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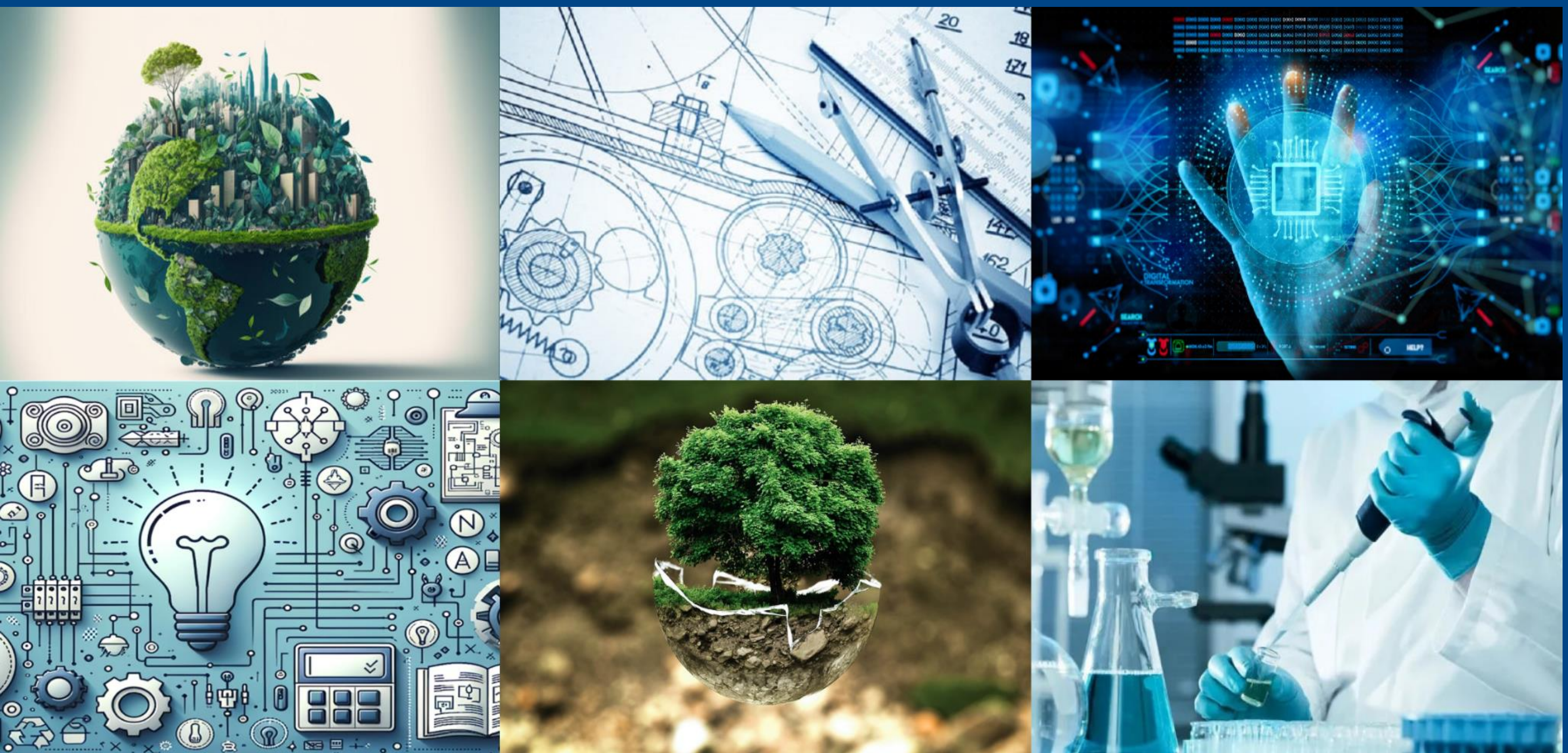

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Real-Time AI-Powered Pallet Counting and Intelligent Tracking System, using YOLO Object Detection Model

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ABSTRACT: This study investigates the automation of pallet counting in warehouse environments using advanced computer vision techniques, specifically the YOLOv8 object detection algorithm and the Roboflow platform for dataset annotation and model training. Manual counting of pallets is a labor-intensive and error-prone process that can significantly disrupt inventory management and supply chain operations. To address these challenges, we collected a comprehensive dataset of warehouse images and videos, capturing pallets under various conditions, including different lighting scenarios and stacking configurations. The dataset was annotated using Roboflowto ensure accurate bounding boxes for pallet detection. The YOLOv8 model was then trained on this annotated dataset, achieving a high mean Average Precision (mAP) score, indicating its effectiveness in detecting pallets in real-time. The trained model was deployed in a user-friendly web application that allows for live video feeds or uploaded images to facilitate automated pallet counting. Results demonstrate that this automated approach significantly reduces the time required for inventory the annotated dataset was used to train the yolov8 model which demonstrated its capacity to accurately detect pallets in real-time warehouse situations by obtaining a high mean average precision map score after training the model was incorporated into a user-friendly web application that allowed warehouse employees to count pallets automatically using provided photos and live video streams by drastically cutting down on the amount of time needed for stock monitoring minimizing human counting errors and offering real-time data insights via interactive dashboards this automated technology improves inventory management adopting this strategy also increases warehouse efficiency by cutting labor expenses overall guaranteeing precise inventory tracking and streamlining operational workflows this study demonstrates the revolutionary potential of incorporating deep learning technology into warehouse operations opening the door for increased industrial process scalability accuracy

KEYWORDS: Unstructured Data, Object Detection, Inventory ,Management, Deep Learning.

I. INTRODUCTION

pallet counting by hand in warehouses is labor-intensive time-consuming and prone to mistakes these errors may result in disparities in inventory records ineffective use of storage space and monetary losses as a result of missing or incorrectly numbered pallets pallet counts require a more accurate automated and efficient technique for businesses that move and store vast quantities of goods conventional inventory tracking techniques such barcode scanning and manual stock taking frequently fall short in offering real-time insight into warehouse operations furthermore human mistake and miscalculation can result in disparities that cause supply chains to break down and create losses modern warehouses can employ automated technologies to increase inventory accuracy and optimize operations thanks to developments in computer vision and deep learning the goal of this project is to create a system that leverages yolo for

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real-time object detection to count pallets in unstructured data sources such pictures and movies simplify processes.operations and human mistake and miscalculation can cause inconsistencies that disrupt supply chains and cause losses modern warehouses can now implement automated technologies to enhance operations and boost inventory accuracy thanks to developments in computer vision and deep learning the goal of this research is to use yolo for real-time object detection to create a system that counts pallets in unstructured data sources like pictures and movies.The creation, deployment, and validation of a unique machine learning solution intended to alleviate a significant operational bottleneck for one of the leading pallet manufacturers in the sector are all covered in depth in this article. The manual counting of pallets is currently a major difficulty .

The creation, deployment, and validation of a unique machine learning solution intended to alleviate a significant operational bottleneck for one of the leading pallet manufacturers in the sector are all covered in depth in this article. The manual counting of pallets is currently a major difficulty due to its time-consuming nature, high reliance on physical labor, and vulnerability to human mistake. By using machine learning to significantly cut down on counting time and improve accuracy, this project seeks to transform the pallet counting process by implementing a highly automated and intelligent system.This initiative's main goal is to reduce the inefficiencies related to the present manual counting approach the crisp-mlq methodology which the system adheres to guarantees an organized technique for putting machine learning models for warehouse management into practice and validating them through methodical analysis development and implementation of machine learning solutions this technique offers a strong framework for tackling business difficulties businesses can improve operational efficiency by maximizing warehouse space and dynamically monitoring inventory levels by detecting pallet issues with real-time data visualization technologies when operational bottlenecks are quickly identified managers can take the necessary steps and make timely well-informed management enhancing inventory accuracy.

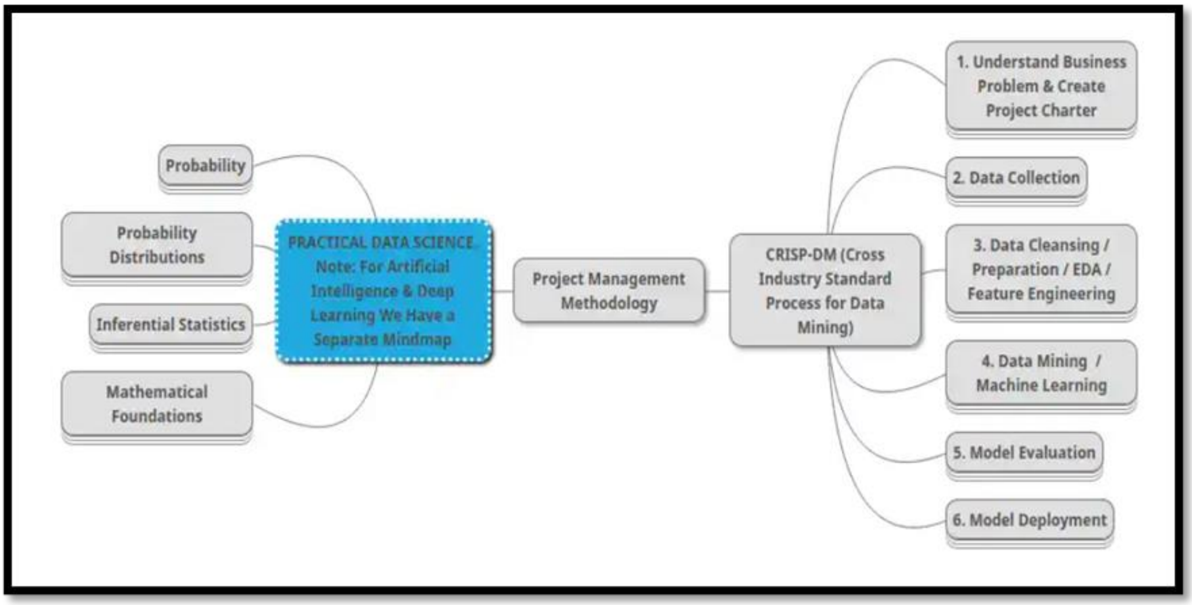

Fig. 1: The CRISP-ML(Q) Framework (Source: Mind Map - 360DigiTMG)

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II. METHODS AND METHODOLOGY

The system follows the CRISP-ML(Q) methodology, ensuring a structured approach to implementing and validating machine learning models for warehouse management. This methodology provides a robust framework for addressing business challenges by systematically analyzing, developing, and deploying machine learning solutions. Integrating real-time data visualization tools further enhances operational efficiency by enabling businesses to dynamically monitor inventory levels, optimize warehouse space utilization, and minimize errors in pallet tracking. Real-time analytics provide immediate insights into stock movements, demand patterns, and operational bottlenecks, allowing managers to make informed decisions quickly. These tools also support predictive analytics to forecast inventory needs accurately, reducing overstocking or stockouts. Additionally, visually engaging dashboards simplify complex data, offering clear performance metrics and actionable insights that improve communication across teams. By leveraging these technologies, businesses can achieve higher customer satisfaction through faster order processing and timely deliveries while optimizing costs and maintaining adaptability in an ever-evolving market landscape.warehouse managers can dynamically track pallet counts, reducing human error and improving inventory accuracy.""The pallet counting workflow follows a structured **machine learning process**, beginning with **data acquisition** from multiple sources, such as warehouse surveillance footage and IoT-based sensors.

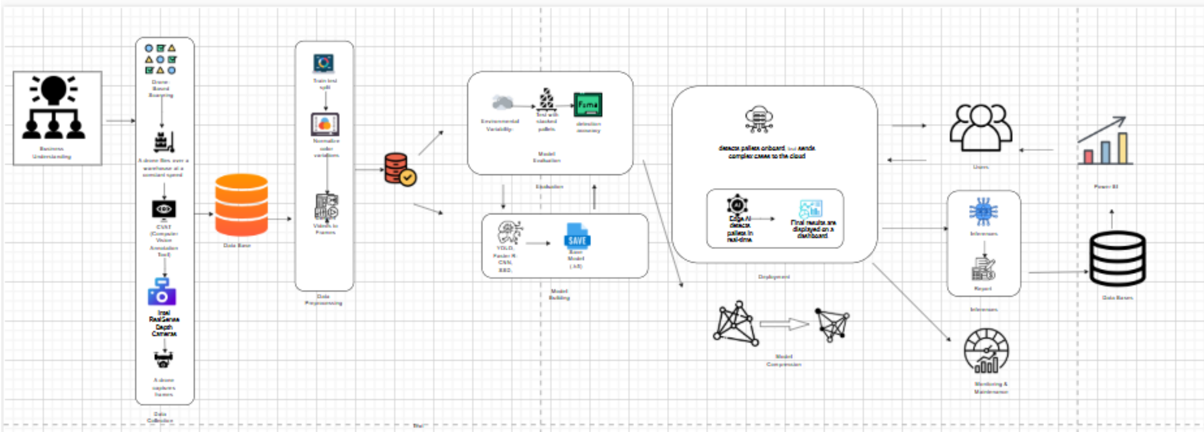

Fig 2 Architecture Diagram Showing the Flow of the Entire Project with Detailed Information (Source: Https://360digitmg.Com/Ml-Workflow)

The diagram presents an automated pallet detection workflow designed for warehouse environments. The process initiates with a clear understanding of business needs, followed by data collection using drones equipped with computer vision tools and RealSense depth cameras to capture images and videos. This data is then preprocessed through steps like train-test splitting, normalization, and video-to-frame conversion, before being stored in a central database. Model building involves the use of pre-trained models like Faster R-CNN, YOLO, and SSD, with the selected model saved for deployment. Model evaluation assesses detection accuracy and robustness under varying environmental conditions and with stacked pallets. The deployment phase employs edge AI for real-time detection and cloud integration for complex cases. Finally, the system provides inferences and reports to users through a user interface, leveraging Power BI for data visualization and continuous monitoring for maintenance, enhancing inventory management and overall operational efficiency.

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III. DATACOLLECTION

The pallet counting workflow follows a structured approach to enhance inventory tracking accuracy and warehouse efficiency. The process begins with **data collection**, where a drone equipped with high-resolution cameras flies over the warehouse at a constant speed, capturing images and videos of stored pallets. These raw visual data inputs are then **stored in a centralized database**, where they undergo preprocessing. The **data preprocessing phase** involves normalizing variations in lighting, angles, and environmental conditions to ensure consistent frame quality. Subsequently, the data is split into training and testing sets, allowing the machine learning model to learn from real-world warehouse conditions.

The model building phase employs advanced deep learning techniques, such as **YOLO (You Only Look Once), Faster R-CNN, and SSD**, to accurately detect and count pallets from unstructured visual data. Once trained, the model is evaluated based on detection accuracy, ensuring that environmental variations and occlusions do not affect performance. After validation, the optimized model is **compressed and deployed** in an edge-computing environment, allowing real-time pallet detection with minimal latency. The system autonomously detects and counts pallets while sending complex cases to the cloud for further processing. A user-friendly **dashboard interface** provides warehouse managers with real-time visualization of pallet counts, discrepancies, and inventory movements, enabling better decision-making. The final results are **integrated with business intelligence tools like Power BI**, allowing organizations to generate detailed reports, monitor trends, and optimize inventory levels. Continuous monitoring and maintenance ensure that the system remains robust and adaptable to dynamic warehouse environments, reducing errors, minimizing manual intervention, and improving overall operational efficiency.

DATA PREPROCESSING

Data preprocessing is a crucial step in ensuring the accuracy and efficiency of the pallet counting system, as it prepares raw, unstructured data for model training and real-time detection. Since pallet images and video feeds are captured in dynamic warehouse environments, preprocessing techniques are applied to enhance image quality, remove noise, and optimize data for deep learning models.

Image and Video Frame Extraction – The raw data consists of continuous video feeds or static images from **warehouse surveillance cameras, drones, and IoT-enabled scanners**. To process this efficiently, the system extracts relevant frames at set intervals to capture pallet positioning and movement.

Noise Reduction and Background Subtraction – Images often contain irrelevant details, such as **shadows, reflections, overlapping objects, and varying lighting conditions**, which may interfere with accurate detection. Techniques such as **Gaussian filtering, histogram equalization, and background subtraction** are applied to minimize noise and enhance contrast.

Object Annotation and Labeling – For the machine learning model to differentiate pallets from other warehouse objects, labeled datasets are essential. Manual and automated annotation tools assign bounding boxes around pallets in the images, ensuring precise labeling of training data.

Data Augmentation for Improved Accuracy – To enhance model generalization and robustness, data augmentation techniques are implemented. These include **image rotation, flipping, scaling, contrast adjustments, and synthetic noise addition** to ensure the model performs well under various environmental conditions.

Feature Extraction and Edge Detection – Advanced **computer vision techniques, such as Sobel filters, Canny edge detection, and contour detection**, are used to extract defining characteristics of pallets, including their shape, edges, and stacking patterns.

Normalization and Standardization – To ensure consistent model input, pixel values are normalized between 0 and 1, preventing bias due to varying image brightness or color scales. Additionally,standardization ensures uniform dimensions across different dataset images.

Splitting Data for Model Training and Evaluation – The preprocessed dataset is divided into **training, validation, and test sets**. The **training set** helps the model learn, the **validation set** fine-tunes hyperparameters, and the **test set** evaluates final accuracy and real-world applicability.

By implementing these preprocessing steps, the pallet counting system ensures that the deep learning model operates with high precision, adapting to real-world warehouse conditions while reducing errors in pallet detection and inventory tracking.

Machine Learning Workflow

collection is performed by obtaining images and video streams from various sources, such as warehouse monitoring systems, Internet of Things (IoT) devices, and automated scanning equipment. The gathered data undergoes preprocessing steps to enhance its quality and promote better model performance, which includes tasks such as noise reduction, background elimination, edge recognition, and feature extraction.

Following this, feature engineering techniques are employed to pinpoint key visual attributes, like pallet size, stacking arrangements, and the gaps between pallets. These optimized datasets are then utilized to train a YOLO-based deep learning model, enabling the system to precisely identify and count pallets in diverse and active warehouse settings. Post-training, the model is subjected to thorough testing and validation to assess its performance, ensuring it achieves the required accuracy levels and maintains adaptability across various lighting conditions, viewing angles, and warehouse configurations.

Upon successful validation, the model is implemented within a real-time monitoring setup, which integrates with a dashboard interface, enabling warehouse managers to observe up-to-the-minute pallet tallies and track inventory movement patterns. This automation negates the necessity for manual counting, drastically minimizing errors, accelerating response times, and improving the quality of operational decision-making

Annotation

Annotation is a critical step in the development of machine learning models for pallet detection. It involves labeling datasets to provide the model with ground truth information, enabling it to learn and identify objects accurately. For pallet detection, annotation typically includes marking bounding boxes, segmenting specific regions, or identifying key points such as pallet edges or corners. In scenarios where real-world data is used, manual annotation can be time-consuming and costly, especially when dealing with densely stacked pallets or complex warehouse scenes. To address this, synthetic data generation has emerged as a powerful alternative. By using tools like NVIDIA's SimReady Assets and USD Scene Construction Utilities, developers can create annotated datasets from simulated environments, reducing the need for manual effort while ensuring diverse and high-quality training data. This approach allows for iterative improvements in the dataset by addressing model failure cases, such as biases towards specific pallet shapes or color

Automation

Automation streamlines the entire workflow of pallet detection, from data collection to real-time inference. By leveraging synthetic data and advanced machine learning models like YOLO or ResNet-based architectures, the process of detecting and counting pallets becomes highly efficient and scalable. Automated systems utilize tools such as drones, IoT sensors, and cameras to capture data in warehouses without human intervention. Pretrained models can then perform tasks like semantic segmentation, object detection, and key point regression to identify pallets and their attributes in real time. Integration with edge computing devices like NVIDIA Jetson AGX Orin enables these models to run efficiently at the edge, providing instant results for warehouse operations. Automation not only eliminates manual counting but also reduces errors, improves accuracy in challenging scenarios (e.g., occluded or damaged pallets), and enhances operational decision-making through real-time monitoring dashboards

Model Building

The process of building a model for pallet counting using YOLO and Roboflow involves several key steps to ensure accuracy, efficiency, and adaptability in warehouse environments. First, data collection is performed by capturing images and videos from warehouse surveillance systems, IoT sensors, or automated scanning devices. These datasets are then uploaded to Roboflow, where annotation tools are used to label pallets in the images, defining bounding boxes and other relevant features. Roboflow's Autodistill-DETIC tool can be leveraged for automatic labeling to accelerate the annotation process.

Once annotated, the data is preprocessed using techniques such as normalization, augmentation, and noise reduction to enhance its quality and diversity. The YOLO architecture, specifically YOLOv8 or YOLOv10, is selected for its real-time detection capabilities and high accuracy in identifying objects within complex environments. Pre-trained weights from Roboflow's Logistics Model can be used as a starting point,

MODEL SELECTION

Significantly reducing training time while improving performance on domain-specific tasks like pallet detection.

The model is then fine-tuned using transfer learning on warehouse-specific datasets hosted on Roboflow Universe. Hyperparameters such as confidence threshold, non-max suppression, and anchor box configurations are optimized during training to improve detection accuracy. Rigorous testing and validation follow the training phase, assessing metrics like Mean Average Precision (mAP) and ensuring robustness under varying conditions such as lighting changes or occlusions.

Finally, the trained model is deployed in a real-time monitoring system integrated with dashboards for live pallet counting. Tools like ByteTrack can be used for object tracking, while Roboflow's Supervision library facilitates counting operations14. This automated solution eliminates manual counting efforts, reduces errors, and provides warehouse managers with actionable insights into inventory trends and movement patterns.

The YOLO (You Only Look Once) model is chosen for its exceptional ability to process unstructured data and deliver high-speed, real-time object detection. This makes it particularly suitable for dynamic warehouse environments where pallets may appear in various orientations, lighting conditions, and stacking configurations. The model's architecture is optimized by fine-tuning key hyperparameters such as the confidence threshold, non-max suppression, and anchor box dimensions to enhance detection accuracy and minimize false positives.Additionally, transfer learning is employed to adapt the pre-trained YOLOmodelwarehouse-specific datasets. This approach leverages existing knowledge from large-scale datasets while refining the model's performance for detecting pallets in real-world scenarios. Warehouse-specific data is collected through video cameras or IoT sensors, and annotated using tools like Roboflow to ensure high-quality training inputs. Techniques such as unique subsampling are applied to reduce dataset size while maintaining diversity, improving computational efficiency without compromising accuracy.

The fine-tuned model undergoes rigorous testing and validation to ensure it meets predefined performance benchmarks, such as achieving over 90% precision and 70% recall with an Intersection over Union (IoU) threshold of 0.5. Once validated, the YOLO model is deployed in real-time pallet counting systems integrated with dashboards for live monitoring. This automation significantly reduces manual effort, improves inventory accuracy, and enhances operational decision-making within warehouses

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MODEL DEPLOYMENT

The YOLO model is deployed using Streamlit, a versatile and intuitive framework for building interactive web applications, offering warehouse managers an efficient platform to monitor pallet counts and inventory in real time. This deployment provides live pallet detection from camera feeds, enabling the model to accurately identify pallets even under challenging conditions such as poor lighting or occlusions. The Streamlit application also includes interactive dashboards that display inventory trends and pallet movement patterns, allowing users to analyze past data and make strategic decisions

software and tools

Building a robust pallet counting deployment using the YOLO model requires careful integration of various tools and technologies to ensure efficiency, scalability, and accuracy. The deployment pipeline begins with model serving, where high-performance solutions like TensorFlow Serving or Triton Inference Server are utilized to manage inference tasks. These servers handle model versioning, batch requests, and resource optimization, enabling real-time processing of video streams. For video processing, OpenCV and FFmpeg play vital roles in handling frame extraction, preprocessing, and encoding/decoding operations. OpenCV's flexibility in image manipulation complements FFmpeg's robust multimedia capabilities, ensuring seamless video handling.regarding warehouse operations. Integration with cloud storage ensures seamless data processing and scalability, while supporting long-term data retention for advanced analytics. Additionally, the system calculates essential performance metrics such as precision, recall, and mean Average Precision (mAP), which are presented on the dashboard to evaluate the model's accuracy and reliability. By automating pallet counting and simplifying access to actionable insights, this deployment enhances operational efficiency, reduces errors, and combines cutting-edge machine learning technology with a user-friendly interface.The YOLO model is fine-tuned on warehouse-specific datasets to enhance detection accuracy under real-world conditions. Once trained, it is deployed using frameworks like Flask or Streamlit for easy accessibility. Streamlit provides an interactive interface where warehouse managers can upload images or videos or view live feeds for real-time pallet detection. Detection results are stored in reliable databases like PostgreSQL or cloud storage solutions such as AWS S3, ensuring secure and scalable data management. This data is then visualized through interactive dashboards using tools like Streamlit, Dash, or Grafana, providing actionable insights into inventory trends and pallet counts.

Streamlit:
Expanding on the Streamlined deployment for pallet counting, we can significantly enhance its functionality and user experience by incorporating several essential features. Firstly, implementing real-time video processing using Streamlit's st.image or st.video components will allow users to analyze live feeds from webcams or IP cameras, which is particularly beneficial in dynamic warehouse settings. Secondly, we can achieve interactive visualizations by integrating charting libraries like Plotly or Altair to display trends in pallet counts over time, providing valuable insights into inventory flow. Additionally, we can include customizable parameters in the Streamlined interface, such as confidence thresholds and object size filters, enabling users to fine-tune the model's performance according to specific warehouse conditions. Furthermore, implementing data export functionalities will allow users to download detection results in formats like CSV or JSON for further analysis or integration with other inventory management systems. To enhance user experience, it is crucial to incorporate error handling and feedback mechanisms that display clear messages in case of invalid inputs or processing errors. Lastly, adding user authentication and authorization features will ensure secure access in enterprise environments. Integrating with cloud storage services would further improve data persistence and accessibility. By incorporating these enhancements, we can create a more robust and user-friendly pallet counting application that meets the needs of modern warehouse operations.

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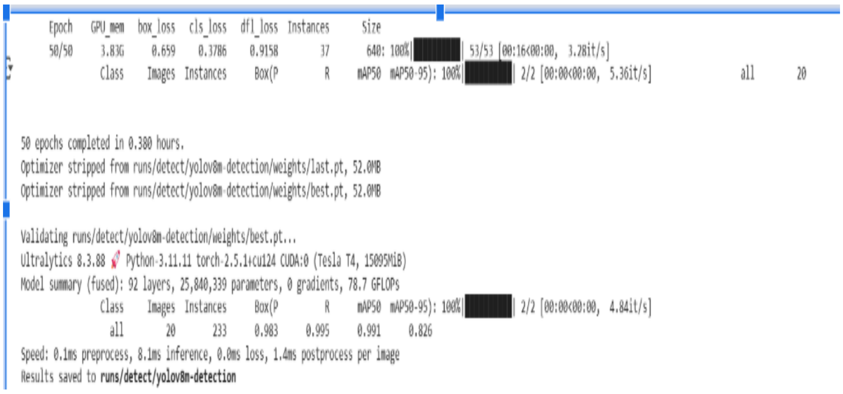
IV. RESULT AND DISCUSSION



```
      Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
      50/50      3.83G      0.659     0.3786     0.9158         37        640: 100%|██████████| 53/53 [00:16<00:00,  3.28it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 2/2 [00:00<00:00,  5.36it/s]        all         20

50 epochs completed in 0.380 hours.
Optimizer stripped from runs/detect/yolov8m-detection/weights/last.pt, 52.0MB
Optimizer stripped from runs/detect/yolov8m-detection/weights/best.pt, 52.0MB

Validating runs/detect/yolov8m-detection/weights/best.pt...
Ultralytics 8.3.88 🚀 Python-3.11.11 torch-2.5.1+cu124 CUDA:0 (Tesla T4, 15095MiB)
Model summary (fused): 92 layers, 25,840,339 parameters, 0 gradients, 78.7 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100%|██████████| 2/2 [00:00<00:00,  4.84it/s]
                   all         20        233      0.983      0.995      0.991      0.826
Speed: 0.1ms preprocess, 8.1ms inference, 0.0ms loss, 1.4ms postprocess per image
Results saved to runs/detect/yolov8m-detection
```

Fig3:Result

Results

The YOLOv8m model was trained for 50 epochs, completing in 0.380 hours. Validation results on a dataset of 20 images showed a high detection performance. The Box precision (Box(P)) reached 0.983, indicating accurate bounding box predictions. The Box recall (R) was 0.995, suggesting that the model identified nearly all pallets present in the images. The mean Average Precision at 50% Intersection over Union (mAP50) was 0.991, and the mean Average Precision between 50% and 95% IoU (mAP50-95) was 0.826. Inference speed was efficient, with the model achieving 8.1ms inference time per image

The YOLOv8m model achieved notable results in pallet detection after being trained for 50 epochs, a process taking 0.380 hours. Performance metrics reveal a strong capacity for accurate and reliable detection. The model's bounding box precision reached 0.983, indicating a low rate of false positive detections, while the bounding box recall was 0.995, demonstrating its ability to identify nearly all actual pallets present in the dataset. Furthermore, the model achieved a mean Average Precision (mAP) of 0.991 when evaluated at a 50% Intersection over Union (IoU) threshold, and 0.826 for mAP evaluated between 50% and 95% IoU, showcasing its robustness at stricter localization standards. With an average inference time of just 8.1 milliseconds per image, the model proves to be computationally efficient, making it suitable for real-time deployment scenarios requiring rapid processing

VI. CONCLUSION

This study introduces a data-driven solution for pallet counting that utilizes the YOLO object detection algorithm for processing unstructured data and employs the CRISP-ML(Q) methodology to ensure quality assurance throughout the machine learning lifecycle. By replacing traditional manual counting methods with automated detection, the system significantly improves inventory management by ensuring greater accuracy, reducing operational costs, and optimizing storage efficiency. The implementation of YOLO enables rapid and precise detection of pallets even in complex warehouse environments, addressing challenges such as occlusions and varying lighting conditions. Future research could focus on enhancing the robustness of the model by integrating IoT-based tracking systems for real-time pallet monitoring and location tracking. Additionally, incorporating robotic automation could enable autonomous navigation and handling of pallets within warehouses, further streamlining operations. These advancements would not only improve operational efficiency but also pave the way for a fully automated and intelligent warehouse management system.

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