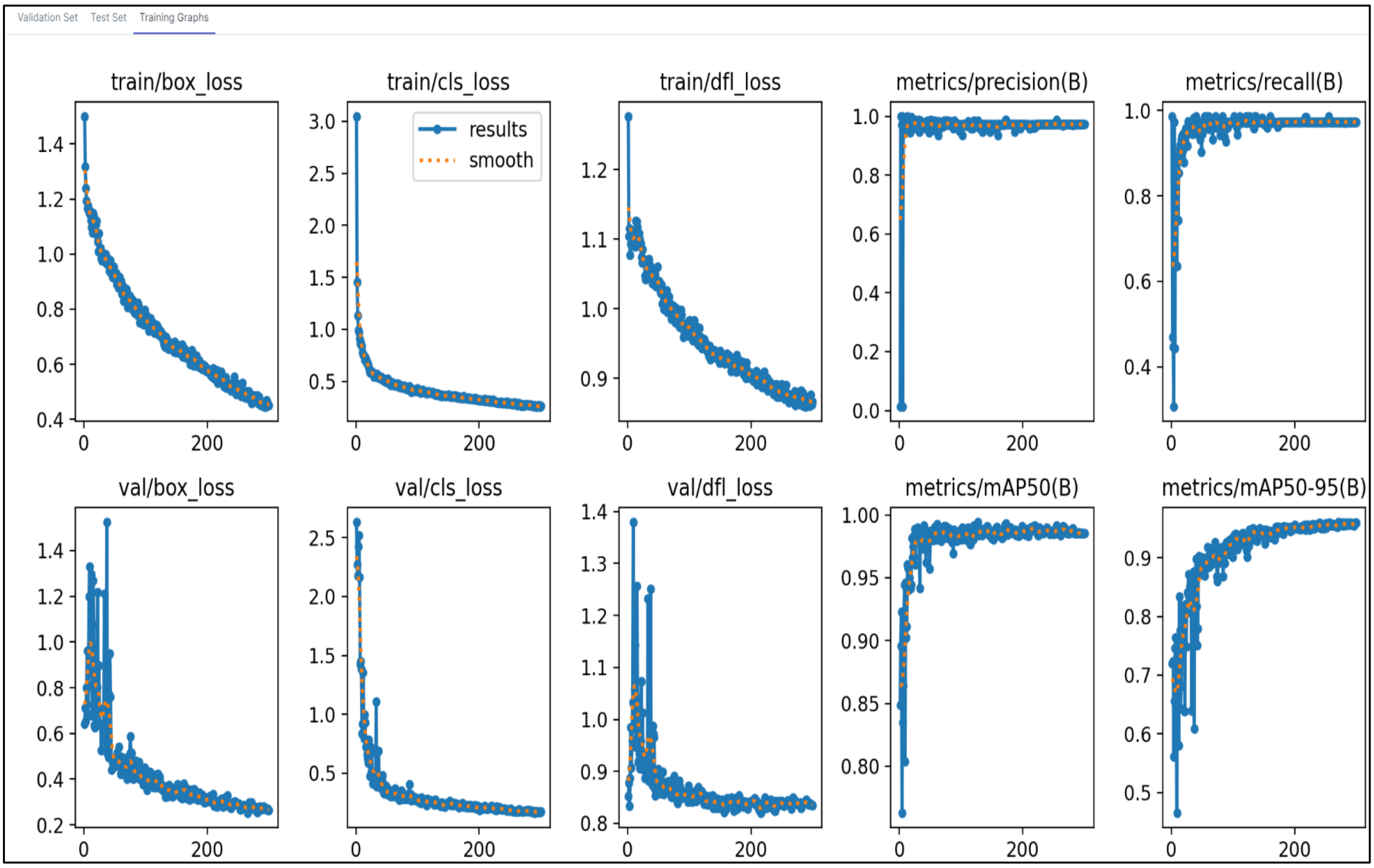

Fig 13 Training Graphs for the YOLO Model, Presenting its Learning Progress and Performance.

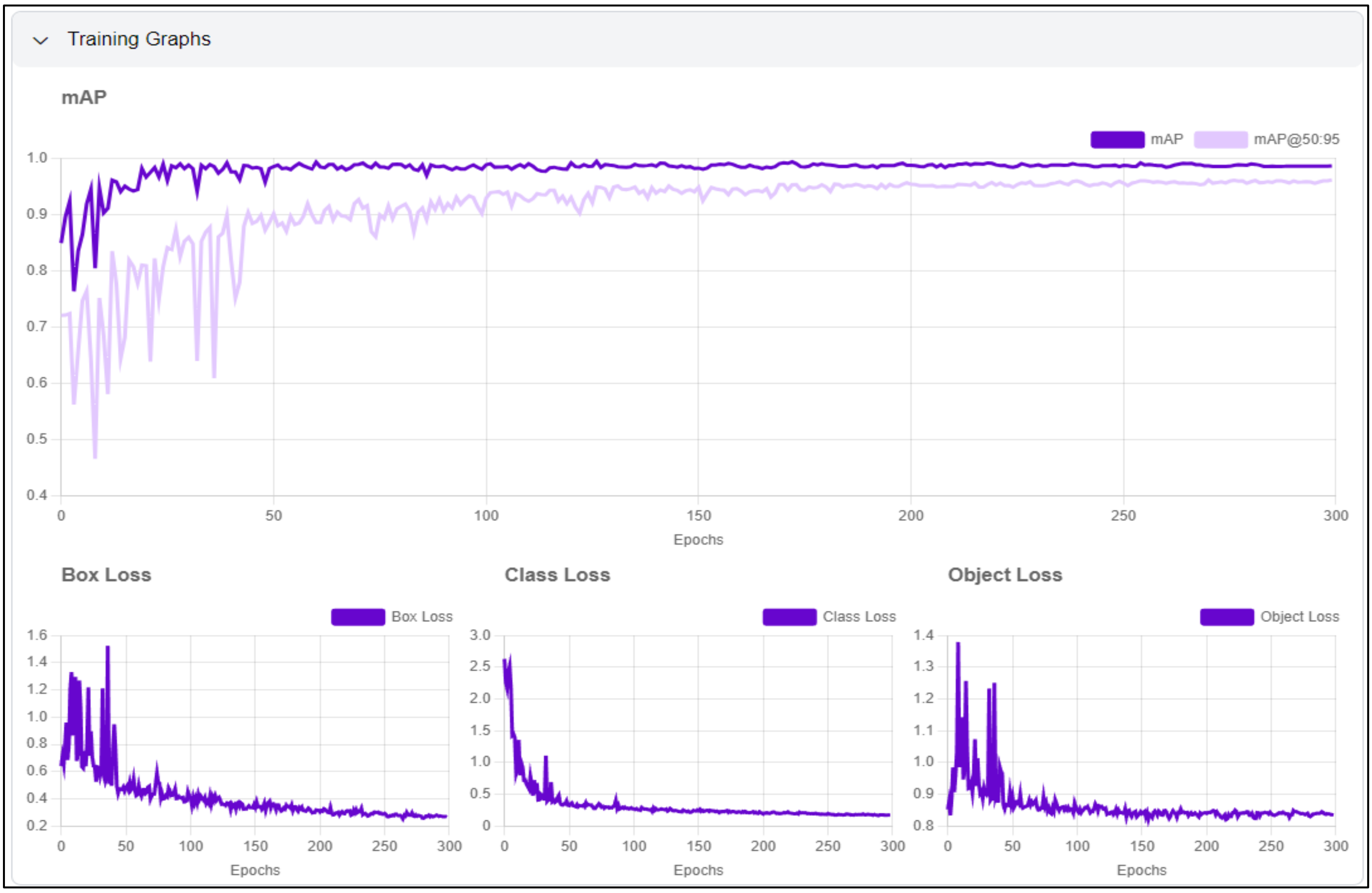

Fig 14 The Reduction of Object Detection Precision Losses via Improved Labeling of Boxes, Classes, and Objects

➢ *Model Evaluation*

To effectively evaluate and select the best model among tracking algorithms like DeepSORT, OC-SORT, and ByteTrack, several key metrics are employed:

- **MOTA: Evaluates tracking accuracy, considering false positives, false negatives, and identity switches.**
- **MOTP: Measures average error between predicted and actual positions.**
- **IDF1: Balances precision and recall for identity tracking.**
- **IDP & IDR: Assess accuracy of identity assignments.**
- **FP & FN: Count incorrect and missed detections.**
- **IDSW: Tracks changes in object identities.**
- **Track Fragmentation: Measures trajectory interruptions.**
- **Precision & Recall: Indicate accuracy of true versus false detections.**
- **MT, PT, ML: Classify tracking completeness of trajectories.**

All parameters together provide a comprehensive level of evaluation ,to compare DeepSORT, OC-SORT and ByteTrack. For detailed investigation and description, tools such as statistical indicators and evaluation methods on websites such as MOTChallenge [18] provide guidelines for evaluating and selecting the best monitoring methods for specific projects.

These metrics provide a comprehensive evaluation of a tracking algorithm's performance, balancing accuracy, precision, and consistency.

Table 1 Evaluation Metrics of DeepSORT

DeepSORT
MOTA: 0.50
MOTP: 0.75
IDF1: 0.76
IDP: 1.00
Precision: 0.75
Recall: 0.76
Track Fragmentation: 0.24
MT: 0.76
PT: 0.00
Mostly Lost: 0.24

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Given these metrics in table 1, **DeepSORT** performs the best among the three algorithms. It has the highest MOTA, MOTP, IDF1, IDP, Precision, Recall, and MT, indicating better overall tracking performance.

➢ *Model Deployment*

We deployed our model using a Streamlit application designed for video processing and displaying annotated outputs. The application identifies and labels wood log stacks as they appear in the video stream, numbering each stack based on its appearance order for easy identification and management. Users upload warehouse videos via the Streamlit interface, where the application processes them frame by frame using YOLOv8 for object detection and DeepSORT algorithm for object tracking. The application provides real-time annotations, displaying each detected and tracked stack with a unique identifier. The annotated video output serves as a visual guide for inventory management, ensuring accurate tracking and retrieval of stacks for shipment. The user-friendly Streamlit interface allows users to upload videos and observe real-time annotations, enhancing operational efficiency and decision-making. This deployment approach optimizes inventory management by leveraging advanced detection and tracking technologies to streamline warehouse operations.

IV. IMPLICATIONS FOR FUTURE RESEARCH

The findings from this study open up several avenues for future research in the domain of wood log inventory optimization leveraging advanced object detection and tracking algorithms:

➢ *Algorithm Improvement:*

While YOLOv8 and DeepSORT have exhibited promising outcomes, further refinement and evolution of these algorithms stand to augment their precision and efficiency. Exploring novel models or hybrid approaches amalgamating the strengths of diverse algorithms could potentially enhance overall performance.

➢ *Real-time Processing:*

The imperative focus on implementing and fine-tuning real-time processing capabilities for extensive industrial applications remains paramount. Ensuring seamless handling of substantial data volumes in real-time, without compromising accuracy, emerges as a critical requirement for practical deployment scenarios.

➢ *Integration with IoT:*

Future investigations may delve into the integration of these algorithms with Internet of Things (IoT) infrastructure, aimed at establishing a more interconnected and automated system for inventory management. This could encompass leveraging sensors and smart devices to furnish real-time inputs to detection and tracking algorithms.

➢ *Scalability and Adaptability:*

Evaluating the scalability of these systems across diverse inventory sizes and types, alongside their adaptability to varying environmental conditions and logistical intricacies, holds significant promise. Such research endeavors could yield valuable insights by testing these systems across different warehouse settings and product types.

➢ *Energy Efficiency:*

Given the computational demands of these algorithms, exploring avenues to enhance their energy efficiency assumes heightened relevance, particularly in resource-constrained operational environments.

➢ *Robustness and Error Handling:*

Further research efforts could concentrate on fortifying the robustness of these systems, ensuring robust error-handling mechanisms that effectively manage challenges such as occlusions, fluctuating lighting conditions, and other real-world complexities.

In essence, addressing these research avenues promises to advance the efficacy and applicability of advanced object detection and tracking technologies in optimizing wood log inventory management, thereby driving efficiencies and operational enhancements in relevant industrial sectors.

V. RESULTS AND DISCUSSION

This examine investigated the impact of mixing YOLOv8 for item discovery and DeepSORT for tracking to optimize tree log stock control in warehouse structures We accomplished comparative evaluation with different tracking algorithms, together with OC-sort and ByteTrack. Time was spent focusing on key features which include a couple of item tracking Accuracy (MOTA), more than one object tracking Precision (MOTP), and IDF1 ratings.Our outcomes consistently display that the YOLOv8-DeepSORT aggregate outperforms the alternatives,with a excessive diploma of accuracy and reliability required for an powerful inventory control.

DeepSORT's performance advantage over OC-kind and ByteTrack highlights its robustness in handling complicated monitoring eventualities in dynamic warehouse environments.Utilizing YOLOv8 for unique item detection, our integrated technique now not handiest boosts monitoring accuracy but additionally complements real-time processing abilties. That is vital for adapting to variable lighting situations, occlusions, and various warehouse layouts, as evidenced via the robustness visible within the screenshots from our video outputs (Ref [Fig 16]).

The realistic implications of our findings are sizeable for advancing inventory control systems in industrial settings. Integrating superior object detection and monitoring era like YOLOv8 and DeepSORT can streamline warehouse operations, reduce mistakes related to guide tracking, and optimize useful resource allocation. The tested effectiveness of our approach underscores its capability to beautify operational performance and accuracy in warehouse logistics.

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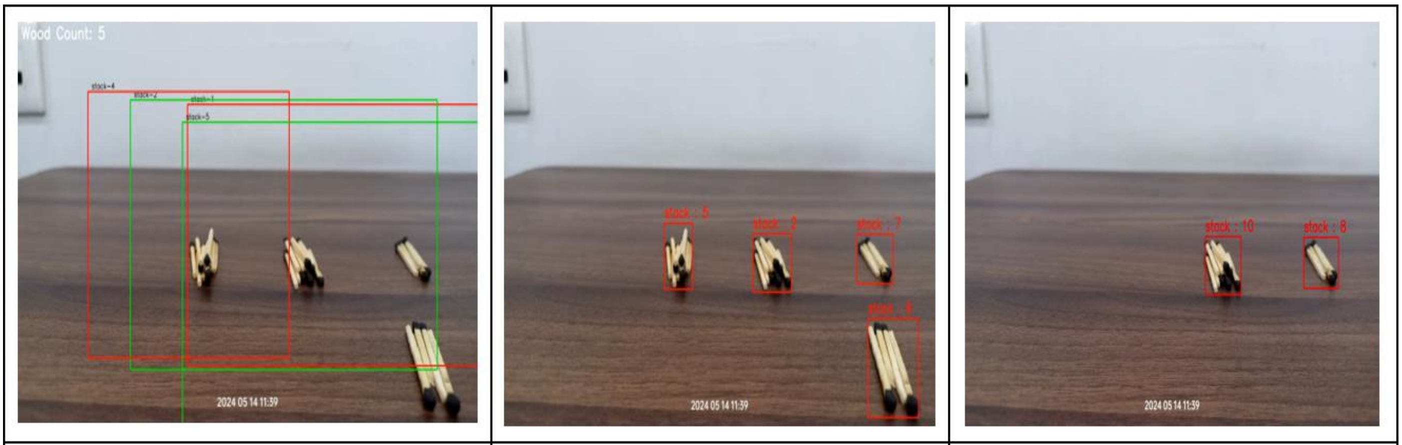

a. Deep SORT	b. OC-SORT	c. ByteTrack

Fig 15 Output Tracking Results using Deep SORT, OC-SORT and ByteTrack with Bounding Boxes on the Object.

VI. CONCLUSION

In conclusion, this study highlights the potential of comprehensive tracing and tracking systems in the quality management of wood relics. By using YOLOv8 for searching and DeepSORT for tracking, the study achieved remarkable improvements in tracking accuracy and efficiency. The application of this technology in a real warehouse demonstrated its practical value for inventory. Future research should extend these findings by investigating further algorithmic improvements, real-time processing capabilities, IoT integration, scalability, energy efficiency, and energy efficiency to further improve the system and they are used in a variety of industrial situations.

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