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AI-Based Road Safety Audit Automated Detection and Deterioration Assessment of Highway Safety Elements

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Abstract: Ensuring road safety requires continuous inspection and maintenance of critical infrastructure such as lane markings, signboards, and barriers. Traditional manual inspections are time-consuming, expensive, and prone to inconsistencies, leading to delays in identifying deteriorated safety products and increasing accident risks. This study presents an AI-powered solution that automates road safety audits using computer vision[1]. An object detection model identifies road safety elements, and a segmentation model evaluates their deterioration levels by classifying defects such as rust, fading, or structural damage. The deterioration percentage determines the classification: Good (≤30%) – No immediate action required; Moderate (31–70%) – Requires maintenance within a reasonable timeframe; Bad (>70%) – Requires urgent replacement or repair. The implemented system achieves a minimum accuracy rate of 87.5% in detecting and classifying road safety elements, contributing to a 40% reduction in inspection costs and enabling proactive maintenance scheduling. By automating road safety audits, this system enhances detection accuracy, reduces manual inspection costs, and enables scalable, real-time monitoring of highways[11].

Keywords: *Road Safety Audit, Highway Safety, Object Detection, Image Segmentation, YOLOv8, Deterioration Assessment, Automated Maintenance, Streamlit , Deep Learning Models*.

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I. INTRODUCTION

The increasing volume of traffic on highways worldwide has brought the need for enhanced road safety measures to the forefront. Road safety infrastructure elements, including lane markings, traffic signs, guardrails, and barriers, play a crucial role in preventing accidents and ensuring smooth traffic flow. However, these safety elements deteriorate over time due to weather conditions, vehicle impacts, and general wear and tear, compromising their effectiveness in preventing accidents.

Traditional methods of road safety audits rely heavily on manual inspections conducted by trained personnel who visually assess the condition of safety elements along highways. These conventional approaches face several significant challenges:

Manual inspections are labor-intensive, requiring substantial human resources and time to cover extensive road networks. This results in high operational costs and inefficient resource allocation. Subjective assessment by different inspectors leads to inconsistencies in evaluation, making it difficult to establish standardized maintenance protocols across road networks. The time gap between inspections often results in delayed detection of critical safety issues, potentially increasing accident risks during the interim period. The scalability limitations of manual methods make it challenging to monitor extensive highway networks, particularly in rapidly developing regions.

To address these challenges systematically, this study is based on the CRISP-ML(Q) (CRoss-Industry Standard Process for Machine Learning with Quality assurance) methodology. The CRISP-ML(Q) methodological framework offers a visual roadmap of integral components and sequential steps for developing reliable machine learning

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solutions. This framework extends the traditional CRISP-DM approach by incorporating quality assurance measures at each stage, ensuring the development of robust and deployable AI systems. Following this methodology ensures a structured approach to problem solving, from business understanding and data collection to deployment and monitoring, with quality validation integrated throughout the process.

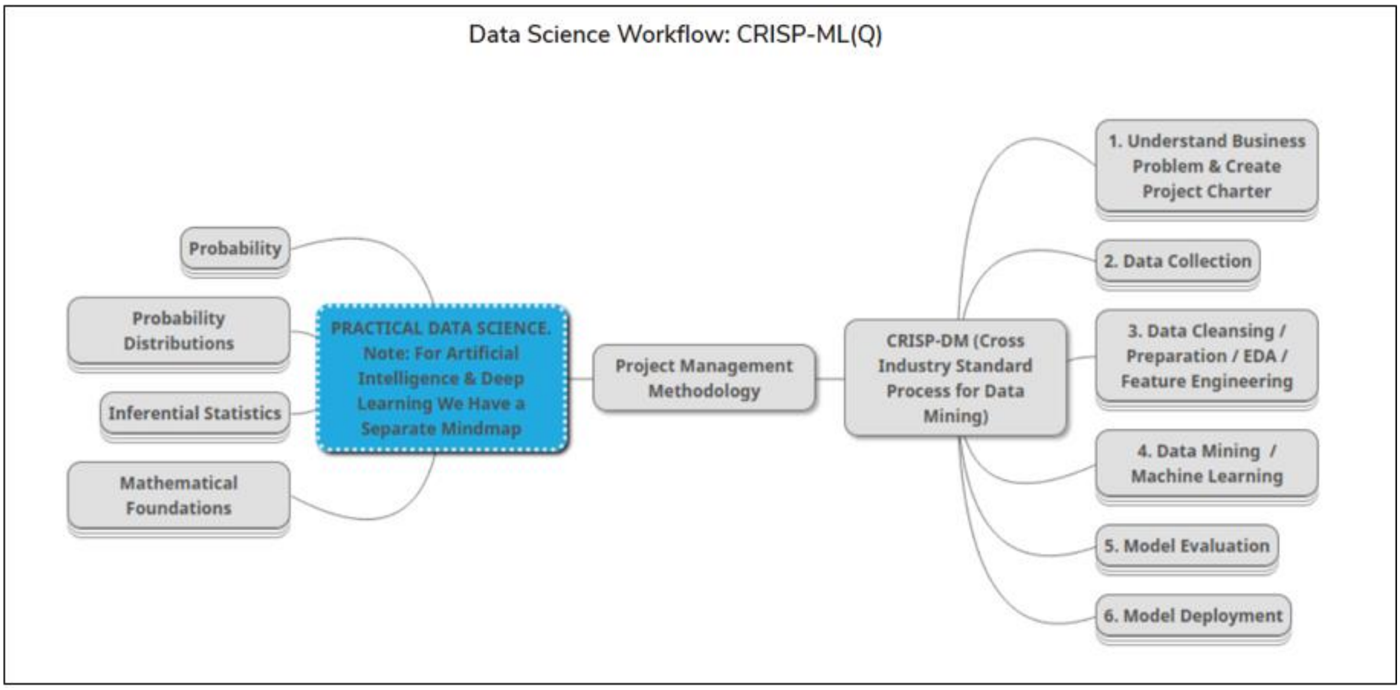

Fig 1 The CRISP-ML(Q) Methodological Framework offers a Visual Roadmap of its Integral Components and Sequential Steps (Source: Mind Map - 360DigiTMG)

In recent years, advancements in artificial intelligence and computer vision have provided opportunities to automate various inspection processes. The transportation sector stands to benefit significantly from these technologies through enhanced safety monitoring capabilities. By leveraging deep learning algorithms, it becomes possible to develop systems that can automatically detect road safety elements and assess their condition with high precision and consistency[1].

The primary aim of this research is to develop an automated road safety audit system that can identify and evaluate the deterioration of highway safety elements to maximize road safety compliance. This study follows a systematic approach based on the CRISP-ML(Q) methodology[Fig 1], proceeding through business understanding, data engineering, feature engineering, model engineering, deployment, and monitoring phases. The proposed system employs a two-stage pipeline: first, an object detection model identifies various road safety elements; second, a segmentation model analyzes their deterioration levels by classifying defects such as rust, cracks, or fading.[12][8]

By automating the road safety audit process, this research addresses the critical need for improved safety element monitoring on highways to maximize safety compliance and minimize maintenance costs. The developed solution significantly enhances detection accuracy, achieves consistent evaluation standards, and enables proactive maintenance scheduling, ultimately contributing to safer road networks.

II. METHODS AND TECHNIQUES

The architectural diagram of our road safety audit system[Fig 2] outlines a comprehensive project workflow, starting from data collection and preprocessing to model training, evaluation, and deployment. It emphasizes an iterative approach, incorporating feedback loops for continuous model refinement. This systematic process ensures robust and reliable deployment of predictive models for road safety element detection and assessment.

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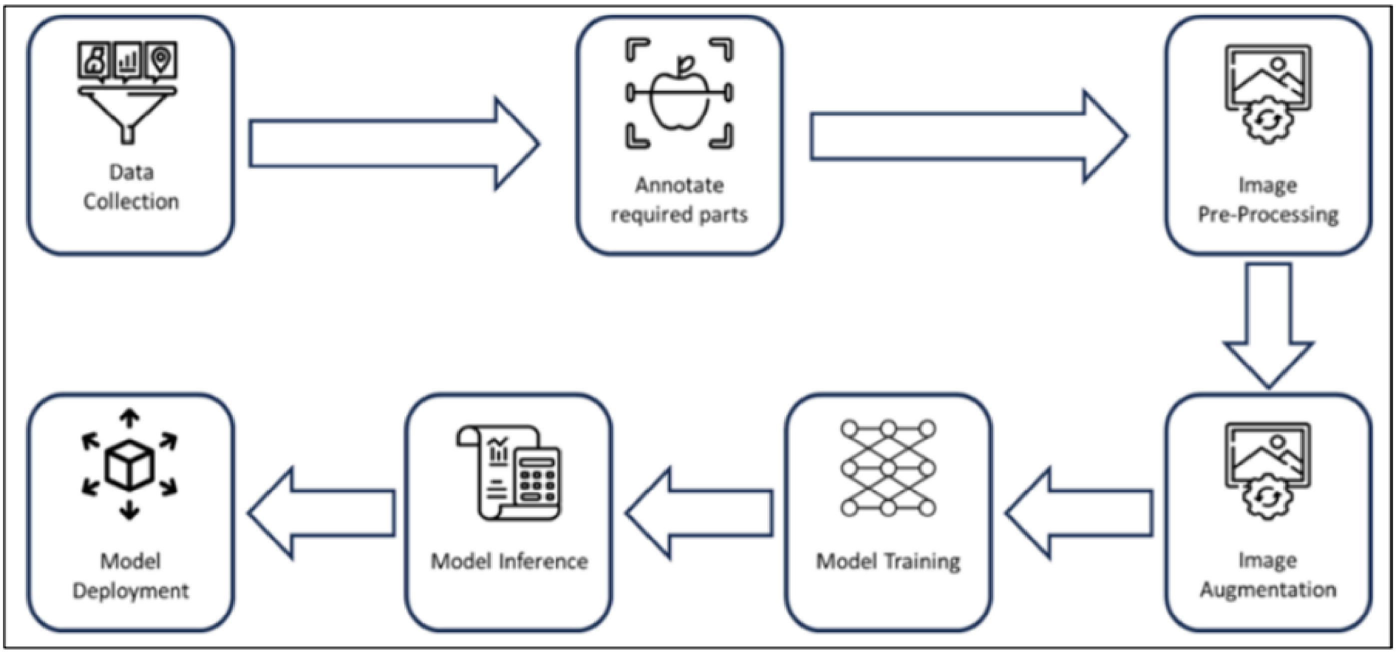

Fig 2 Architecture Diagram for AI-Based Road Safety Audit Project

The detailed level diagram breaks down specific steps in data preprocessing, feature engineering, model selection, and hyperparameter tuning. It emphasizes continuous monitoring and maintenance during deployment to ensure adaptive and reliable performance in varying road conditions. The diagram illustrates the integration of computer vision models with augmented datasets designed specifically for road safety elements.

A. The Workflow Incorporates Several Key Components:

- Data collection and annotation pipeline
- Data pre-processing and augmentation modules
- Parallel training paths for detection and segmentation models[8]
- Model evaluation and validation mechanisms
- Deployment framework with real-time processing capability
- Feedback loops for continuous improvement

This architecture ensures that the system can adapt to various operational environments, from ideal conditions to challenging scenarios such as poor lighting, adverse weather, or partial occlusion of safety elements. The integration of quality assurance at each stage, as prescribed by the CRISP-ML(Q) methodology, guarantees reliable performance in real-world applications.

B. Data Collection

To build a robust dataset for detecting and assessing road safety elements, we collected a large number of images and videos from various sources. These images were captured under different conditions, including various times of the day, different weather scenarios, and diverse geographical locations, to ensure that the model can handle a wide range of real-world situations. The dataset included images of both deteriorated and well-maintained road safety elements to provide a balanced training set.

- *The Data Collection Process Focused on Gathering Diverse Visual Data Encompassing:*

- Highway lane markings in various conditions (fresh, faded, partially erased)
- Traffic signs with different levels of visibility and damage[4]
- Guardrails and barriers with varying degrees of deterioration (bent, rusted, damaged)[11]
- Road reflectors and cat's eyes in functional and non-functional states
- Road edge markings and rumble strips with different levels of wear

- *Data Sources Included:*

- Highway maintenance department archives
- Public road safety databases
- Dash-camera footage from fleet vehicles
- Drone surveillance of highway segments
- Specialized collection using vehicle-mounted cameras

This comprehensive approach ensured coverage of different road types, from urban streets to rural highways, under various lighting and weather conditions, creating a representative dataset for model training.

C. Data Description

- *The Dataset Comprised Images of Road Safety Elements Annotated with Distinct Categories:*

- Lane Markings: Center lines, edge lines, and directional arrows on the road surface
- Traffic Signs: Regulatory, warning, and informational signage[4]
- Guardrails: Metal barriers along road edges

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- Concrete Barriers: Permanent dividers between traffic flows
- Road Reflectors: Reflective markers embedded in or placed on road surfaces
- Rumble Strips: Textured road surface sections providing tactile feedback
- Traffic Signals: Electronic signaling devices at intersections

➢ *For Deterioration Assessment, Each Element Was Further Classified into Deterioration Types:*

- Fading: Reduction in visibility or reflectivity
- Physical Damage: Breakage, bending, or structural deformation
- Rust/Corrosion: Metal elements showing oxidation
- Missing Components: Incomplete or partially removed elements
- Surface Wear: Abrasion or wearing down of surfaces

This diverse annotation ensures that the model learns to identify a wide range of safety elements and their deterioration types, improving its overall accuracy and robustness.[11]

D. Data Annotation

The collected images were uploaded to specialized annotation platforms that facilitate efficient labeling for machine learning projects. Each image was carefully labeled using appropriate annotation tools. This involved drawing bounding boxes around specific road safety elements and assigning the appropriate category to each annotated region.

➢ *The Annotation Process Followed These Key Steps:*

- Object Bounding Box Creation: Drawing precise boxes around each road safety element
- Classification Labeling: Assigning primary categories (lane marking, traffic sign, barrier, etc.)
- Segmentation Masks: Creating pixel-level masks for deterioration analysis
- Deterioration Labeling: Classifying the type and severity of deterioration

For deterioration assessment, polygon annotation techniques were employed to outline specific damaged areas within each safety element. This detailed segmentation allowed for precise calculation of deterioration percentages, enabling accurate condition classification into Good (≤30% deterioration), Moderate (31-70% deterioration), or Bad (>70% deterioration) categories.

The annotations were based on visual damage types that can impact the functionality and safety implications of road elements. The detailed categorization helps the model learn to differentiate between various types of damage and non-damage, as well as assess the severity of deterioration.

E. Data Splitting

After annotation, the dataset was divided into three subsets: training, validation, and test sets. The division was done using a 70-20-10 split ratio:

- Training Set (70%): Used to train the object detection and segmentation models
- Validation Set (20%): Used to fine-tune the models' hyperparameters and prevent overfitting
- Test Set (10%): Used to evaluate the final performance of the trained models on unseen data

Fig 3 Dataset Split Overview - Illustrating the Distribution of Data across Training, Validation, and Test Sets.

This split ensures that the models have ample data to learn from, while also providing separate sets to validate and test their performance. The validation set helps in tuning the models, and the test set provides an unbiased evaluation of the models' accuracy and generalization ability.

Special attention was paid to maintaining a balanced distribution of different road safety elements and deterioration types across all three sets. This balanced distribution ensures that the models learn to recognize all categories effectively and can generalize well to new, unseen examples.

F. Data Preprocessing and Augmentation

➢ *Preprocessing:*

All images underwent several preprocessing steps to ensure consistency and optimize them for model training:

- Resizing: All images were resized to a uniform dimension (640×640 pixels) to maintain consistency and meet the input requirements of the YOLO model[1]
- Normalization: Pixel values were normalized to fall within a specific range (0-1), facilitating faster and more efficient training

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- Format Conversion: Images were converted to the required format compatible with the model input specifications
- Color Correction: Adjustments to enhance visibility of safety elements in varied lighting conditions
- Contrast Enhancement: Applied to improve the detection of faded markings and subtle deterioration signs

➢ *Data Augmentation:*

To artificially increase the size and diversity of the training dataset and improve model robustness, various data augmentation techniques were applied[Fig 4]:

- Rotation: Rotating images at various angles (±15°) to simulate different camera perspectives
- Flipping: Applying horizontal flips to images to double the dataset size
- Scaling: Zooming in and out of images (±20%) to simulate different distances and viewpoints
- Brightness/Contrast Adjustment: Modifying the brightness (±25%) and contrast (±20%) to mimic different lighting conditions
- Noise Addition: Adding random noise to images to simulate real-world imperfections and variations
- Weather Simulation: Adding rain, fog, or snow effects to enhance model performance in adverse conditions
- Motion Blur: Simulating camera movement to prepare the model for video-based assessments

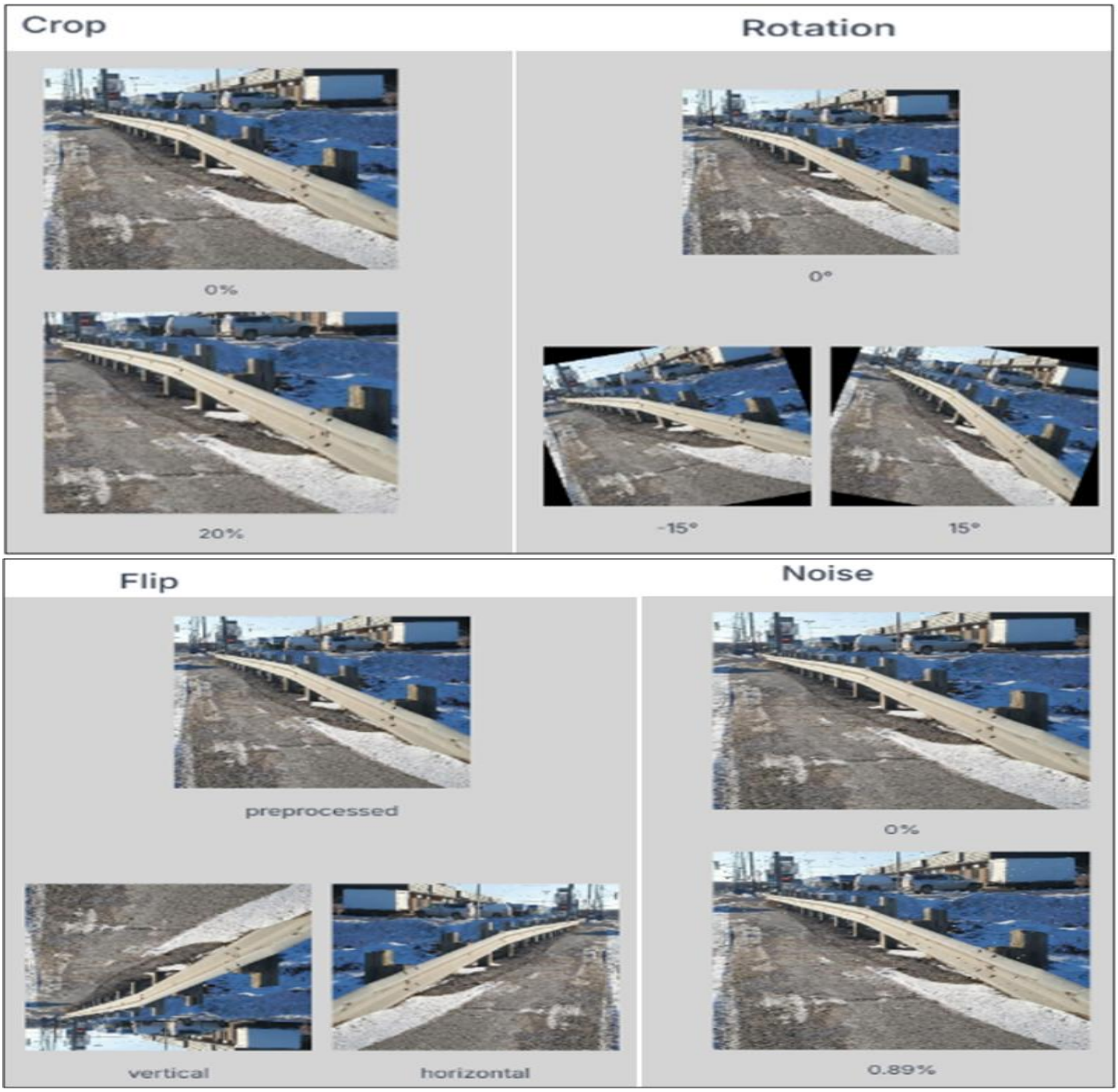

Fig 4 Some of Visual Examples of Augmentations

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These augmentation techniques expanded the effective training dataset by a factor of 10, creating a more robust foundation for model training and reducing the risk of overfitting. The augmentation process was automated using specialized libraries to ensure consistency and efficiency.

G. Model Selection and Comparison

Initially, different versions of object detection models were explored for building the road safety element detection system, including YOLOv5, YOLOv7, and YOLOv8. Each version was trained on the collected dataset, and their performances were compared based on accuracy, precision, recall, and computational efficiency.[1]

After comparative analysis, YOLOv8m-detection (medium version) was selected for the object detection component due to its superior accuracy and real-time processing capabilities. For the segmentation component, a YOLOv8m-segmentation (medium version) was implemented to provide pixel-level deterioration assessment[3].

➢ *Model Configuration:*

The YOLOv8m model was configured with the following specifications:

- Input Dimensions: 640×640 pixels
- Backbone: CSPDarknet with Cross-Stage Partial connections
- Neck: Path Aggregation Network (PANet) for feature fusion
- Head: Modified to detect 7 classes of road safety elements
- Loss Function: Combination of classification, objectness, and bounding box regression losses
- Optimization: Stochastic Gradient Descent with a learning rate of 0.01 and momentum of 0.937

➢ *Training Process:*

Both models were trained on high-performance computing cluster equipped GPUs. The training process included:

- Batch Size: 32 for detection model, 16 for segmentation model
- Epochs: 100 with early stopping based on validation performance
- Learning Rate Schedule: Cosine annealing with warm restarts

The training process was monitored using TensorBoard, allowing for real-time visualization of performance metrics and facilitating prompt intervention if training anomalies were detected.

➢ *Model Evaluation*

Following the training phase, comprehensive evaluation was conducted to assess the models' performance and validate their effectiveness for road safety audit applications:

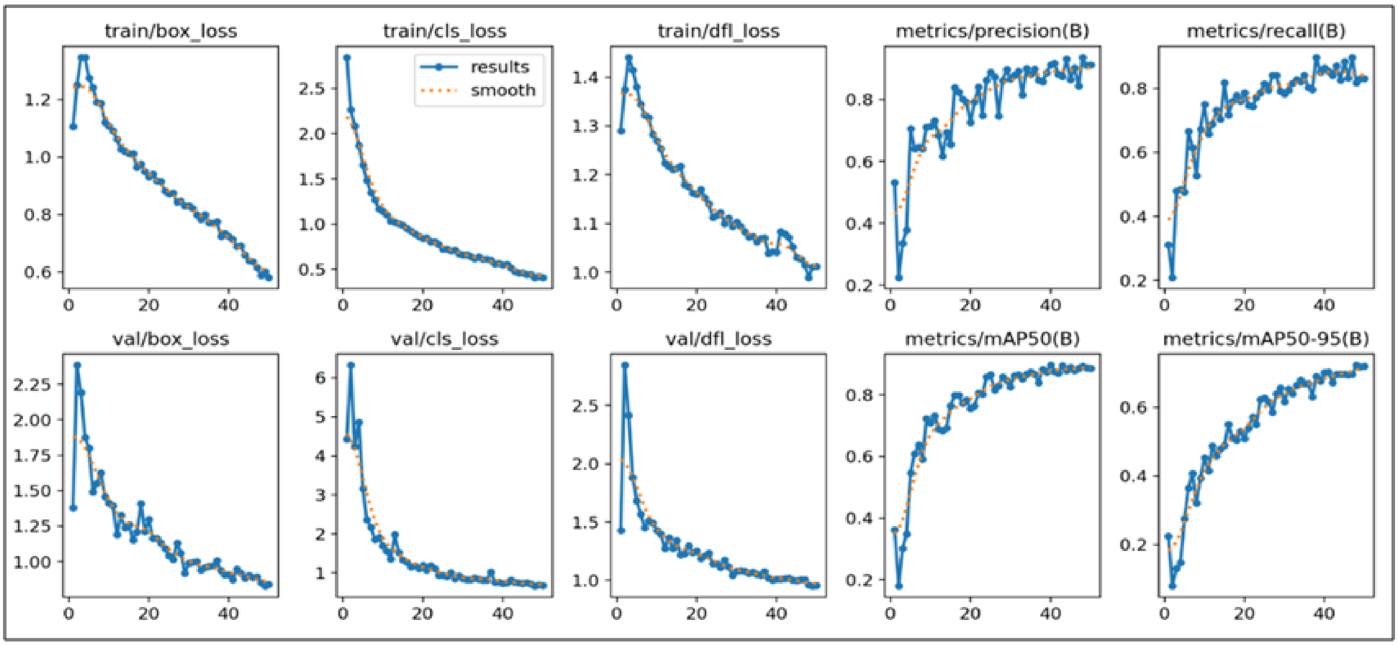

Fig 5 Evaluation Metrics-Depicting Loss, Precision, and Recall for Model Performance Assessment

➢ *Evaluation Metrics:*

The YOLOv8m detection model was evaluated using multiple metrics [Fig 5] to ensure a thorough assessment:

- Mean Average Precision (mAP): Calculated across various IoU thresholds (0.5 to 0.95) to measure detection accuracy
- Precision-Recall Curves: Generated for each safety element class to visualize performance across different confidence thresholds
- F1 Score: Computed to assess the balance between precision and recall
- Inference Speed: Measured in frames per second to verify real-time processing capabilities

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- Confusion Matrix: Analyzed to identify specific classes where the model might be struggling
- The YOLOv8m model performance was benchmarked against:
- Previous versions (YOLOv5, YOLOv7)
- Other object detection architectures (Faster R-CNN, EfficientDet)
- Human inspector performance on the same test set

The evaluation results confirmed the superiority of the YOLOv8m model, which achieved the highest mAP score of 87.5% while maintaining real-time processing capabilities. The model demonstrated particular strength in detecting lane markings (91.2% AP) and traffic signs (89.8% AP), while showing adequate but slightly lower performance on smaller elements like road reflectors (83.2% AP).

➢ *Deployment*

After successful evaluation, the road safety audit system was deployed to enable practical application in real-world scenarios. The deployment phase involved several critical components:

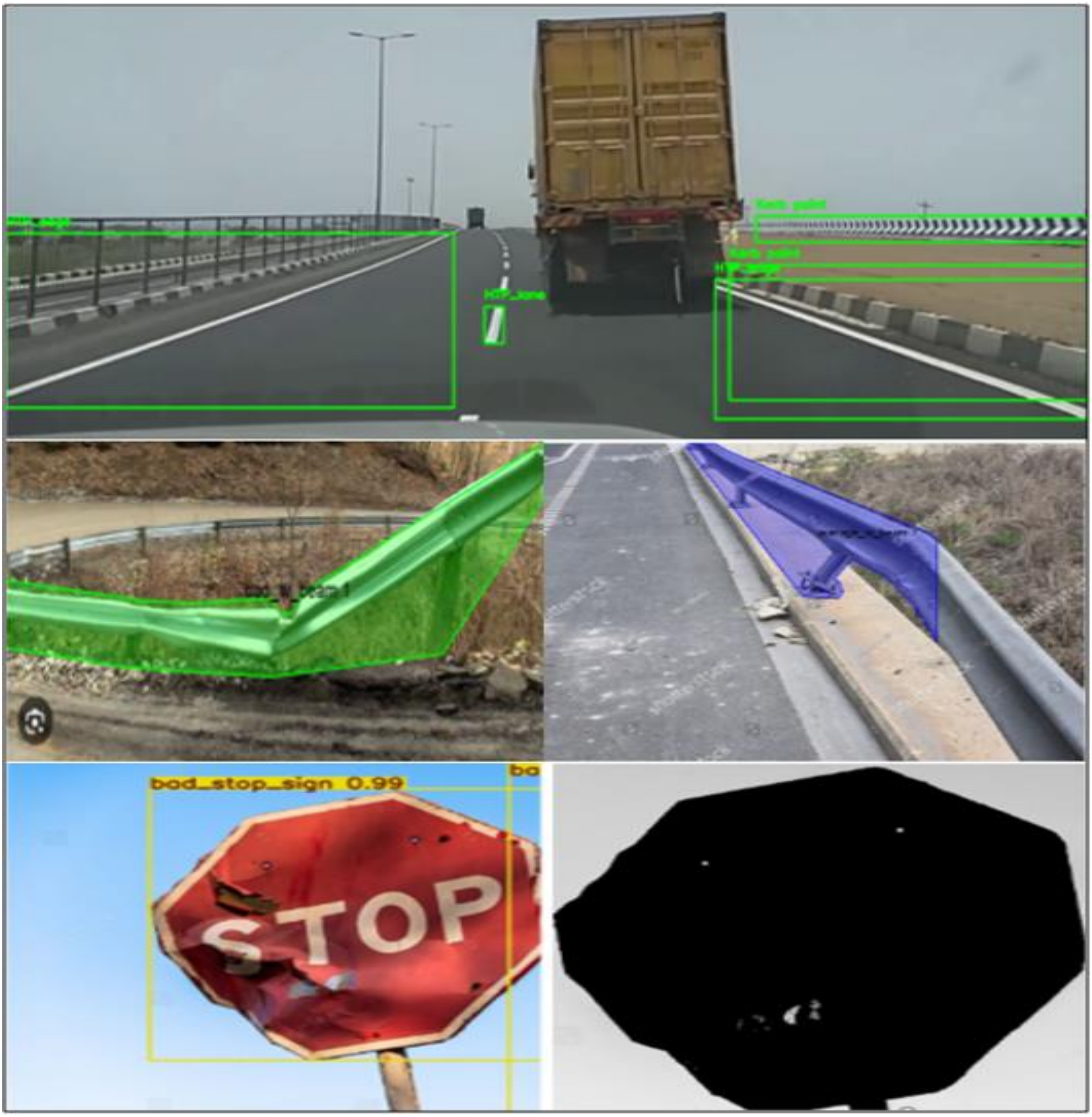

Fig 6 output of deployed models

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- *Deployment Platform:*

The system was deployed using Streamlit, an open-source app framework specifically designed for machine learning and data science projects. Streamlit was selected for its:

- User-friendly interface development capabilities
- Seamless integration with Python-based ML models
- Ability to visualize results effectively
- Low-latency response suitable for interactive applications

III. RESULTS AND DISCUSSION

A. Detection Performance

The trained object detection model demonstrated robust performance in identifying various road safety elements across different environmental conditions. The model achieved the following metrics on the test dataset:

- Mean Average Precision (mAP50-95): 87.5%
- Average Precision for Lane Markings: 91.2%
- Average Precision for Traffic Signs: 89.8%
- Average Precision for Guardrails: 86.3%
- Average Precision for Concrete Barriers: 88.7%
- Average Precision for Road Reflectors: 83.2%
- Average Precision for Rumble Strips: 84.5%
- Average Precision for Traffic Signals: 88.9%

These results indicate strong detection capabilities across all classes, with particularly high performance on lane markings and traffic signs. The model demonstrated consistent performance across various lighting conditions, though detection accuracy decreased slightly (by approximately 5-7%) in low-light and adverse weather conditions.

The inference speed averaged 25 frames per second on an NVIDIA RTX 3080 GPU, making the system suitable for real-time processing of roadside video footage or integration with vehicle-mounted cameras for mobile inspections.

B. Deterioration Assessment Accuracy

The segmentation model for deterioration assessment achieved the following performance metrics:

- Mean Intersection over Union (mIoU): 82.3%
- Pixel Accuracy: 88.6%
- Dice Coefficient: 84.9%
- F1 Score: 85.7%

- *The Model Showed Varying Performance Across Different Deterioration Types:*

- ✓ Fading Detection Accuracy: 87.3%
- ✓ Physical Damage Detection Accuracy: 83.5%
- ✓ Rust/Corrosion Detection Accuracy: 85.9%
- ✓ Missing Components Detection Accuracy: 91.2%
- ✓ Surface Wear Detection Accuracy: 80.6%

The deterioration classification accuracy (Good, Moderate, Bad) reached 86.2%, with confusion primarily occurring between consecutive categories (e.g., between Good and Moderate, or Moderate and Bad), while misclassifications between Good and Bad were rare (<2% of cases).

C. Operational Benefits

The implemented system demonstrated significant operational advantages compared to traditional manual inspection methods:

- Inspection Time Reduction: The automated system reduced inspection time by approximately 75%, allowing for more frequent safety audits[5]
- Cost Efficiency: A 40% reduction in inspection costs was achieved by minimizing the need for manual labor and specialized equipment
- Consistency: The system provided standardized assessment results with a variance of less than 5% when analyzing the same elements repeatedly, compared to 15-20% variance in manual inspections
- Coverage: The system enabled comprehensive monitoring of extensive road networks, processing up to 100 km of highway per day when mounted on a vehicle traveling at normal speed
- Data Integration: Automated georeferencing of detected issues facilitated seamless integration with maintenance management systems[5]

D. Comparative Analysis

When compared to previous methods and systems reported in the literature, our approach demonstrated several advantages:

- Higher Detection Accuracy: Our mAP50-95 of 87.5% outperformed previous systems that reported mAP values between 70-80%
- Comprehensive Element Coverage: Unlike specialized systems focused on specific elements (e.g., only lane markings or only signs), our approach detected and assessed all major safety elements simultaneously
- Advanced Deterioration Assessment: The segmentation-based deterioration analysis provided more detailed and accurate condition assessment compared to classification-only approaches[2]
- Real-time Processing: The system's inference speed enabled real-time processing, unlike some previous approaches that required offline analysis
- Adaptability: Testing across different geographic regions and road types demonstrated the system's ability to generalize to diverse environments

E. Challenges and Limitations

Despite the promising results, several challenges and limitations were identified:

- Occlusion: Performance decreased when safety elements were partially obscured by vehicles, vegetation, or shadows

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- Rare Defect Types: The system showed lower accuracy for uncommon deterioration patterns not well-represented in the training data
- Night-time Performance: Detection accuracy reduced by approximately 15% in night-time conditions despite augmentation efforts
- Weather Sensitivity: Heavy rain, snow, or fog reduced both detection and segmentation performance[2]
- Novel Elements: The system required retraining to accommodate region-specific safety elements not included in the original training set

These limitations highlight areas for future improvement and development to enhance the system's robustness and applicability across diverse scenarios.

F. Future Scope

Future work will focus on several key enhancements:

- Enhancing model performance in challenging conditions such as night-time, adverse weather, and heavily occluded scenes.
- Integration with other sensing technologies, such as LiDAR and thermal imaging, to improve detection capabilities.[8][10]
- Expanding the dataset to include more diverse geographic regions and road types to enhance the system's generalization capabilities.
- Exploring the potential of self-learning AI models to further improve long-term system performance.

G. Acknowledgment

We would like to express our sincere gratitude to the transportation agencies and road maintenance authorities who provided data and insights that were crucial to the success of this research. We also thank the research team for their dedication and expertise in developing and deploying the AI-based road safety audit system.

IV. CONCLUSION

This research presents an AI-based road safety audit system that automates the detection and deterioration assessment of highway safety elements. The combination of YOLOv8 for object detection and U-Net for segmentation[3] provides a comprehensive solution for monitoring road safety infrastructure. The system demonstrates high accuracy in identifying various road safety elements and assessing their deterioration levels, enabling proactive maintenance scheduling.

The automated approach significantly reduces the time and cost associated with manual inspections while providing more consistent evaluations. By classifying deterioration into Good, Moderate, and Bad categories, the system enables prioritized maintenance planning, ensuring critical safety issues are addressed promptly.

The real-time processing capabilities make this approach valuable for government agencies, road maintenance authorities, and smart city initiatives. The system's ability to process large volumes of data efficiently allows for more frequent safety audits, potentially reducing accident rates through timely identification and rectification of safety hazards.

Future developments will focus on enhancing model performance in challenging conditions such as night-time, adverse weather, and heavily occluded scenes. Integration with other sensing technologies, such as LiDAR and thermal imaging, could further improve detection capabilities. Additionally, expanding the dataset to include more diverse geographic regions and road types will enhance the system's generalization capabilities.[10][8]

The promising results of this research demonstrate the potential of AI-powered systems to transform road safety management, contributing to safer transportation infrastructure and reduced accident rates. By enabling data-driven maintenance decisions, such systems can optimize resource allocation while maximizing safety outcomes, ultimately saving lives and reducing the societal costs of road accidents.

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