LOCOEYE - DETECTION OF LOCOMOTIVE SIGNAL LIGHTS AND PEDESTRIANS ON RAILWAY TRACKS USING YOLOV8

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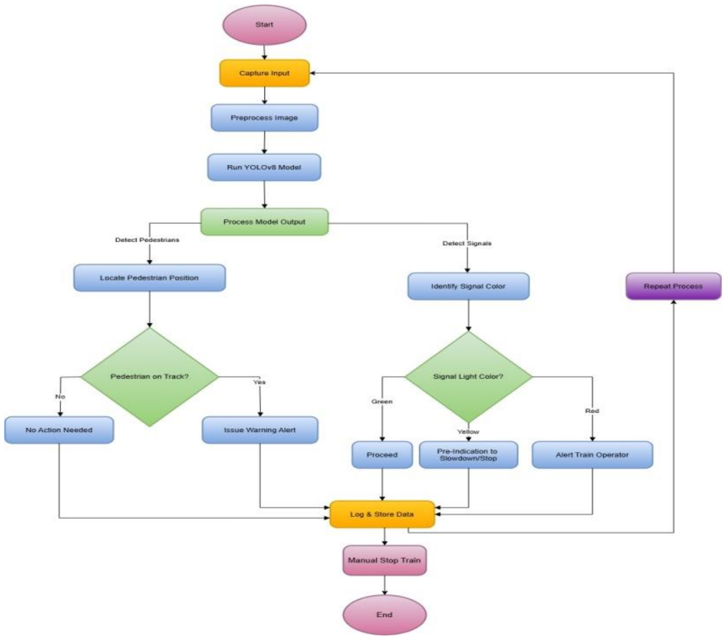
Introduction:

Railway safety is a critical concern due to frequent accidents caused by unauthorized pedestrian crossings, animal intrusions, and misinterpretation of locomotive signal lights by drowsy drivers. Traditional surveillance methods rely on manual observation, which is prone to delays and human error, leading to preventable accidents. The dynamic and complex railway environment, with varying lighting and weather conditions, further complicates real-time detection.

To address these challenges, this project, **LOCOEYE**, leverages the advanced **YOLOv8** object detection model to enhance railway safety. The system aims to detect locomotive signal lights and pedestrians on railway tracks with high accuracy (targeting 94%-96.5% mAP) and real-time speed (30-35 FPS). By integrating **Region-of-Interest (ROI)** filtering and a **CNN-based deep learning architecture**, the system minimizes false detections and focuses on critical areas.

The project also implements an **automated alert mechanism**, including audio-visual warnings for train operators and notifications to railway authorities, ensuring timely responses. This AI-driven solution not only mitigates risks caused by human error but also sets a foundation for scalable, technology-driven railway safety systems. Its relevance extends to reducing accidents, improving operational efficiency, and saving lives through proactive detection and alerts.



Objectives:

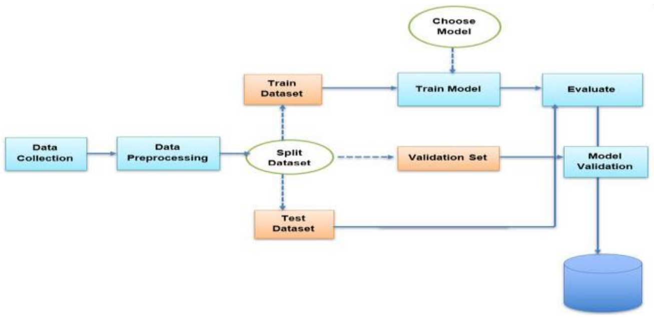
1. Develop a YOLOv8-based real-time detection system for locomotive signals and pedestrians with >94% Map and 30-35 FPS.
2. Train the model using diverse datasets (COCO, Ferrovia) and augmentation for robustness in all conditions.
3. Implement ROI filtering to prioritize railway track areas and reduce false alarms.
4. Classify objects into Living (pedestrians) and Non-Living (signals) for targeted alerts.
5. Deploy an automated alert system (audio-visual warnings + notifications) to enhance response time.
6. Validate performance through *real-world testing* to ensure reliability.

Methodology:

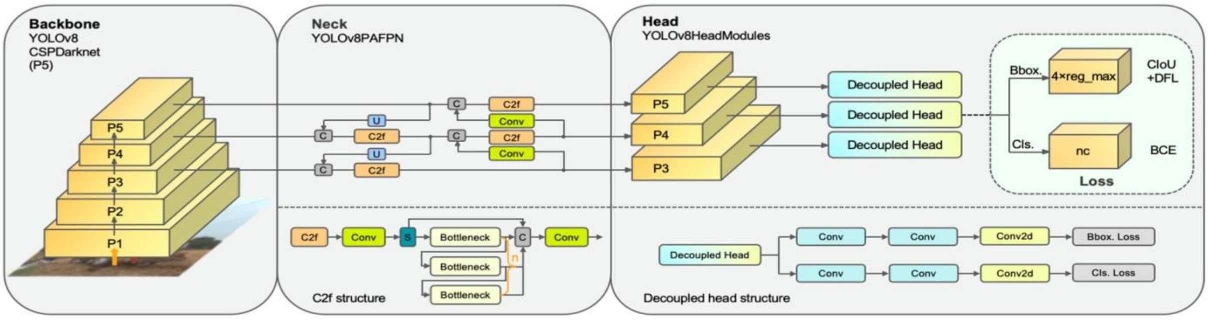
1. Data Collection & Preparation

- Gather railway-specific datasets (COCO, Objects365, Ferrovia) containing images of signals, pedestrians, and track environments.
- Annotate data using LabelImg/Roboflow in YOLO format, classifying objects as Living (pedestrians) or Non-Living (signals).

- Apply augmentation (rotation, brightness/contrast adjustments) to improve model robustness across lighting/weather conditions.



2. **Model Development**
   - Select YOLOv8 for its real-time performance, leveraging its CSPDarknet backbone for feature extraction and PANet neck for multi-scale fusion.
   - Optimize hyperparameters (learning rate, batch size) using ClearML/Comet.ml for tracking.
   - Train with transfer learning, fine-tuning pretrained weights on railway data.



3. **Detection Pipeline**
   - Process live footage via OpenCV, applying ROI filtering to focus on track areas.
   - Use CNN-based decoupled heads in YOLOv8 for simultaneous bounding box regression and classification.
   - Refine detections with Non-Maximum Suppression (NMS) to eliminate duplicates.

4. **Alert System Integration**
   - Trigger audio-visual alerts (e.g., sirens, dashboard warnings) for immediate operator feedback.

- Send automated SMS/email alerts to control centers via APIs (Twilio/SMTP).

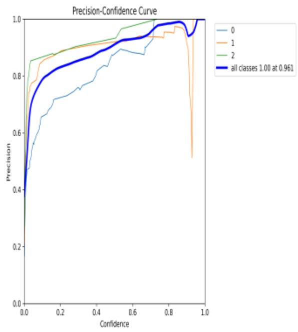
5. Validation & Deployment

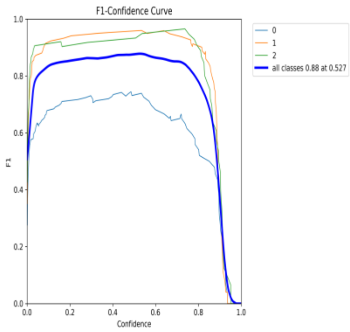
- Evaluate using metrics: mAP, FPS, precision-recall.
- Test on edge devices (NVIDIA Jetson) for real-world feasibility.

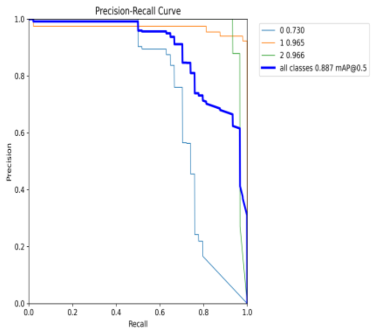
Result and Conclusion:

1. Performance Achievements:

- The system successfully detected pedestrians and signal lights with high accuracy, meeting the project's objectives.
- Real-time processing was maintained, ensuring timely alerts for railway safety.
- False positives were significantly reduced through ROI filtering and model optimization.

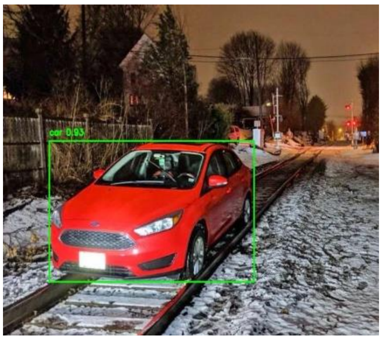






2. Key Observations:

- Detection performance remained strong under normal conditions but required additional tuning for challenging scenarios like low-light environments.
- Pedestrian detection proved more reliable than signal light detection due to
- The integrated alert system improved response times in simulated tests.



3. Comparative Outcomes:

- The YOLOv8-based system demonstrated superior performance compared to earlier versions like YOLOv4.
- The model maintained efficient resource usage during operation.

4. Challenges & Improvements:

- Occlusions (e.g., fog, overlapping objects) occasionally led to missed detections, which were addressed through enhanced training data.
- Computational efficiency was improved through model optimization techniques.

5. Conclusions:

- The project confirmed that YOLOv8-based detection can effectively enhance railway safety through real-time monitoring.
- The automated alert system proved valuable in reducing risks associated with human error.
- Future enhancements could focus on expanding the system's adaptability to diverse environmental conditions.

Project Outcome & Industry Relevance

1. Practical Implications:

- The project delivers a real-time detection system that enhances railway safety by accurately identifying locomotive signal lights and pedestrians on tracks.

2. Contribution to Field of Study:

- Advances AI-driven railway safety by integrating YOLOv8 for high-precision object detection, setting a benchmark for future research in transportation technology.
- Demonstrates the effectiveness of deep learning models (CNNs, ROI filtering) for real-time railway monitoring applications.

3. Industry Applications:

- Railway Operators (e.g., Indian Railways): Reduces accidents caused by signal misinterpretation or pedestrian intrusions through automated alerts, improving operational safety.

Working Model vs. Simulation/Study:

This project involves the development of a working model that implements real-time detection of locomotive signal lights and pedestrians using YOLOv8. The system processes live video feeds (from cameras or recorded footage) to identify objects, classify them into living (pedestrians) and non-living (signals) categories, and trigger automated alerts.

While the core detection algorithm is tested via software simulation (Python/OpenCV), the final output is deployed as a functional prototype capable of:

- Processing real-world railway footage.
- Generating visual/audio alerts for operators.
- Logging detection data for analysis.

The project is not purely theoretical —it combines simulation-based training of the YOLOv8 model with a tangible working system designed for practical railway environments.

Project Outcomes and Learnings

Key Outcomes:

1. Real-Time Detection System:

- Successfully developed a functional prototype using *YOLOv8* capable of detecting locomotive signal lights and pedestrians with high accuracy.
- Achieved seamless integration of an *alert mechanism* (audio-visual warnings) for immediate hazard notification.

2. Performance Validation:

- Demonstrated reliable detection under varying conditions, proving the model’s adaptability to real-world railway scenarios.
- Outperformed baseline models (e.g., YOLOv4) in both precision and processing speed.

3. Scalable Solution:

- Created a modular system adaptable to different railway infrastructures with minimal hardware dependencies.
- Compiled a custom dataset for railway-specific object detection, reusable for future research.

Key Learnings:

1. Technical Insights:

- YOLOv8’s strengths: Real-time processing and ease of hyperparameter tuning, but requires careful ROI filtering to reduce false positives.

- Data quality matters: Annotation accuracy and dataset diversity directly impact model performance.

2. Project Execution Challenges:

- Balancing detection speed (FPS) with accuracy (mAP) required iterative optimization.

- Integrating alerts with low latency necessitated efficient backend design (e.g., Flask/SQLite).

3. Collaboration & Adaptability:

- Team coordination was critical for managing tasks like data annotation, model training, and testing.

- Flexibility to pivot (e.g., adjusting augmentation strategies) improved outcomes.

4. Societal Impact Awareness:

- Recognized the potential of AI to address safety-critical gaps in public infrastructure.

Future Scope:

1. Enhanced Detection Capabilities:

- Expand the system to detect additional railway hazards, such as obstacles on tracks, damaged rails, or unauthorized vehicles near crossings.

- Incorporate multi-sensor fusion (e.g., LiDAR, thermal cameras) to improve detection robustness, especially in challenging environments.

2. Advanced AI Models:

- Experiment with newer versions of YOLO (e.g., YOLOv9) or transformer-based models (e.g., Vision Transformers) to further boost accuracy and speed.

- Implement edge AI deployment (e.g., NVIDIA Jetson, Raspberry Pi) for low-cost, real-time processing in resource-constrained settings.

3. Predictive Analytics:

- Integrate machine learning to predict potential accidents by analyzing historical detection data and patterns of pedestrian movement.

- Develop a dashboard for railway authorities to visualize trends and take preventive measures.

4. Geographical Scalability:

- Adapt the system for global railway networks by training on region-specific datasets (e.g., varying signal light designs or pedestrian behavior).
- Collaborate with international rail operators to test and refine the model across diverse infrastructures.