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ARTIFICIAL NEURAL NETWORKS AND DEEP LEARNING - AI253IA

ENHANCING RAILWAY SAFETY THROUGH HUMAN ACTIVITY RECOGNITION

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INTRODUCTION

- The primary objective of this study is to develop an automated, robust, and real-time human activity detection system to enhance railway safety by addressing the critical issue of unauthorized human presence on railway tracks.
- Develop a system capable of identifying unauthorized human presence on railway tracks with high accuracy under diverse environmental conditions (e.g., lighting, weather, and occlusion).
- Create a specialized dataset representing real-world scenarios for training and testing the model to ensure relevance and robustness.

MOTIVATION

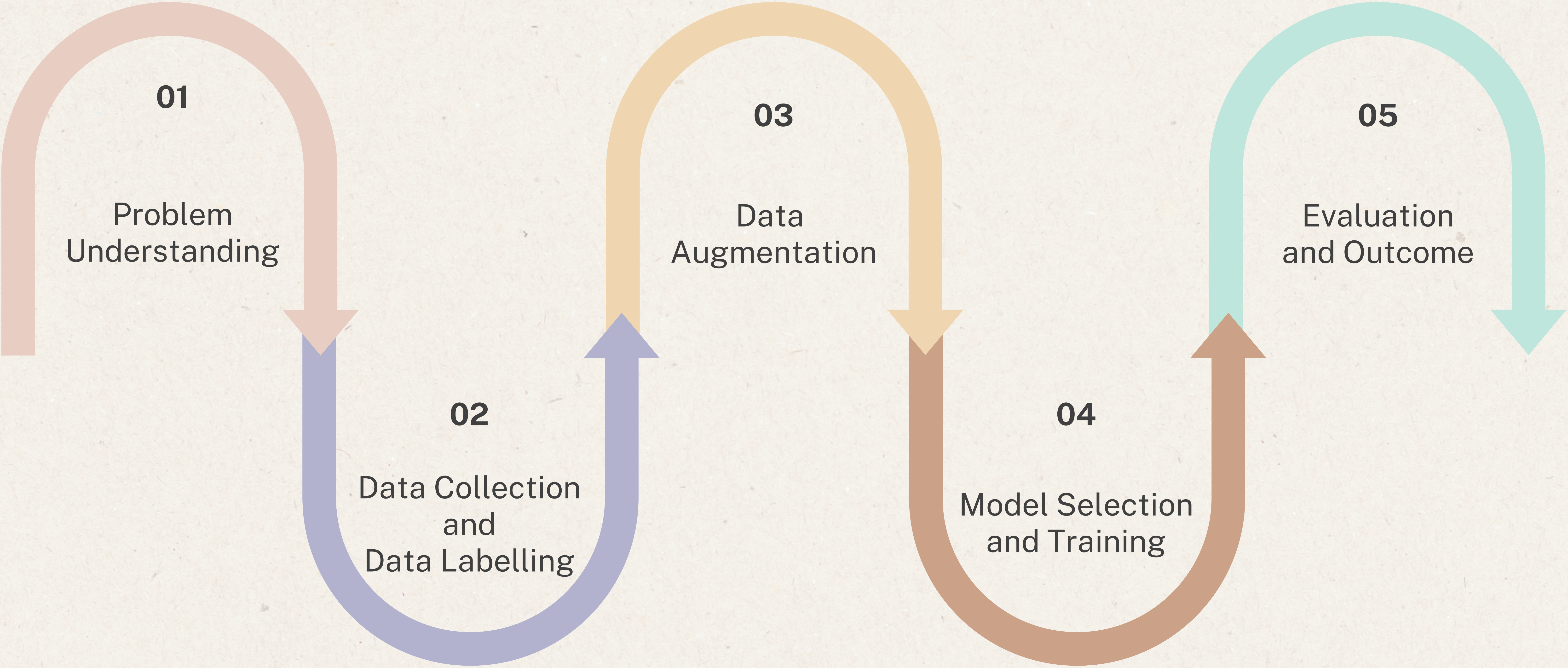
- The motivation for this work is to address the high number of fatalities from unauthorized human presence on railway tracks in India. Traditional safety measures are insufficient for real-time monitoring.

- By leveraging advancements in deep learning and the YOLO algorithm, this project aims to develop an automated system that can detect human presence on tracks in real-time, providing timely alerts to prevent accidents and save lives.

OBJECTIVES

- Enhance railway safety through human activity detection.
- Enable real-time monitoring and automated alerts.
- Achieve high accuracy and speed with YOLO models.
- Promote AI adoption and support preventive measure

THE WORKFLOW



Data Collection Strategy

- Device: Samsung 50 MP GN5 sensor, f/1.88 aperture, with 1080x1080 median resolution.

- Diversity: 1,000 original images under various lighting and weather conditions.
- Environmental Variability: Included partial occlusions from infrastructure or vegetation.
- Annotation Process
- Tool Used: Roboflow for bounding box annotations.
- Classes: Standing, Sitting, Lying, and Track.
- Quality Control: Manual labeling, thorough review to ensure precision.

Data Collection Strategy

Data Augmentation & Splits

- The purpose of augmentation is to expand dataset and improve model generalization.
- Methods: Horizontal flips, ±15° rotations, grayscale (20% images), ±20% brightness, ±15% exposure .
- This helped us to expanded the dataset to over 3,700 images.

- Data Distribution

Annotations by Class

- Track: 1,819
- Standing: 1,782
- Sitting: 1,406
- Sleeping: 689

- Split
  - Training: 70% (2,635 images)
  - Validation: 20% (754 images)
  - Testing: 10% (377 images)

The Model

- **Key Parameters**:
  - Batch Size: 16, optimized for memory usage and stable gradient updates.
  - Epochs: 50, allowing thorough training without overfitting.
  - Learning Rate: 0.00125, balanced for steady convergence.
  - Optimizer: AdamW

- **Data Augmentation**: Applied techniques like flipping, scaling, and rotation to enhance the model's adaptability to real-world scenarios and reduce overfitting

- **Early Stopping and Metric Monitoring**: Implemented early stopping based on validation loss, and monitored metrics such as mAP50, mAP50-95, precision, and recall.

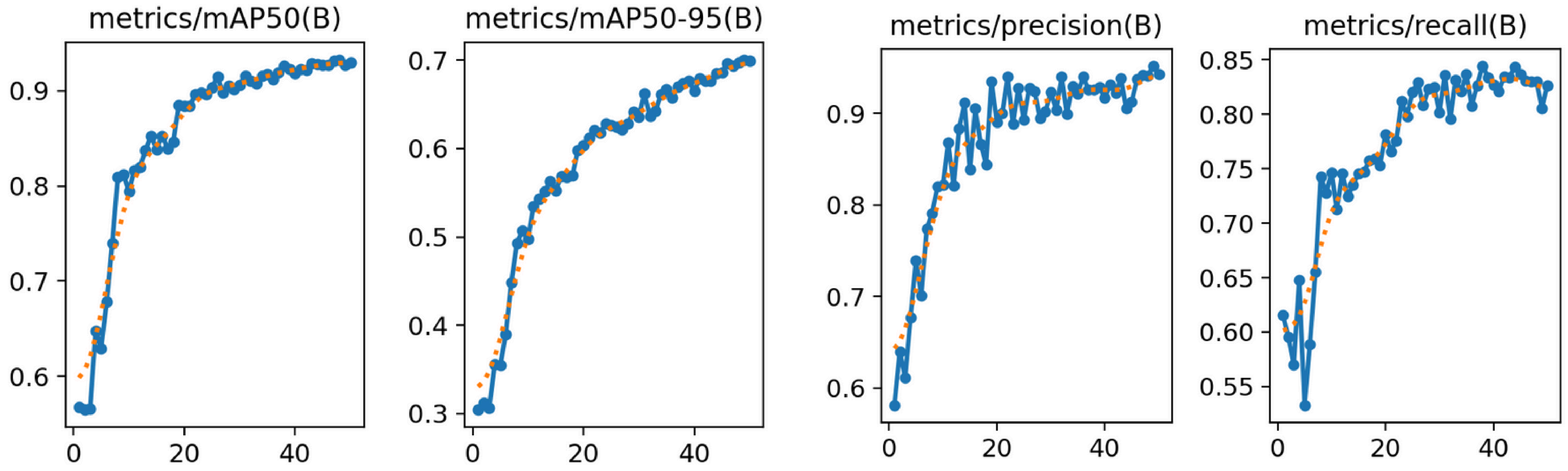
Outcome

Performance

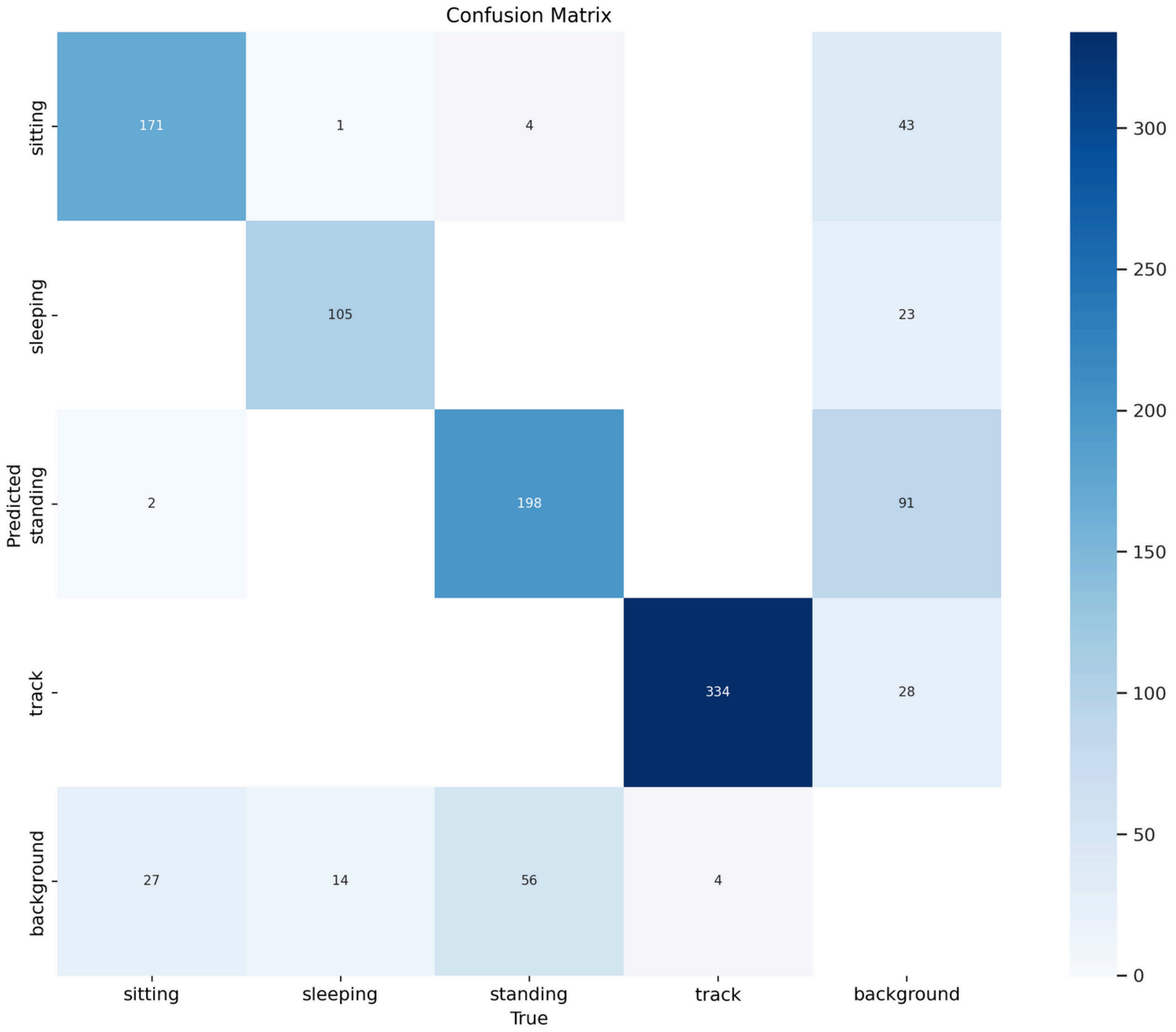
- Efficient Training on Google Colab: Utilized T4 GPU on Google Colab with well-tuned parameters (batch size: 16, epochs: 50, learning rate: 0.00125), achieving both speed and accuracy.

Evaluation Metrics Summary:

- mAP50: 92.3%
- mAP50-95: 69.5%
- Precision: 94.4%
- Recall: 81.1%

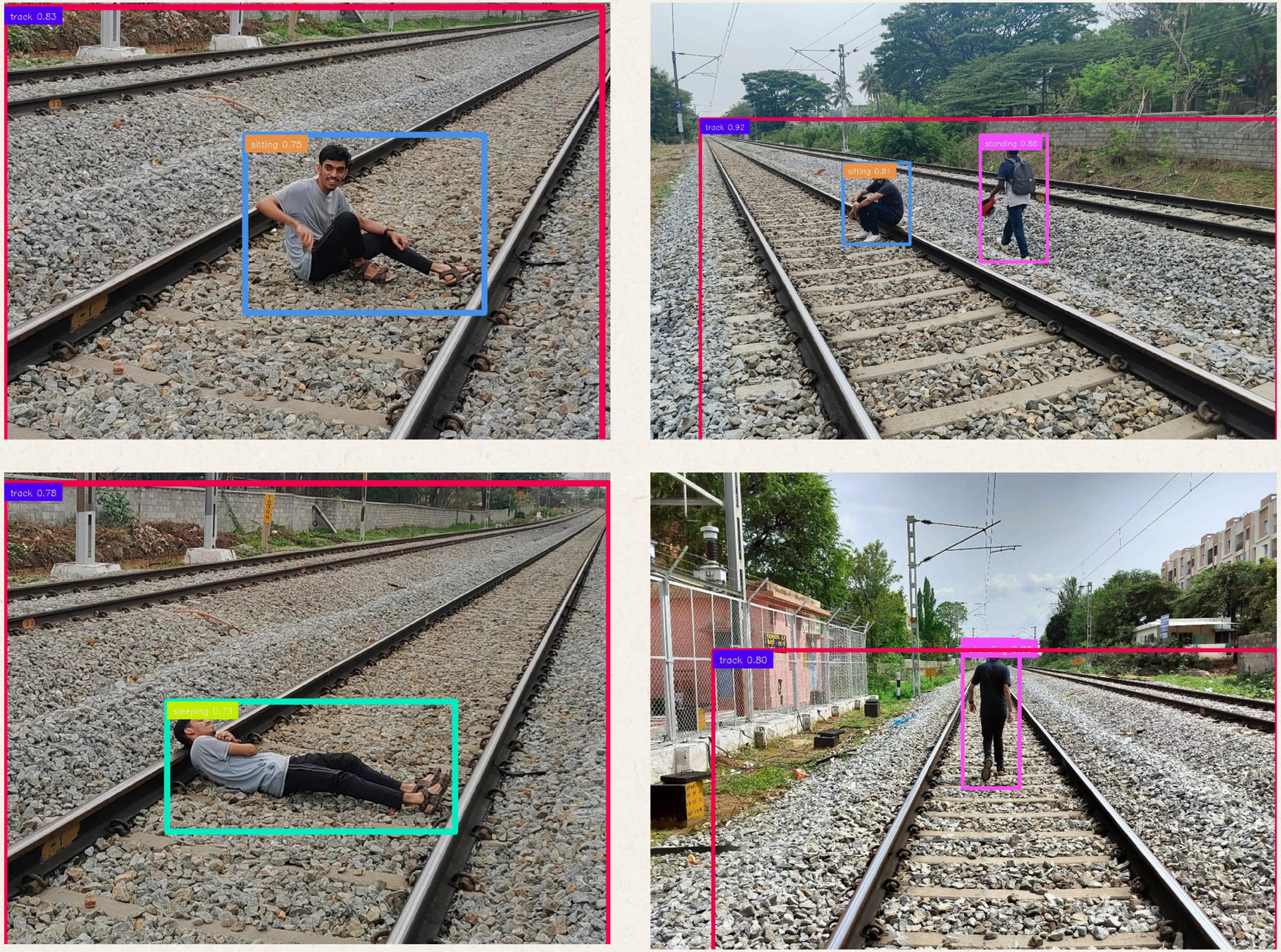


Results



Confusion Matrix
sitting
sleeping
standing
track
background
Predicted
True
171
1
4
43
105
23
2
198
91
334
28
27
14
56
4
300
250
200
150
100
50
0

Results



track 0.83
sitting 0.75
track 0.92
sitting 0.81
standing 0.86
track 0.78
sleeping 0.73
track 0.80