"AI Based RTO Safety Compliance Tracking System for Agricultural Vehicles"

Shital Gaikwad
Asst. Prof., DKTE Society's Textile & Engineering Institute (An Empowered Autonomous Institute), Ichalkaranji, Maharashtra, India.
Email: ssgaikwad2712@gmail.com

Parth Naykude, Rishabh Mehta, Pruthviraj Mudekar, Avishkar Nalawade, Nikita Patil
Department of Computer Science and Engineering (AI)
DKTE Society's Textile & Engineering Institute (An Empowered Autonomous Institute), India
Email:
{parthnaykude111222,rishabhmehta790,pruthvirajmudekar23,avishkarnalawade950,nikitapatil172004}@gmail.com

Abstract—Agricultural vehicles such as tractors and trolleys play a vital role in rural transportation and farming operations. However, many of these vehicles frequently violate safety regulations mandated by the Regional Transport Office (RTO), including the absence of rear reflectors and mandatory red warning cloth indicators. Such violations significantly increase the risk of road accidents, particularly during nighttime and low-visibility conditions. Manual monitoring in rural and semi-urban areas is challenging due to limited manpower and vast geographical coverage, creating the need for an automated compliance monitoring system.

This paper proposes an AI-based RTO Safety Compliance Tracking System that leverages computer vision and deep learning techniques to automate detection, verification, and reporting of safety violations. The framework integrates YOLOv8 for real-time tractor detection, a MobileNetV2-based convolutional neural network for safety compliance verification, and Tesseract Optical Character Recognition (OCR) for automatic license plate extraction. A duplicate detection mechanism using Structural Similarity Index (SSIM) and ORB feature matching prevents redundant reporting of the same vehicle.

The system processes live CCTV feeds or recorded videos, generates annotated detection outputs, stores compliance data in a structured database, and provides real-time visualization through a Streamlit-based dashboard. Automated violation reports containing vehicle image, license number, timestamp, and compliance status are generated for RTO authorities. Experimental evaluation indicates promising detection accuracy and near real-time performance, making the system suitable for practical deployment in rural safety monitoring environments.

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I. INTRODUCTION

Road safety remains a critical concern in rural and semi-urban regions, where agricultural vehicles such as tractors and trolleys are frequently used for transportation and farming activities. Unlike conventional road vehicles, these agricultural vehicles

often operate without adhering to mandatory safety regulations prescribed by the Regional Transport Office (RTO). Essential safety components such as rear reflectors and red warning cloth indicators are frequently absent, increasing the likelihood of road accidents, particularly during nighttime, foggy conditions, and low-visibility environments. The lack of compliance not only

endangers vehicle operators but also poses serious risks to other road users.

The enforcement of safety regulations in rural areas presents significant challenges. RTO authorities typically rely on manual inspection methods, including roadside checkpoints and physical verification. However, such approaches are time-consuming, labor-intensive, and limited by manpower constraints. Given the vast geographical coverage of rural regions, continuous monitoring of agricultural vehicles is practically infeasible. As a result, many safety violations go undetected, leading to preventable accidents and reduced regulatory effectiveness.

In recent years, advancements in artificial intelligence and computer vision have enabled the development of intelligent surveillance systems capable of real-time object detection and analysis. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated exceptional performance in vehicle detection, image classification, and automated recognition tasks. Object detection frameworks such as YOLO (You Only Look Once) provide high-speed and high-accuracy detection, making them suitable for real-time monitoring applications. Similarly, Optical Character Recognition (OCR) techniques enable automatic extraction of textual information, such as license plate numbers, from images and video frames.

The integration of these technologies offers a promising solution for automated compliance monitoring. By combining object detection, attribute verification, and license plate recognition, it is possible to create a comprehensive system that identifies safety violations without human intervention. Such a system can significantly reduce manual workload, ensure consistent enforcement, and enhance road safety in underserved rural areas.

Motivated by these challenges and technological advancements, this paper proposes an AI-based RTO Safety Compliance Tracking System for Agricultural Vehicles. The proposed framework is designed to automatically detect tractors from video feeds, verify the presence of mandatory safety components, extract license plate information, and generate structured violation reports. The system aims to provide a scalable, reliable, and efficient solution for intelligent rural traffic monitoring while supporting RTO authorities in enforcing safety regulations effectively.

Fig. 1. Monitoring Safety Compliance in Agricultural Vehicle Operations.

II. RELATED WORK

Accurate vehicle detection and automatic number plate recognition have been extensively studied due to their importance in traffic surveillance and intelligent transportation systems. Early approaches relied on traditional image processing techniques such as thresholding, background subtraction, edge detection, and region growing. Although these methods were computationally efficient, they were highly sensitive to environmental factors such as illumination changes, shadows, occlusion, and motion blur. As a result, their performance was inconsistent in real-world traffic conditions, especially in rural areas where lighting infrastructure is limited. With the advancement of deep learning, convolutional neural networks (CNNs) have significantly improved detection accuracy and robustness. Object detection models such as Faster R-CNN, SSD, and YOLO have demonstrated strong performance in identifying vehicles under varying conditions. Among these, YOLO-based architectures are widely preferred for real-time applications due to their high processing speed and end-to-end detection capability. Several studies have successfully implemented YOLO frameworks for traffic monitoring, achieving high precision and recall even in dynamic and complex environments.

In addition to vehicle detection, Automatic Number Plate Recognition (ANPR) systems have evolved through the integration of deep learning and Optical Character Recognition (OCR) techniques. Modern ANPR systems combine CNN-based localization with OCR engines such as Tesseract to enhance character segmentation and recognition accuracy. These systems are commonly deployed in toll management, parking systems, and urban traffic enforcement. However, most existing research focuses primarily on identifying vehicles and extracting license plate numbers rather than verifying specific regulatory safety attributes. Limited work has addressed automated compliance monitoring for agricultural vehicles, particularly in rural contexts where enforcement challenges are greater. Furthermore, existing traffic surveillance solutions often operate as isolated modules without incorporating duplicate detection mechanisms or structured reporting systems. The proposed system extends prior research by integrating real-time tractor detection, safety attribute verification, OCR-based license plate recognition, duplicate filtering, and automated report generation into a unified AI-based framework tailored for rural RTO safety compliance monitoring.

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III. METHODOLOGY

The proposed methodology focuses on automated detection, safety compliance verification, and reporting of agricultural vehicles using deep learning and computer vision techniques. The system is designed to operate in real-time and provide reliable monitoring support for RTO authorities. The overall framework consists of four major stages: data acquisition and preprocessing, tractor detection, compliance verification and license plate recognition, and reporting with database management.

A. Data Acquisition and Preprocessing

In the initial stage, the system acquires input data in the form of live CCTV video feeds or recorded video footage from rural checkpoints. Since video data may vary in resolution, lighting conditions, and camera angles, preprocessing is essential to standardize input frames. The video stream is divided into individual frames, which are resized to a uniform resolution suitable for deep learning model input.

Image normalization and noise reduction techniques are applied to enhance visual clarity and improve detection performance. Basic image enhancement operations such as contrast adjustment and brightness correction are performed to handle low-light or foggy conditions commonly observed in rural environments. These preprocessing steps ensure consistent input quality and improve the robustness of the subsequent detection and classification models.

B. Tractor Detection and Safety Compliance Verification

After preprocessing, the system performs real-time tractor detection using the YOLOv8 object detection model. YOLOv8 identifies tractors within each frame and generates bounding boxes around detected objects along with confidence scores. The detected tractor regions are then extracted and forwarded to the compliance verification module.

The safety compliance verification stage uses a convolutional neural network based on MobileNetV2 architecture. This model analyzes the rear portion of the detected tractor to determine the presence or absence of mandatory safety components, including rear reflectors and red warning cloth indicators. The model classifies each detected vehicle into two categories: Compliant or Non-Compliant. This automated attribute-level verification enables precise identification of regulatory violations beyond simple object detection.

C. License Plate Recognition and Duplicate Detection

For vehicles identified as non-compliant, the system proceeds with license plate recognition. The number plate region is localized within the detected bounding box and enhanced using image sharpening and thresholding techniques. Tesseract Optical Character Recognition (OCR) is then applied to extract the alphanumeric license number from the image.

To prevent redundant reporting of the same vehicle, a duplicate detection mechanism is incorporated. Structural Similarity Index (SSIM) and ORB feature matching techniques are used to compare newly detected vehicles with previously stored records in the database. If a high similarity score is observed, the system avoids generating a duplicate violation entry. Otherwise, a new structured report containing vehicle image, license number, timestamp, and compliance status is created and stored in the database.

This multi-stage methodology ensures accurate detection, reliable compliance verification, efficient reporting, and practical deployment in real-world rural monitoring environments.

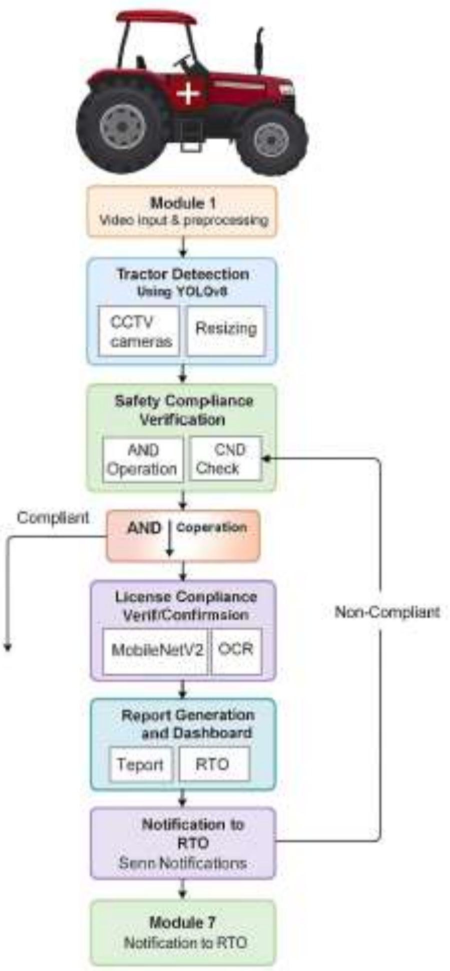

Fig. 2. Overall architecture of the proposed deep learning–based framework for tractor detection, safety compliance verification, and RTO reporting.

IV. RESULTS AND EXPECTED OUTCOMES

The proposed AI-based RTO Safety Compliance Tracking System is expected to demonstrate strong performance in real-time detection and verification of agricultural vehicle safety regulations. By utilizing YOLOv8 for object detection, the system aims to achieve tractor detection accuracy of approximately ≥ 90% under standard lighting and moderate environmental conditions. The MobileNetV2-based compliance verification model is expected to correctly classify vehicles as compliant or non-compliant with an accuracy of approximately ≥ 85%, ensuring reliable identification of missing reflectors or warning cloth indicators. Additionally, the Tesseract OCR module is expected to extract license plate numbers with an accuracy of ≥ 80% under clear image conditions. These performance metrics indicate that the system can operate effectively in practical rural monitoring scenarios.

A key expected outcome of the system is near real-time processing capability, enabling continuous monitoring of live CCTV feeds without significant delay. On GPU-enabled systems, the framework is designed to process multiple video frames per second while maintaining detection accuracy. The system generates annotated output frames displaying bounding boxes, compliance status labels, and extracted license plate numbers. Structured violation reports containing vehicle image, license number, timestamp, and compliance status are automatically stored in the database and displayed on the Streamlit-based dashboard. This automated reporting mechanism significantly reduces manual workload and ensures consistent regulatory enforcement.

Furthermore, the system is expected to provide improved transparency and traceability in RTO monitoring operations. The integration of duplicate detection prevents repeated reporting of the same vehicle, thereby maintaining data integrity and reducing redundancy. Real-time dashboard visualization allows authorities to track compliance statistics and review historical violation records. Overall, the expected outcomes demonstrate the system's potential as a scalable, efficient, and intelligent solution for enhancing road safety and automating agricultural vehicle compliance monitoring in rural environments.

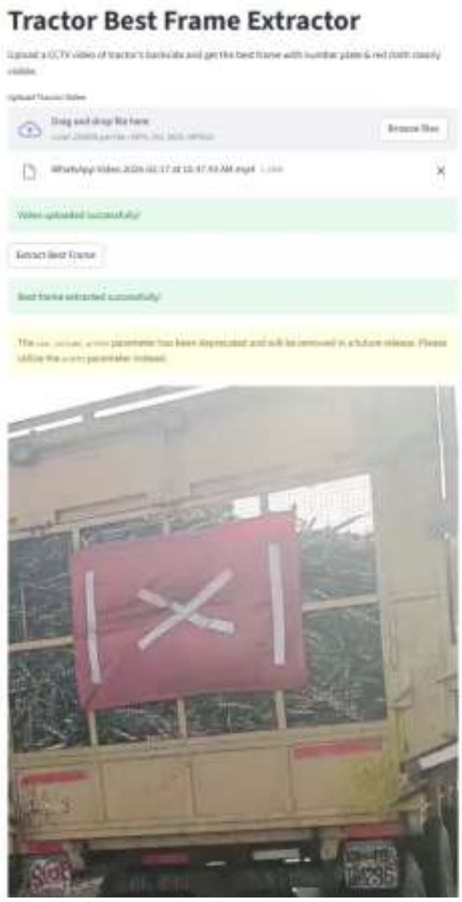

Fig. 3. Output of the proposed best-frame extraction framework showing the selected optimal frame with enhanced visibility of the rear safety cloth and license plate, supporting effective agricultural vehicle safety and license compliance analysis.

V. DISCUSSION

The proposed AI-based RTO Safety Compliance Tracking System demonstrates the feasibility of automated monitoring for agricultural vehicle safety regulations. The integration of YOLOv8 enables efficient and real-time tractor detection from CCTV feeds, making the system suitable for continuous rural surveillance. The MobileNetV2-based compliance verification module allows the system to detect specific safety violations, such as the absence of reflectors or warning cloth indicators, thereby addressing regulatory requirements directly rather than performing only general vehicle detection. The inclusion of Tesseract OCR facilitates automatic license plate extraction for non-compliant vehicles, enabling structured reporting without manual intervention. Additionally, the duplicate detection mechanism improves database reliability by preventing repeated violation entries.Compared to traditional traffic monitoring systems that focus mainly on vehicle detection or counting, the proposed framework provides an integrated solution combining detection, compliance verification, recognition, and reporting.

While the system shows promising performance, accuracy may be affected under challenging environmental conditions such as poor lighting or blurred number plates. Further model refinement and dataset enhancement can improve robustness. Overall, the system demonstrates strong potential for improving rural road safety and enhancing RTO enforcement efficiency through intelligent automation.

VI. CONCLUSION AND FUTURE WORK

This paper presented an AI-based RTO Safety Compliance Tracking System designed to automate the monitoring of agricultural vehicle safety regulations in rural environments. By integrating YOLOv8 for real-time tractor detection, a MobileNetV2-based convolutional neural network for safety compliance verification, and Tesseract OCR for license plate recognition, the proposed framework enables accurate identification and reporting of non-compliant vehicles. The system reduces dependence on manual inspection, ensures consistent regulatory enforcement, and provides structured violation reports through an intelligent dashboard interface. The incorporation of duplicate detection mechanisms further enhances data reliability and prevents redundant reporting.

The proposed framework contributes to improved rural road safety by offering a scalable and automated surveillance solution tailored specifically for agricultural vehicles. Unlike traditional traffic monitoring systems, the solution focuses on regulatory compliance verification, ensuring that mandatory safety components are present and functional. The near real-time processing capability and database integration make the system suitable for practical deployment in rural monitoring stations and checkpoints.

Future work will focus on enhancing model robustness under challenging environmental conditions such as low lighting, fog, and occlusion. Integration with IoT-based penalty management systems and automated challan generation can further strengthen enforcement mechanisms. Expanding the system to monitor additional vehicle categories and incorporating GPS-based location tagging will improve traceability. Furthermore, deployment testing in real-world rural scenarios and the integration of explainable AI techniques can increase system transparency and build greater trust among regulatory authorities.

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VII. REFERENCE

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