AI - Based Road Safety Audit System

Pravin Waghmare[1]; Sapna Sonawane[2]; Siva Kumar[3]; Roopa Mulukutla[4]; Indu Palam[5]; Vallepu Dayakar[6]; Harinee Ganapathy Subramani[7]; Bharani Kumar Depuru[8]

[1,2,3,4,5,6,7,8,] AISPRY Education Centre in Bengaluru, Karnataka

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Abstract: Indian road networks currently rely on manual safety audits that are costly, time-consuming, and pose safety risks to inspection personnel. This paper proposes an AI-driven road safety audit system that uses advanced object detection to automatically identify and evaluate critical road safety features (such as crash barriers, speed breakers,pavement marker insertions, road markings, and signboards) from highway images and video. By leveraging our client's products in our analysis, the system is fully tailored to Indian road infrastructure, ensuring standard safety installations. (https://law.resource.org/pub/in/bis/irc/translate/irc.gov.in.sp.099.2013.html) The proposed approach addresses high inspection costs by minimizing the need for manual checks. Our AI system should increase Road Safety Awareness among an ordinary Indian citizen, resulting in lower risk of accidents on Indian National/State Highways. Expected outcomes include significant cost savings, lower chance of accidents,and Highway compliant safety features imposed at all high risk - medium risk zones. For example, targeting maintenance activities like repainting faded lane lines or repurposing signage and enhanced highway safety compliance through timely interventions. In conclusion, this AI-based road audit framework offers a scalable solution to improve road safety management in India, providing actionable insights for road contractors and authorities while emphasizing the importance of such data-driven audits in policymaking and infrastructure development. This Road Safety Audit System should also serve as a guideline for all Indian drivers who should be in a position to make effective suggestions for the overall road safety of India.

Keywords: *Object Detection, Road Safety Audit, YNM Road Safety, Road Infrastructure, Road Markings, Signage, Barriers, Pavement Markers, Highway Safety, Road Contractors.*

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I. INTRODUCTION

➢ *Our Research was done Using A Triangular Approach. this Approach Comprised of the Following Aspects:*

- IRC Manual which lists the description of various road safety features as specified by the NHAI (https://nhai.gov.in/) on Indian National Highways. This step also ensured we understand the data well before we collect it.
- Data collection was done on Indian National Highway videos, State Highway videos, Travel Vlogs, regular videos of people observing the application of road safety features in India, and images. Tools: Youtube, Shutterstock,iStock. [1,2,5]
- Data Annotation was done using Roboflow for the first part of our data collection. The second part of our data collection was annotated using Digital Sreeni, an on premise Data Annotation tool. Reason behind choosing an On Premise Data Annotation Tool like Digital Sreeni: There were concerns of copyright infringement for the client. Hence , we moved to an on premise Digital Annotation Tool. (https://github.com/bnsreenu/digitalsreeni-image-annotator)

➢ *Data Collection - Phase 1:*

Data was collected on 1000 images per class which were extracted using 15 fps on Roboflow amongst the following eight classes, which are as follows:

Table 1 Data Collection

Class No.	Road Safety Element	Description
1	Hot Thermoplastic Paint (Edge Line, Lane Line)	Lane separation and edge delineation
2	Cold Plastic Rumble Marking Paint	Vibratory markings for driver alerts
3	Road Pavement Markers	Reflective markers for night visibility
4	Water-Based Kerb Paint	Markings on road dividers and median kerbs

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5	YNM Informatory Sign Boards	Directional, warning, and regulatory signs
6	Single W Beam Crash Barriers	Safety barriers preventing vehicle run-offs
7	Rubber Speed Breakers	Raised road structures to slow vehicles
8	Raised Pavement Markers	Embedded markers for lane guidance

➢ *Data Collection - Phase 2:*

Data was collected on 500 images per class which were extracted using 15 fps on Roboflow amongst the following five classes, which are as follows:

- Arrow Boards
- Traffic Cones
- Rumble Strips
- Stop Signs
- Reflective Sheeting [3, 5]

Table 2 Data Collection

Class No.	Road Safety Element	Description
1	Arrow Boards	Sign Boards with left, right arrow, indicating curve ahead
2	Traffic Cones	Orange cones with white reflective sheeting so that drivers know that road work is ahead.
3	Solar LED Lights	Used to guide drivers during night time, low light conditions, inclement weather conditions.
4	Stop Signs	Used to tell vehicles to stop
5	Reflective Sheeting	Reflects light from vehicle back to it , helping drivers in night time conditions, low light conditions, inclement weather conditions, and unusual terrains where driving is a challenge.

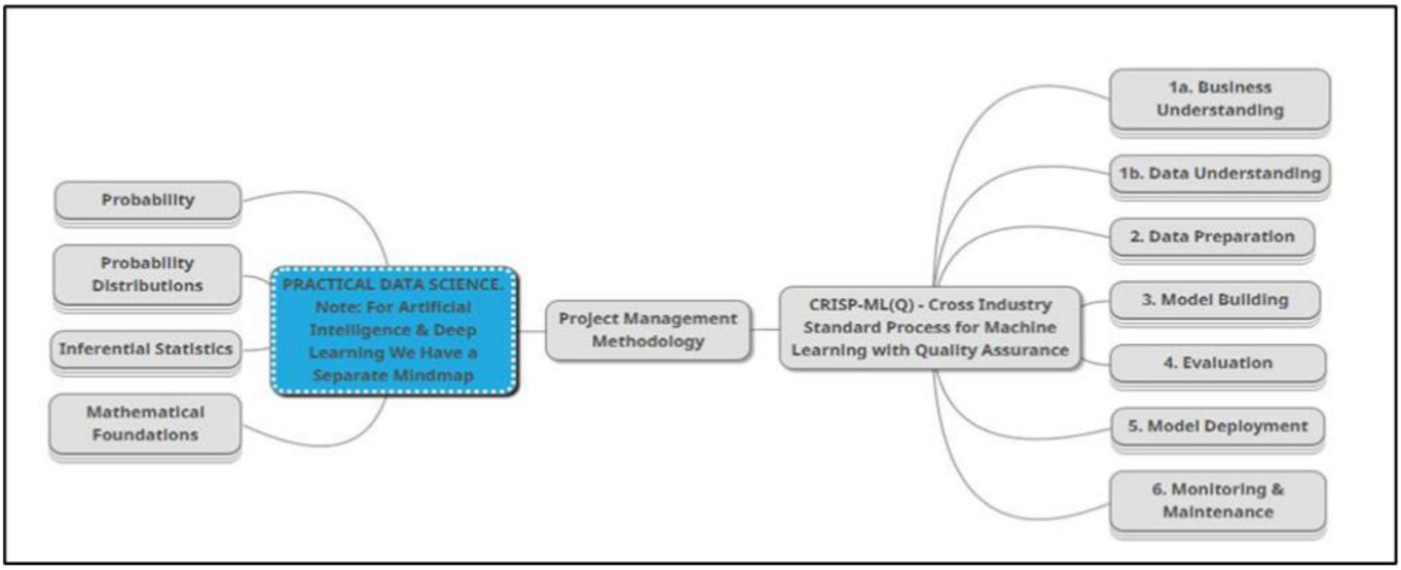

Fig 1 The Project follows the CRISP-ML (Q) Methodology (a Structured Framework for Machine Learning and AI Development.) [9]

II. METHODS AND TECHNOLOGY

A. *System Infrastructure for Model Training*

The dataset was processed and trained using high-performance hardware. The system configuration included the following:

Table 3 System Requisites for Application Development using Yolov8 Pretrained Model

Component	Specification
Operating System	Ubuntu 20.04 / Windows 10
Processor	Intel Xeon Family, 2.5 GHz
GPU	NVIDIA T4 Tensor Core, 16 GB VRAM
Clock Speed (GHz)	2.5
CPU architecture	X86 64
vCPUs	8
Memory (GB)	32
Memory per vCPU (GB)	4.0
GPU Compute Capability	7.5

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Video Memory (GB)	16
Storage	1 TB SSD
Frameworks	PyTorch 2.0, YOLOv8, YOLOv9, OpenCV, Roboflow
Software Dependencies	Python 3.9, CUDA Toolkit 11.8, cuDNN, TensorRT
GPU Compute Capability	7.5

B. Project Architecture

➢ *High-Level Architecture:*

The high-level architecture [9] defines the end-to-end workflow of the system, including data collection, model processing, and deployment. The figure below illustrates the core components and their interactions. [Fig 2]

➢ *Key Components*

- *Data Collection & Storage*

✓ Images and videos of highways are collected from cameras, YouTube, and open-source datasets.
✓ Data is stored in Amazon S3, ensuring scalability and accessibility [9].

- *Operational Platform*

✓ AWS EC2 instances handle all data processing and model training.
✓ The system uses Python-based scripts for automation.

- *Model Training & Evaluation*

✓ The collected dataset is annotated and pre-processed before feeding into YOLOv8 small and medium models for object detection.
✓ Hyperparameter tuning is performed to optimize precision, recall, and mean Average Precision (mAP).

- *Deployment & Real-Time Processing*

✓ The trained model (best.pt) is integrated into a Streamlit-based application.
✓ Deployed on AWS EC2 to enable real-time detection and monitoring.
✓ Results are continuously monitored for accuracy improvements.

➢ *High-Level Workflow*

- Data Source: Data is ingested from image datasets.
- Data Storage: Stored in Amazon S3 for preprocessing.
- Model Training: Runs on AWS EC2 with YOLOv8 for object detection.
- Deployment: Integrated into a Streamlit web app for end-user accessibility.
- Monitoring & Maintenance: Real-time evaluation ensures continued performance improvements

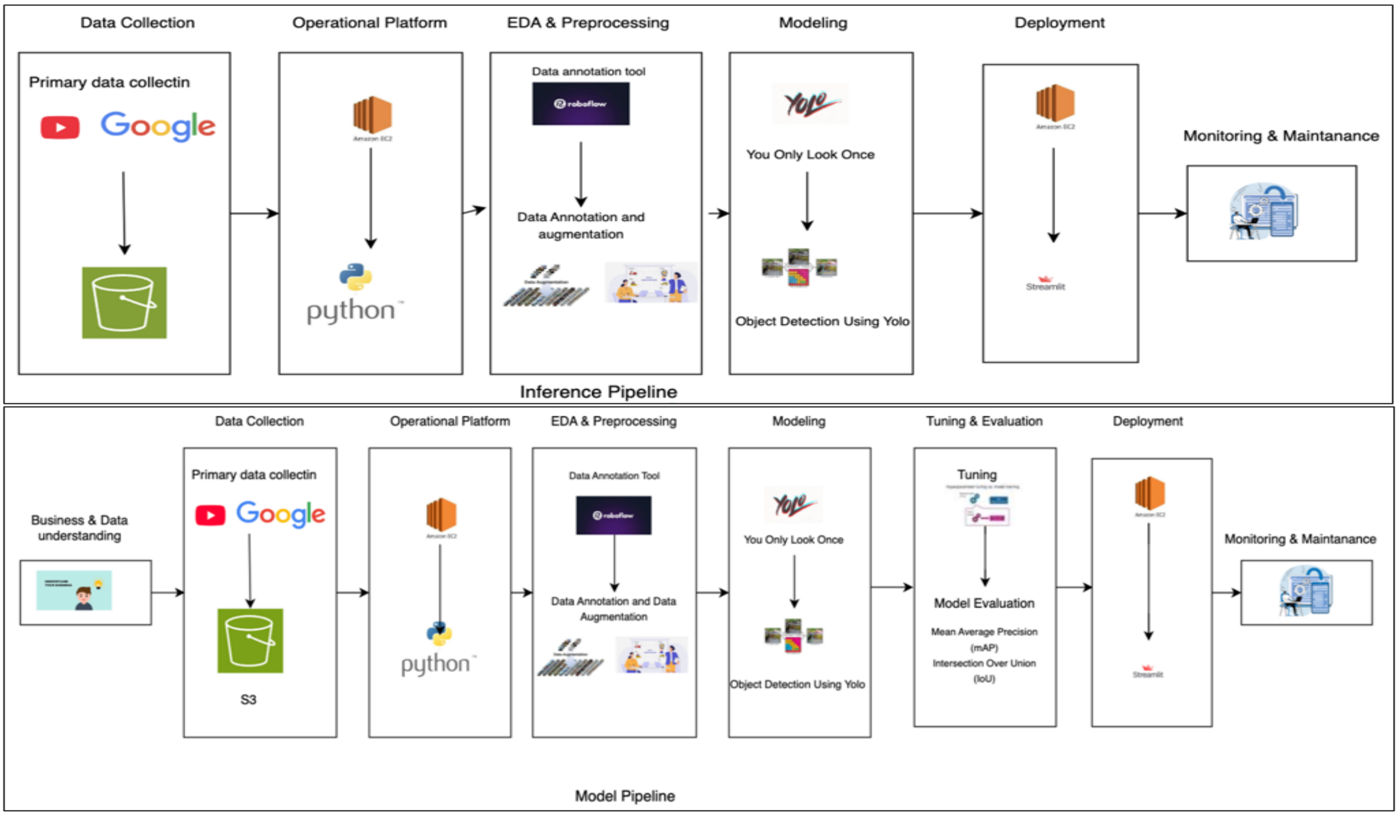

Fig 2 High-Level System Architecture (Shows the end-to-end AI Pipeline, Including data Collection, Preprocessing, Model Training, Deployment, and real-time Inference.)

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➢ *Low-Level Architecture Diagram:*

The Low-Level Architecture provides an in-depth breakdown of how data flows through each stage of the system, from data collection to deployment. Each step plays a critical role in ensuring the AI model performs accurately and efficiently in real-world highway safety inspections.[Fig 3]

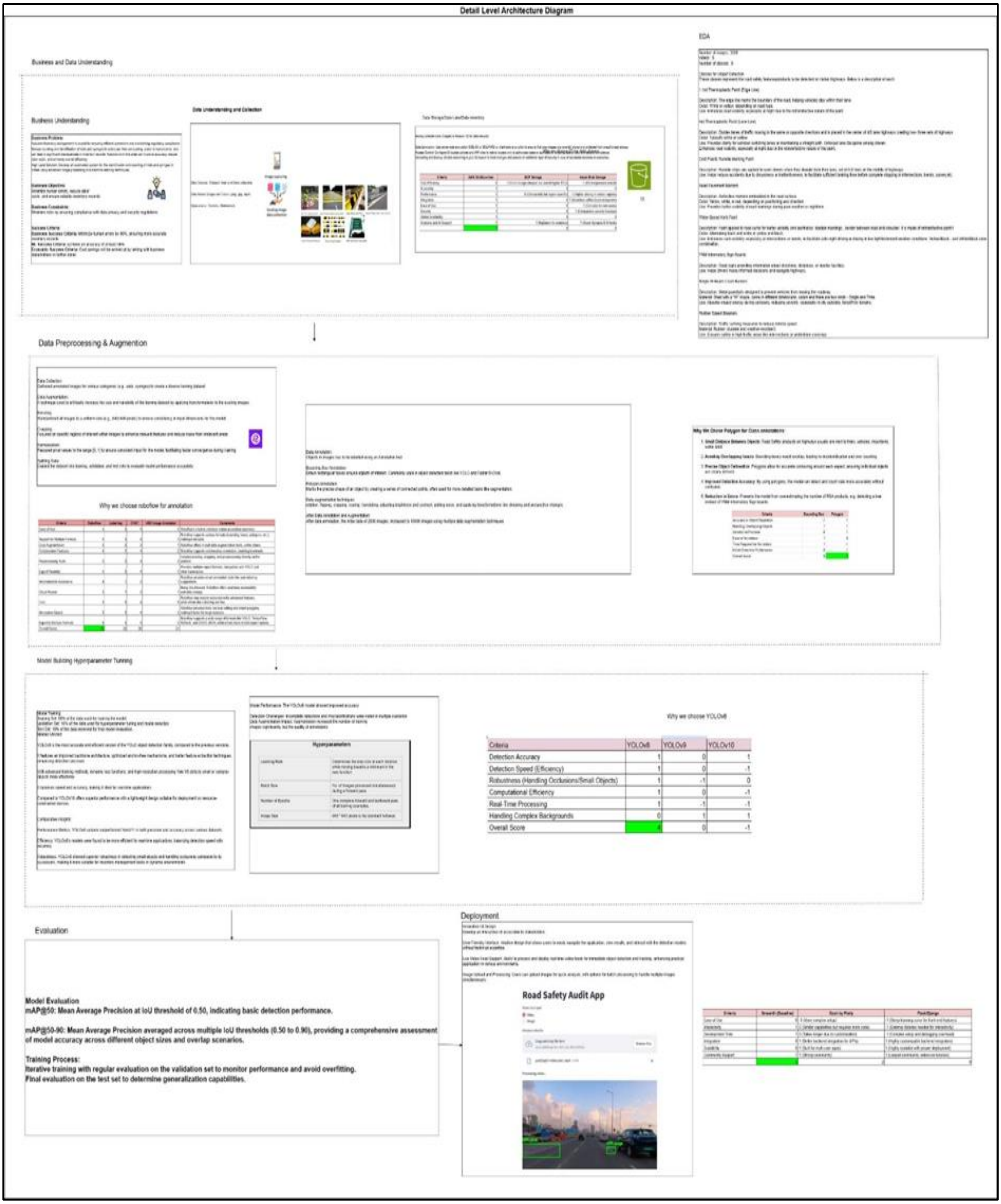

Fig 3 Detailed Level Architecture Diagram Developed in draw.io (Shows end-to-end Pipeline of Each and Every step in the CRISP ML(Q) Process)

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III. EXPLORATORY DATA ANALYSIS (EDA)

A. EDA Architecture:

Step-by-step methodology in which raw images/videos evolve into a structured, labeled dataset suitable for YOLOv8 training:

➢ *Data Ingestion and Initial Inspection*

- Source Aggregation: The pipeline begins by collecting high resolution raw images and videos from open source (e.g., YouTube, Shutterstock, iStock). Using these images we created synthetic datasets of images. This approach ensures the model trains on a variety of road safety object features that come in different shapes and sizes, ensuring appropriate amount of generalization and to detect such containers accurately in diverse scenarios.
- Quality Checks: The raw data is stored in a data warehouse where preliminary checks are conducted to ensure files are intact and meet minimum resolution requirements.

➢ *Video Analytics & Frame Extraction*

- Frame Sampling: From each video, frames are extracted at a chosen rate (e.g., 3 fps), resulting in a diverse image set.
- Early Distribution Analysis: The distribution of frames is inspected to identify potential overrepresentation of certain lighting conditions, angles, or weather scenarios.

➢ *Data Preprocessing & Augmentation*

- Preprocessing: Standard image-processing steps—such as resizing, normalization, and noise reduction—are performed to maintain consistent input dimensions and quality.
- Augmentation: Techniques (e.g., flipping, rotation, color jittering) are applied to combat overfitting and enhance model robustness. During EDA, augmented samples are visually inspected to confirm realistic transformations.[6, 9]

➢ *Defining Classes & Annotation Tools*

- Class Identification: Based on the project's scope (e.g., crash barriers, road signs, lane markings), the relevant object classes are finalized.
- Annotation Verification: Annotation tools (e.g., Roboflow or similar) are used to label each image. EDA includes verifying a subset of annotations to check for labeling errors or class confusion.
- This diverse and precisely labeled dataset ensures the model learns to recognize these objects even in cluttered or complex scenes, mimicking real-world conditions.

➢ *Data Balancing*

- Class Distribution Analysis: The dataset is examined for class imbalances (e.g., some classes may have far fewer images).
- Balancing Strategy: Oversampling minority classes, undersampling majority classes, or targeted augmentation ensures each class is adequately represented.

➢ *Dataset Generation & Statistical Summaries*

- Final Dataset Compilation: A labeled dataset—organized into training, validation, and test splits—is generated.
- Summary Statistics: During EDA, researchers compile quantitative metrics (e.g., total images, class frequencies, average object count per image) and qualitative insights (e.g., example annotations). These statistics guide subsequent hyperparameter tuning and model design.

Through these EDA steps, researchers gain a comprehensive understanding of the data's composition and potential biases before proceeding to YOLOv8 model training [6], hyperparameter tuning, and final model evaluation. This iterative EDA process is crucial for optimizing object detection performance and ensuring that the resulting model generalizes well to real-world road safety scenarios.

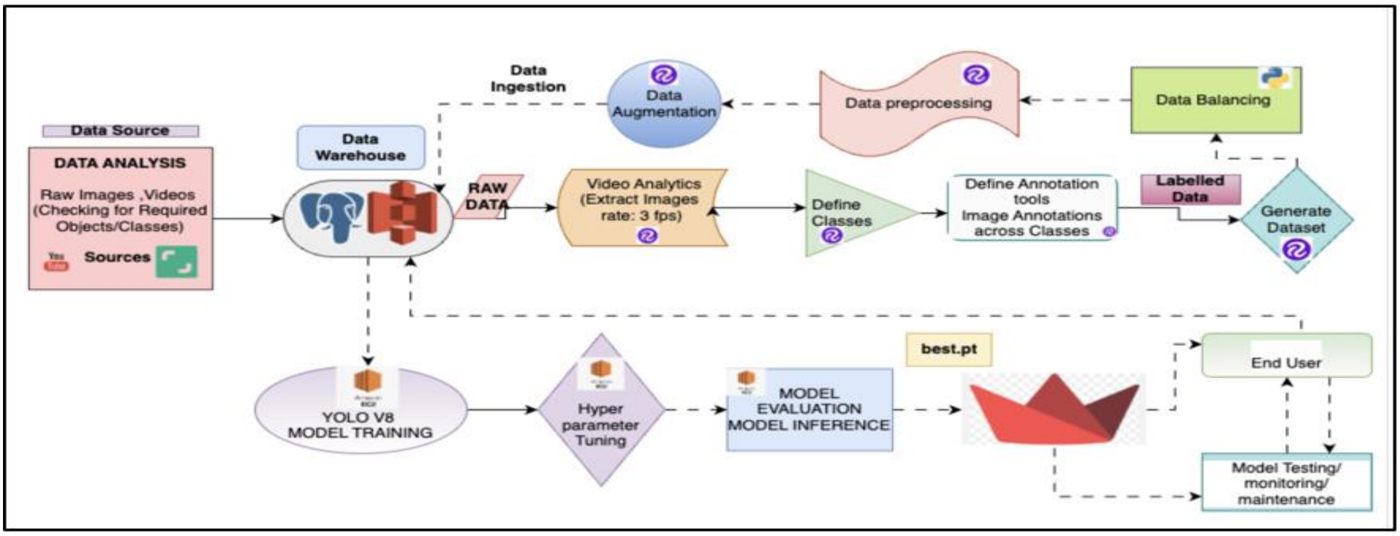

Fig 4 Detailed work flow of how Exploratory Data Analysis is done in an Object Detection Project

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IV. DATA COLLECTION & STORAGE

➢ *Data Sources & Dataset Overview*

The dataset for this project includes images and videos from various sources:

Table 4 Data Collection [6, 8, 9] (Illustrates how data is Collected from Multiple Sources (YouTube, Stock Websites, Live Video Captures))

Source	Description	Purpose
YouTube	Publicly available traffic videos from highways, intersections, and urban roads.	Gather diverse road conditions (day/night, fog, rain, high/low traffic).
Stock Footage Websites (Shutterstock, Getty, Pexels, etc.)	High-resolution images/videos of roads, markings, and barriers	Supplement dataset with professional-quality images.
Live Video Capture	Footage captured using mobile cameras.	Collect real-time highway scenarios for custom training.
Open-Source Datasets (e.g., Google Open Images)	Pre-annotated images of road signs, lane markings, and traffic objects.	Reduce manual annotation effort for standard road features.

- YouTube & Open Datasets: Used as secondary sources for diverse environmental conditions.
- Synthetic Data Generation: Some edge cases were simulated to enhance detection robustness.

Fig 5 Data Collection – Phase 1

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Fig 6 Data Collection -Phase 2

➢ *Importance of Data Collection in Object Detection Problem:*

- A diverse and large dataset [6, 9] improves model generalization.
- Capturing different road conditions (day/night, fog, rain) ensures robust performance from the Yolov8 model.
- A High Resolution image is beneficial for accurate detection using Yolov8 models.
- Hence > 90% of the project was focussed on getting high resolution images, videos on Indian National Highways only.

➢ *Challenges in Data Collection*

Table 5 Challenges in Data Collection

Challenge	**Description**
Class Imbalance	Certain classes, such as pavement markers, had lesser number of images, requiring augmentation and balancing.
Lighting Variations	Images captured under daylight and artificial lighting to improve model generalization.
Object Occlusion	Some road safety elements were partially obstructed, necessitating precise annotation.

➢ *Data Warehouse (Storage)*

- All collected data is stored in Amazon S3, which ensures scalability and fast access.
- Metadata (e.g., timestamp, counting, user login) is stored in PostgreSQL for indexing.

➢ *Benefits of Using AWS S3 & PostgreSQL*

- Scalability: Easily handles large volumes of highway images/videos.
- Reliability: Ensures quick retrieval of training data for efficient model updates.

V. DATA ANNOTATION

Annotation is a crucial step where the chosen classes which are the highway safety features that are being considered for this project, become Training labels.

➢ *Data Annotation Tools Used*

Table 6 Comparison of Data Annotation Tools (Explains the annotation process using LabelImg, Label Me, DigitalSreeni, and Roboflow, highlighting different annotation types.)

Tool	**Annotation Type**	**Reason for Selection**
LabelImg	Bounding Box	Simple tool for fast annotation, suitable for objects with fixed shapes.
LabelMe	Polygon	Useful for irregular shapes like lane markings.
DigitalSreeni	Bounding Box & Polygon (SAM-2)	Supports semi-automated annotation, improving speed & accuracy.
Roboflow	Bounding Box & Polygon	Provides cloud-based annotation, supports dataset management & augmentation, and integrates well with YOLO, TensorFlow, and PyTorch.

➢ *Digital Sreeni:*

- Developed by an Indian American Professor/Researcher Dr.Srinivas
- Supports both manual & semi-automated annotation.
- Exports in YOLO, COCO JSON, Pascal VOC formats.
- Helps label complex road elements like faded lane

➢ *Annotation Methodology*

To ensure high-quality object detection, **polygon annotation** [9] were performed using Roboflow. This method was essential for irregularly shaped objects like lane markings and crash barriers. The annotation process included:

- Identifying key features of each road safety element.
- Applying precise enclosing polygons.
- Verifying annotations for consistency and accuracy.

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➢ *Quality Assurance in Annotation*

Table 7 Quality Assurance in Annotation

Verification Step	Description
Quality Control	Checked resolution, clarity, and object visibility.
Completeness Check	Ensured all critical features were captured.
Consistency Analysis	Multiple annotators reviewed labeled data to minimize errors.

VI. DATA BALANCING

➢ *To improve model accuracy, data balancing strategies were implemented:*

Table 8 Data Balancing

Strategy	Implementation
Oversampling	Increased underrepresented classes through augmentation.
Class Splitting	Divided hot thermoplastic paint into edge lines and lane lines.
Under-sampling	Reduced overrepresented classes where necessary.

VII. DATA PREPROCESSING

Once raw data is collected, it undergoes multiple preprocessing steps to ensure high-quality input for model training. [Table 4]

Table 9 Data Preprocessing Techniques Used for YOLOv8 Model Training

Step	Description
Auto-Orient	Ensures all images are upright, preventing misaligned objects.
Static Crop	Crops central 25-75% regions to remove unwanted background noise.
Dynamic Crop	Focused cropping applied to specific objects (e.g., Crash Barriers) for better annotation precision.
Resize	Resizes all images to 640×640 for YOLOv8 compatibility.
Grayscale	15% of images converted to grayscale to improve robustness under different lighting conditions.

➢ *Data Preprocessing*

- Reduces data inconsistencies, improves model accuracy.
- Optimizes data for YOLOv8, ensuring more precise detection of smaller and distant objects.[6, 9]

VIII. DATA AUGMENTATION

Data augmentation [6] artificially inflates the training dataset, improving model generalization.[Table 5]

Table 10 Data Augmentation Strategies Used for YOLOv8 Model Training

Augmentation Type	Description
Flip	Applies horizontal & vertical flipping to create diverse orientations.
Rotation	Rotates images randomly between -15° and +15°.
90° Rotate	Applies 90° clockwise/counter-clockwise rotations.
Crop	Zooms in/out to simulate real-world occlusions (0%-20% zoom range).
Shear	Shears objects horizontally/vertically by ±10°.
Brightness & Saturation	Adjusts brightness & saturation between -25% and +25%.
Exposure & Hue	Varies exposure by ±15% and hue by ±15°.
Blur & Noise	Introduces motion blur & 0.1% random noise for real-world variability.

➢ *Data Augmentation*

- Prevents overfitting, ensuring the model learns generalized features.
- Improves small-object detection (e.g., Raised pavement markers).[6, 9]

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IX. MODEL BUILDING

➢ *Building a Road Safety Feature Object Detection Application using YoloV8 architecture:*

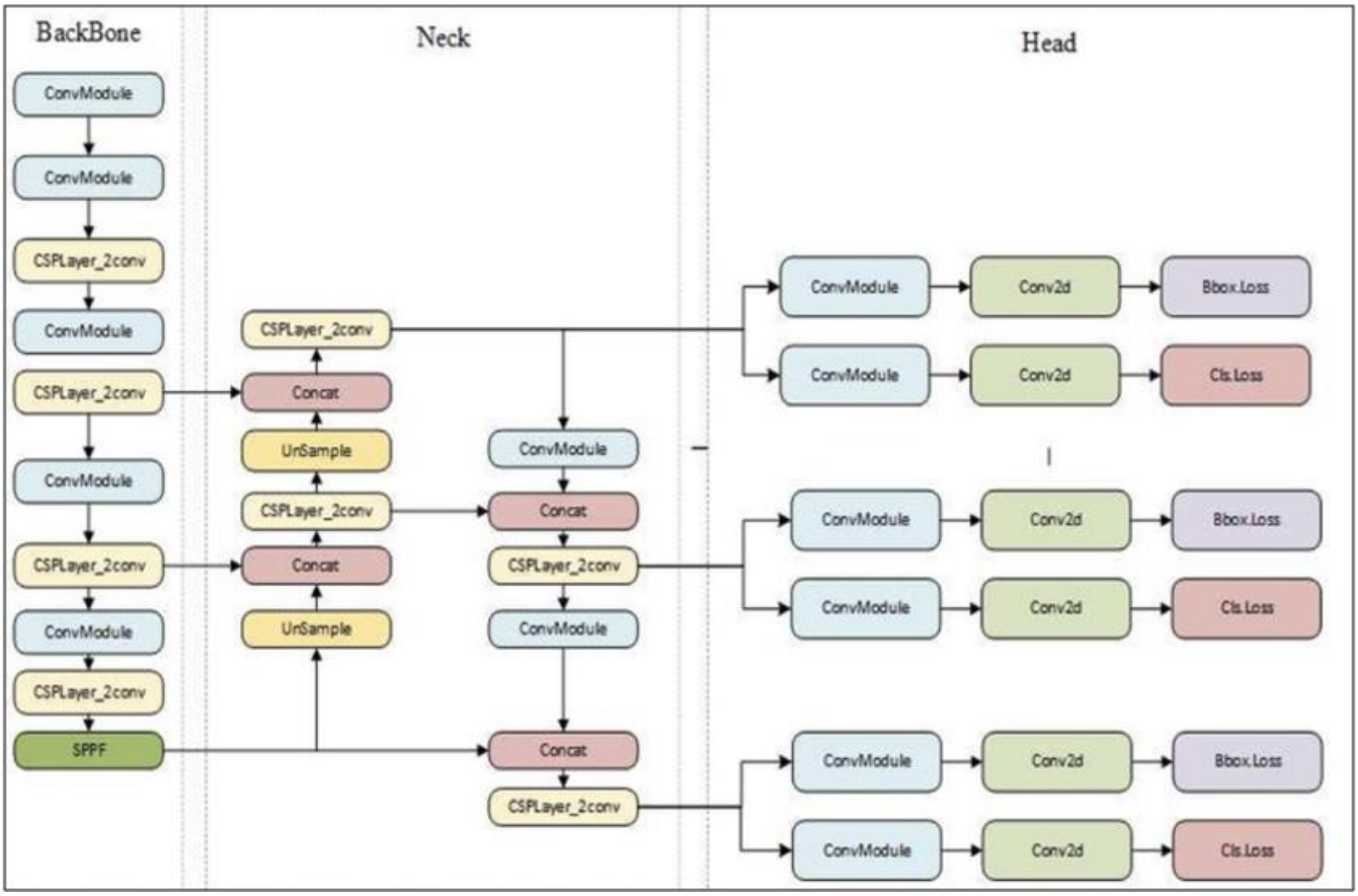

Fig 7 Yolov8 Network architecture [2, 9]

X. MODEL TRAINING & HYPERPARAMETER TUNING

The preprocessed and augmented dataset is fed into YOLOv8 for training.

➢ *YoloV8:*

- Uses an anchor-free detection mechanism [2,9], improving object localization.
- Lighter & faster than YOLOv5, making it ideal for real-time inference.
- High mAP@50 (92.3%), ensuring accurate detection of road safety features.

➢ *Hyperparameter Tuning*

- Improves model convergence, reducing false positives.
- Ensures faster training without sacrificing accuracy.[6, 9]

Table 11 Hyperparameter Tuning Strategies for YOLOv8 Model Optimization

Hyperparameter	**Optimized Value**	**Impact**
Learning Rate	0.01	Controls weight updates, preventing overfitting.
Batch Size	16	Balances GPU memory usage & speed.
IoU Threshold	0.5	Ensures optimal bounding box accuracy.
Confidence Threshold	0.25	Filters low-confidence detections.

Table 12 Performance Comparison of YOLOv8s and YOLOv8m with 30 and 50 Epochs

Model	**Epochs**	**mAP(50-95)**	**mAP@50**
YOLOv8s	30	66%	80.40%
YOLOv8m	30	71%	88.20%
YOLOv8s	50	74%	93.50%
YOLOv8m	50	78%	93.30%

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XI. MODEL EVALUATION

➤ *Confusion Matrix Analysis*

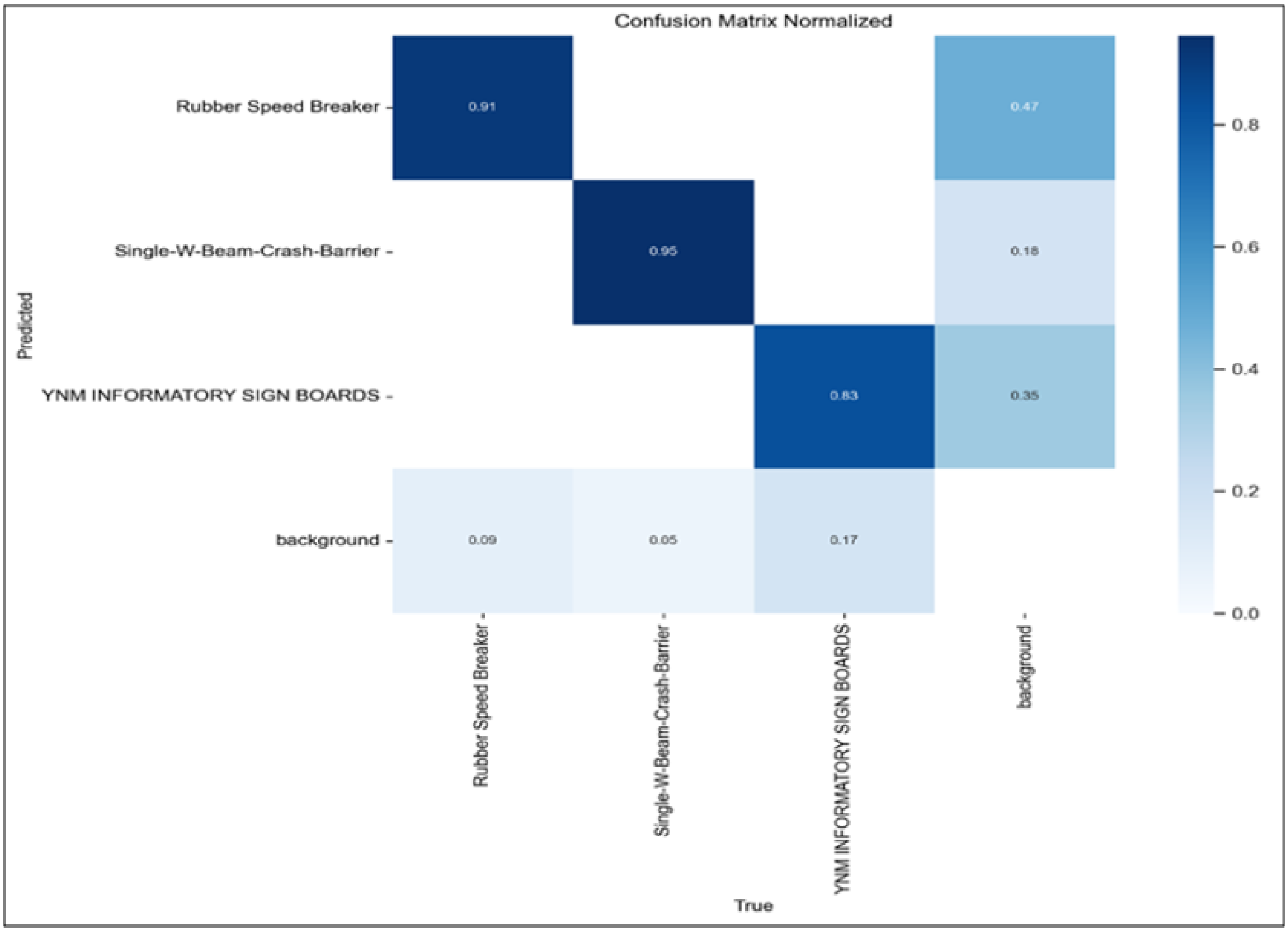

Fig 8 Confusion Matrix Analysis

➤ *Findings from Confusion Matrix:*

- Rubber Speed Breakers detected with 91% accuracy.
- Crash Barriers classified correctly 95% of the time.
- Sign Boards had an 83% accuracy, with some misclassification with the background.

➤ *Improvements Suggested:*

- Additional hard negative mining to reduce false positives.
- Implementing multi-scale feature extraction to enhance low-light detections.

➤ *Performance Metrics*

Table 13 Evaluation Results of YOLOv8 for Highway Safety Monitoring

Metric	**YOLOv8 Performance**
mAP@50	92.30%
mAP@50-95	78.60%
Precision	89.70%
Recall	85.20%
Inference Speed	15 ms per image

➤ *Precision, Recall, and m AP Analysis*

- Precision (89.7%) → Low false positives.
- Recall (85.2%) → Few missed detections.
- Inference Time (15 ms) → Suitable for real-time processing.

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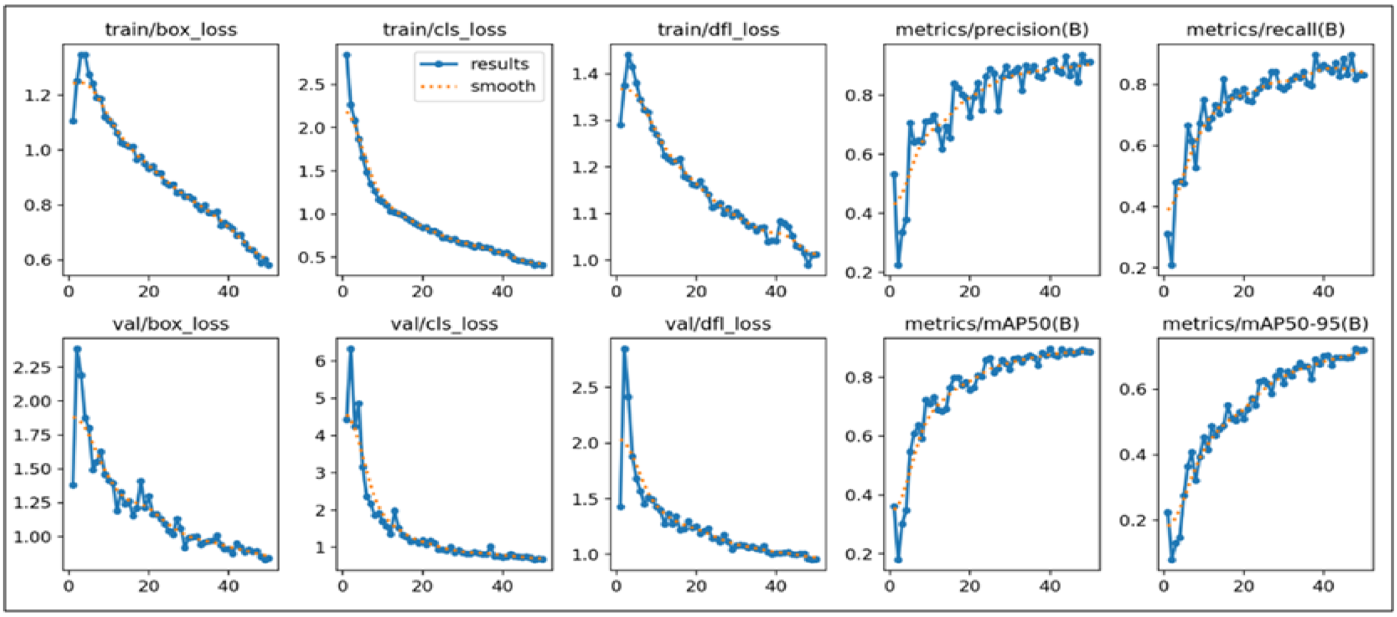

Fig 9 Training Loss/class, Validation Loss/class,Training Loss/box, Validation Loss/box, Precision, Recall, mAP50-95

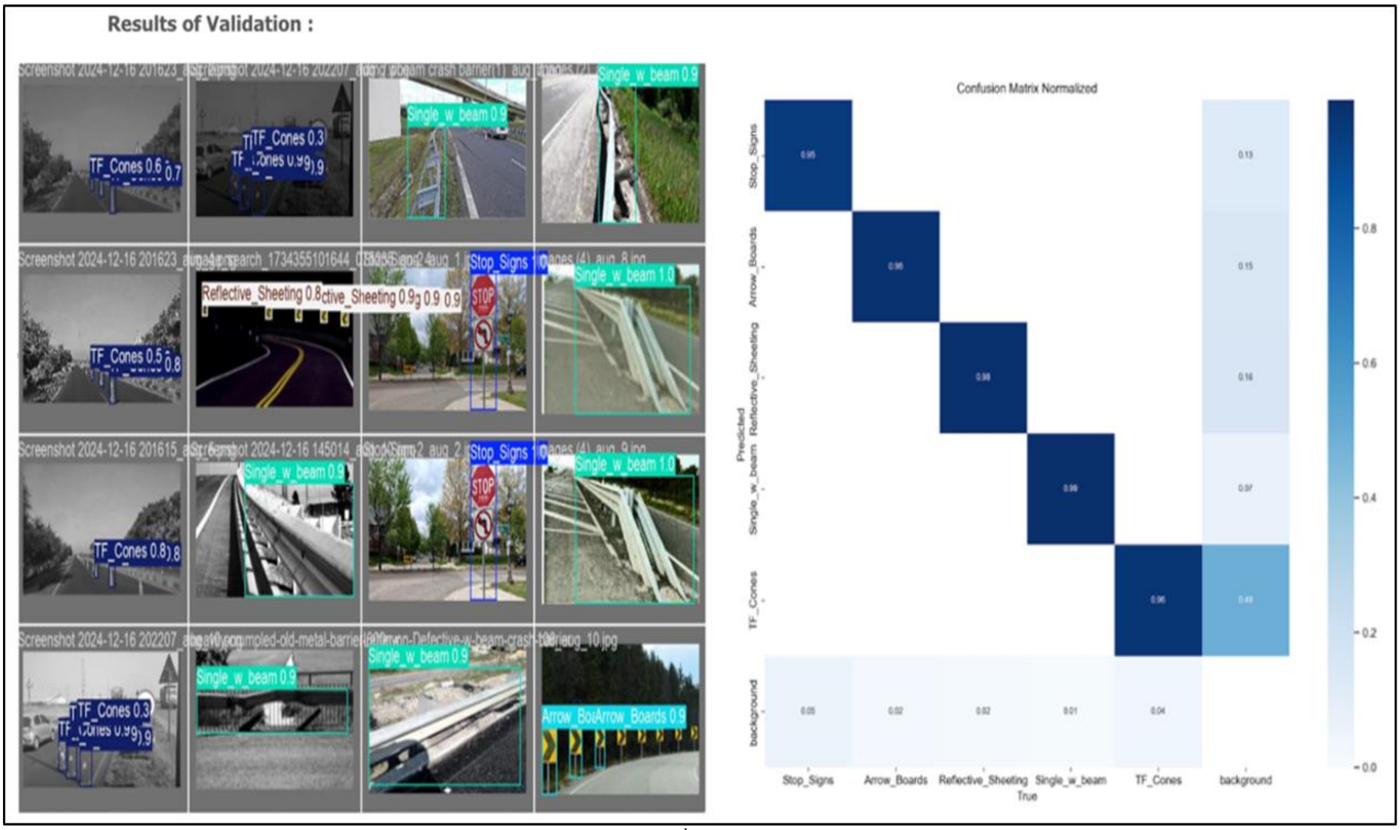

Fig 10 Results of Validation for 2nd Dataset along with Confusion Matrix

XII. MODEL DEPLOYMENT & TESTING

➢ *Deployment*

- Model deployed in a Streamlit-based web app.
- Hosted on AWS EC2, allowing real-time detection.

➢ *Testing*

- Evaluated on >500 images, >100 videos.
- Real-world performance validated with IoT-integrated road cameras.

➢ *AWS EC2 & Streamlit*

- Scalability: Can process multiple real-time feeds.
- Flexibility: Supports batch and real-time inference.

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➢ *Post-Deployment Monitoring*

- The model is continuously monitored using feedback-based retraining.
- Detection anomalies (e.g., false positives) trigger fine-tuning cycles.

➢ *Post-Deployment Monitoring*

- Ensures model accuracy remains stable as road conditions change.
- Allows real-time adaptation to new safety features & road markings.

➢ *Challenges in Model Accuracy*

Model accuracy often drops in deployment due to differences between training and real-world data, especially in videos where motion blur, lighting changes, and varying angles affect detection. Overfitting to training images can limit generalization, leading to lower performance on unseen data. Video-specific issues like FPS mismatch and frame skipping can cause missed detections, while incorrect confidence thresholds and NMS settings may filter out valid objects. Poor annotation quality and inconsistent input resolutions further impact accuracy. To improve performance, even more diverse training data, object tracking, and optimized inference settings should be implemented.

XIII. CONCLUSION

This study presents an AI-powered Road Safety Audit System designed to automate the identification and assessment of critical road safety features using YOLOv8 object detection models. By integrating machine learning and computer vision, the system enhances inspection accuracy, efficiency, and scalability, thereby reducing dependency on manual safety audits. The model, trained on diverse datasets with extensive preprocessing and augmentation, exhibited high detection precision for essential road features, including lane markings, crash barriers, signboards, and speed breakers.

The deployment of this system through a Streamlit-based UI on AWS EC2 enables real-time monitoring of road safety elements from both images and videos, providing actionable insights for road infrastructure maintenance, regulatory compliance, and policy formulation. The findings indicate that this AI-based approach effectively recognizes road safety elements under varying environmental conditions, making it a practical tool for road authorities, maintenance teams, and transportation planners.

Despite its success, several challenges were encountered, including imbalanced datasets, annotation complexities, and real-time processing limitations. To address these, multiple dataset versions were developed, semi-automated annotation tools were employed, and hyperparameter tuning was refined to enhance detection accuracy. The study demonstrates that AI-driven road safety audits can transform traditional highway inspections, reducing the likelihood of road-related incidents and ensuring compliance with safety regulations.

A. Future Scope

The AI-based Road Safety Audit System presented in this research has demonstrated its potential in automating road infrastructure inspections, significantly improving efficiency, accuracy, and compliance monitoring. However, there are several areas where the system can be further enhanced and expanded to address broader road safety challenges.

➢ *Integration with LiDAR and Multi-Sensor Fusion*

Future enhancements can incorporate LiDAR-based depth estimation, thermal imaging, and radar sensors to improve object detection, particularly in low-light and adverse weather conditions. Multi-sensor fusion can provide 3D spatial awareness, making road safety audits more precise.

➢ *Implementation of Real-Time Edge AI Systems*

Deploying lightweight AI models on embedded devices such as NVIDIA Jetson, Raspberry Pi, and IoT-enabled road cameras can enable on-device processing. This will reduce dependency on cloud computing and make real-time road safety monitoring scalable.

➢ *Automated Identification of Road Defects*

The model can be extended to detect potholes, cracks, worn-out lane markings, and uneven road surfaces, providing predictive maintenance insights to highway authorities and reducing accident risks.

➢ *Adaptive Learning through Federated AI Models*

Implementing federated learning will allow the system to continuously improve without compromising data privacy. Road safety data collected from different regions can be used to update models dynamically while ensuring local variations in road infrastructure are accounted for.

➢ *Integration with Traffic Violation Monitoring*

The system can be integrated with automated traffic enforcement mechanisms to detect violations such as speeding, lane indiscipline, and unauthorized road sign modifications. This would improve law enforcement efficiency and enhance overall traffic management.

➢ *Expansion to International Road Safety Standards*

While this research focuses on Indian National and State Highways, future work can align with global traffic safety standards such as AASHTO, ISO 39001, UNECE regulations, enabling the system to be adopted across different countries.

By incorporating these advancements, the AI-driven Road Safety Audit System has the potential to become a comprehensive, real-time, and autonomous safety monitoring solution, transforming highway management, predictive maintenance, and road safety compliance worldwide.

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