ML-based YMS (Yard Management System) Automation: Can Technology Replace Human Labor?

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Introduction

The primary objective of this project is to explore the feasibility of automating Yard Management System (YMS) processes in a transportation company using machine learning (ML) technologies. We aim to assess if advanced AI and ML can fully replace human roles or significantly enhance efficiency in YMS tasks. Additionally, this research will examine the broader economic and societal impacts of such automation, considering how humans might adapt in a system where these technologies become integral. The first phase will involve empirically evaluating AI and ML's potential to optimize or support human tasks in YMS.

Main Technology

< YOLO (You Only Look Once) >

YOLO is a **real-time object detection algorithm** known for its speed and accuracy. It frames object detection as a single regression problem, predicting bounding boxes and class probabilities directly from full images in one evaluation. In our project, YOLO is used to quickly and accurately detect container numbers from video footage, streamlining the identification process at entry gates.

< AWS Textract >

AWS Textract is a machine learning service that **extracts text** and data from scanned documents and **images**. It goes beyond simple **OCR** by understanding the structure of documents, including forms and tables. In our project, Textract reads and interprets container numbers from images processed by YOLO, providing scalable and accurate OCR capabilities that enhance the efficiency of our logistics system.

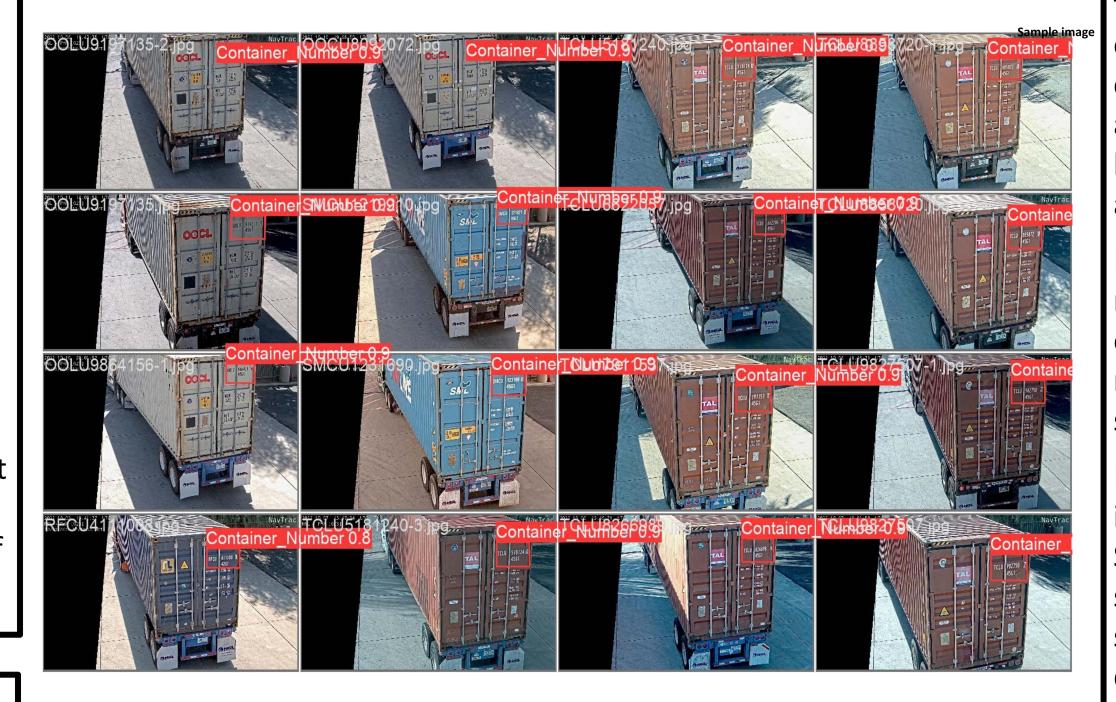
WorkFlow

- **Detection and Video Storage**: CCTV detects truck movement, saving video to a dated folder(YYYYMMDD).
- **Backend Processing**: Backend extracts images from video and uses YOLO to detect container number and size.
- **OCR and Data Extraction**: Sends images to AWS Textract for container number and size extraction.
- Data Storage and API Integration: Saves JSON results and images to S3.
- Frontend Integration: Frontend pulls data and images from S3 for display.

Model

The image demonstrates the performance of a trained model designed to recognize container numbers from CCTV footage. Developed with a dataset of 2,000 meticulously labeled images, this model accurately detects and extracts container numbers, significantly enhancing the system's efficiency and reliability. And through AWS Textract, we can get the exact container numbers.

Notably, the model precisely isolates and extracts the required information from the back of the container, demonstrating that the software can effectively replicate human visual perception in this context.



References

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- 2. OPTICAL CHARACTER RECOGNITION TECHNIQUE ALGORITHMS.
- 3. YOLOV: Making still image object detectors great at video object detection
- 4. A vision-based application for container detection in Ports 4.00
- 5. Ai city challenge 2020-computer vision for smart transportation applications
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- 7. Will AI Benefit or Harm Workers?
- 8. New Research May Calm some of the AI Job-loss Clamor-For Now

Future Implications and Challenges of Automation

The potential for AI, machine learning, and deep learning technologies to replace human jobs is substantial. However, achieving full automation requires significant capital investment, with numerous technical challenges and limitations to address. Our research demonstrates that specific tasks within a transportation company's Yard Management System (YMS) can be partially automated to reduce human intervention. For instance, using machine learning and AWS Textract for tasks such as identifying container numbers, plate numbers, and container size, we reduced manual processing time from 5-10 minutes to under 10 seconds, showcasing a significant efficiency advantage.

Nevertheless, several challenges remain. Beyond container identification, further validation is needed to assess container seals, driver credentials, chassis ownership, and other details. More complex decision-making tasks, such as container parking location, loading/unloading scheduling, and gate assignments, add additional layers of complexity, making full automation challenging. Only large corporations may have the resources to undertake such complete automation due to the high initial costs and ongoing experimentation required.

For AI to fully replace human roles, certain conditions are essential. Advanced robotics are needed for handling exceptions and problem-solving in physical environments. Human intervention is often required for issues such as camera malfunctions or data processing errors, so managing all scenarios solely through systems has its limitations.

Economic benefits from increased efficiency are evident, though substantial initial investments are required, with a potentially long ROI realization period. Smaller companies may find it difficult to justify such investments until AI-based solutions as a service (AI-as-a-service) become more accessible. Additionally, AI systems' error rates and reliability need improvement, particularly for critical data processing tasks, where human oversight remains necessary.

In considering automation, it is crucial to evaluate its ethical and societal impacts. While AI may displace certain jobs, it also creates opportunities for new roles. As the job market evolves, discussions on how humans and AI can coexist in the workplace are essential. In conclusion, while AI and machine learning may increasingly replace knowledge-based roles, total job displacement requires solving challenges like physical intervention and exception handling. Ultimately, a gradual shift in job roles is likely as AI adoption grows.



