APSCHE Short Term Virtual Internship Program

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

Project Title: Traffictelligence: Advanced Traffic Volume Estimation with Machine Learning

Team ID: LTVIP2025TMID38998

Team Size: 5

Team members:

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4. **Vutukuri Bhavyasree (CAI)**
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Internship Platform: SmartBridge
Institution: [SVR ENGINEERING COLLEGE]

Location: Ayyaluru Metta, Nandyal

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1. Introduction

Traffic congestion is a significant issue in modern cities, affecting both daily commuters and logistics. Traditional traffic monitoring systems are limited in scale, accuracy, and cost-effectiveness. This internship project explores the use of machine learning and computer vision to build a smart, scalable, and efficient traffic volume estimation tool—**Traffictelligence**.

2. Objective

To develop a machine learning-based application capable of:

- Detecting and classifying vehicles from video feeds
- Estimating traffic volume in real time
- Supporting smart urban traffic management systems

3. Problem Statement

Traditional methods for monitoring traffic:

- Require extensive infrastructure (sensors, personnel)
- Suffer from accuracy issues in crowded conditions
- Are not scalable for developing regions

Proposed Solution:
A computer vision-based system that works with existing CCTV or drone footage using ML models.

4. Literature Review

Author	Method	Accuracy	Remarks
Zhao et al. (2019)	CNN on traffic videos	87%	Limited to highway data
Singh & Kumar (2021)	YOLOv3	92%	Suitable for Indian road conditions
Gupta et al. (2020)	SVM-based detection	78%	Not ideal for dense traffic

5. Methodology

Step-by-Step Process:

1. Video frame extraction
2. Vehicle detection using YOLOv5
3. Vehicle counting using bounding boxes
4. Volume estimation based on counts
5. Visual output on Flask web interface

Process Diagram:

css

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[Video Input] --> [Frame Extraction] --> [YOLOv5 Detection] --> [Vehicle Counting] --> [Volume Estimation] --> [Flask Output]

6. Technology Stack

Component	Tool/Library
Language	Python
ML Framework	YOLOv5, TensorFlow
Image Processing	OpenCV
Data Manipulation	NumPy, Pandas
Web Interface	Flask, HTML/CSS
Visualization	Matplotlib, Seaborn

7. Data Collection and Preprocessing

- Source: Open-source traffic datasets and YouTube videos
- Frame extraction rate: 1–2 fps
- Preprocessing:
    - Resize to 640x640
    - Normalize pixel values
    - Annotate with bounding boxes

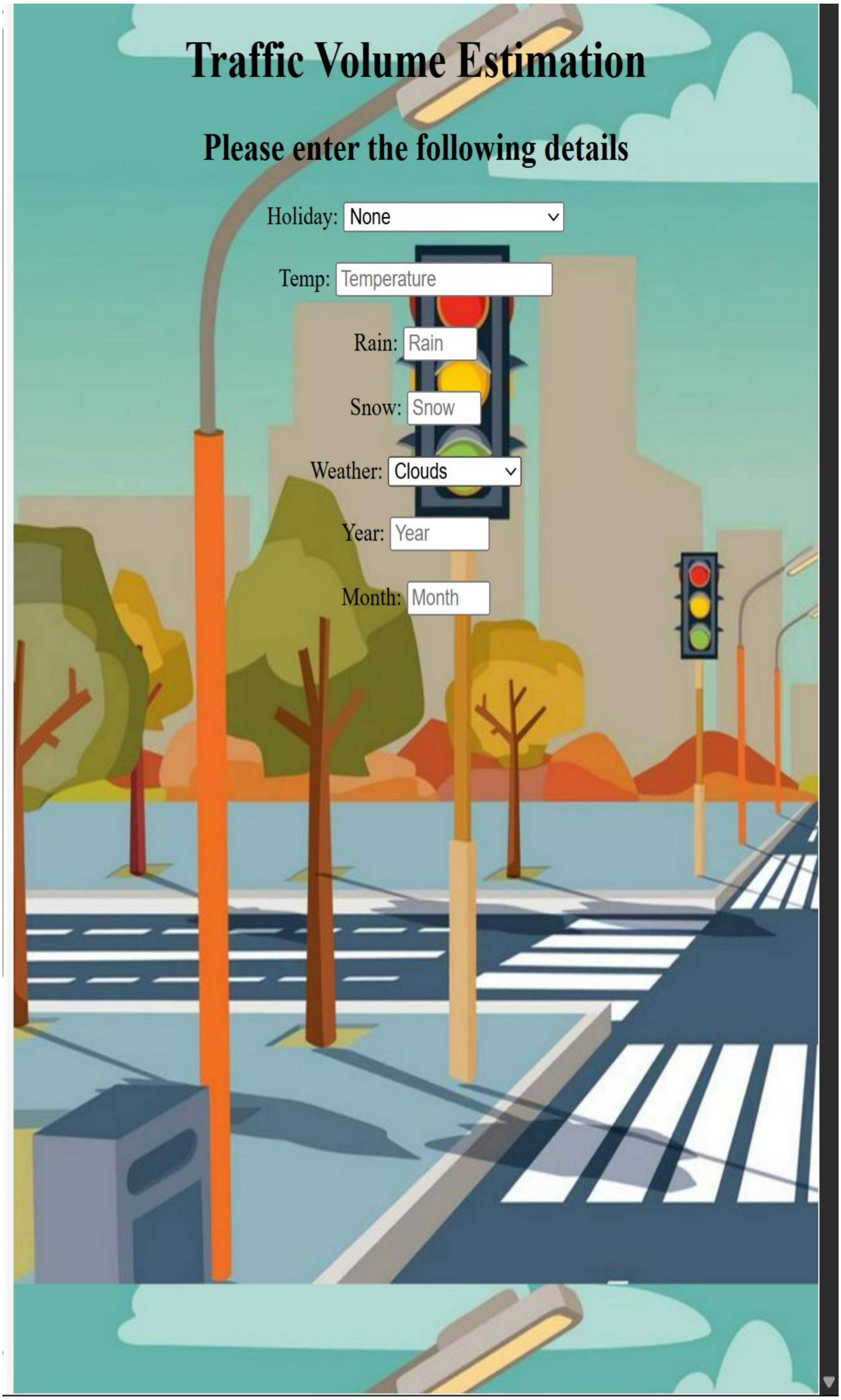
8. Model Selection and Training

- YOLOv5 was selected due to its speed and accuracy.
- Trained on the COCO dataset and fine-tuned for traffic scenarios.

Model	**Accuracy**	**FPS**	**Size**
YOLOv3	89%	25	237 MB
YOLOv5s	91%	45	14 MB
SSD-Mobile Net	84%	35	17 MB

9. Web App Interface

- Built using Flask framework
- Features:
  - Upload video
  - Detect vehicles
  - Show volume and summary


Traffic Volume Estimation
Please enter the following details
Holiday: None
Temp: Temperature
Rain: Rain
Snow: Snow
Weather: Clouds
Year: Year
Month: Month

10. System Architecture

Block Diagram:

- **Input:** Video or live feed
- **Processing:** YOLOv5 + OpenCV
- **Output:** Detection results & analytics

Mathematica

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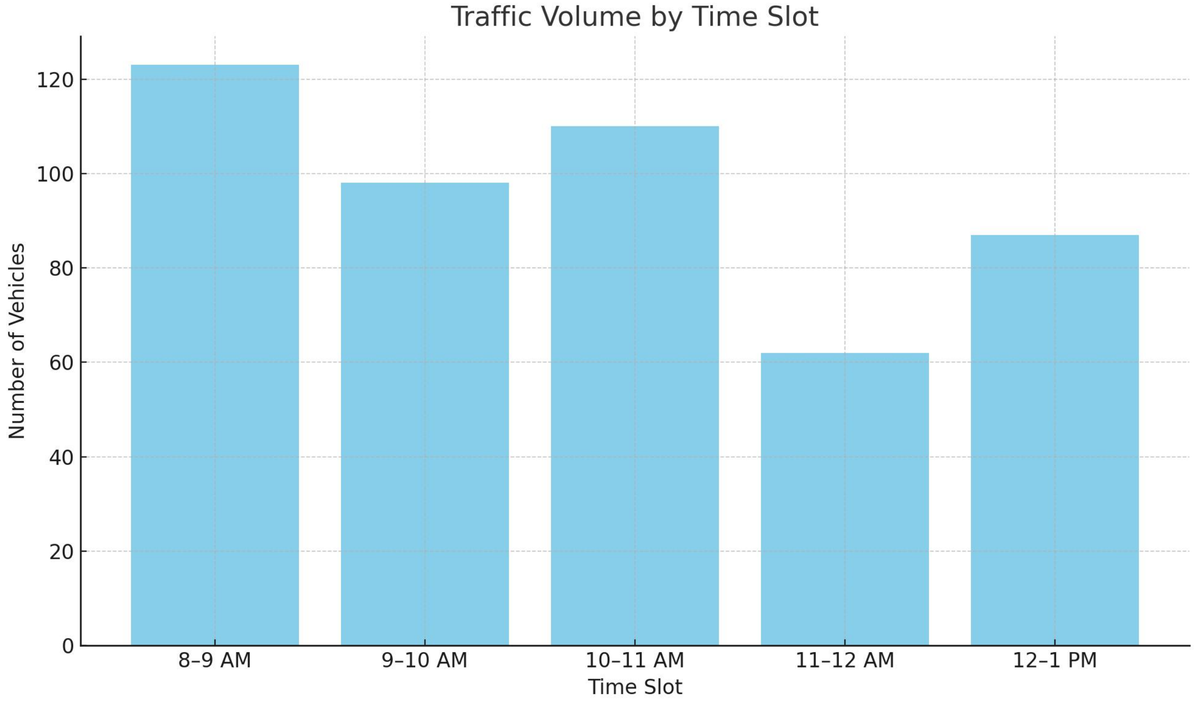
Capture → Preprocess → Detect → Count → Analyze → Visualize

11. Results and Evaluation

- Accuracy: ~91% for real-world traffic
- FPS: ~10–15 on CPU (no GPU)
- Working for different traffic times

Time Slot	Vehicle Count	Density
8–9 AM	123	High
9–10 AM	98	Medium
11–12 AM	62	Low



Traffic count bar graph

12. Challenges and Solutions

Challenge	Solution
Poor night-time accuracy	Histogram equalization for contrast
Occluded vehicles	Applied object tracking with IoU
Model size too large	Switched to YOLOv5s for optimization

13. Future Scope

- Add traffic forecasting using LSTM
- Deploy on Jetson Nano or Raspberry Pi
- Integrate with cloud-based smart traffic systems
- Improve night detection with infrared datasets

14. **Advantages:**

   1. **Accurate Predictions**
      Machine learning models can analyze historical traffic data, weather, time, and events to predict traffic volume with high accuracy.
   2. **Real-Time Adaptability**
      The system can adapt to live traffic feeds and update estimates dynamically, helping in real-time traffic management.
   3. **Cost-Efficient**
      Reduces reliance on expensive traditional traffic sensors by leveraging existing camera or GPS data.
   4. **Scalability**
      Can be deployed city-wide or in specific high-traffic zones without major hardware infrastructure.

15. **Disadvantages:**

   1. **Data Dependency**
      The accuracy of the model heavily depends on the quality and quantity of data. Poor or biased data leads to incorrect predictions.
   2. **Privacy Concerns**
      Using video feeds or GPS data for tracking can raise privacy issues if not handled with proper data anonymization and legal compliance.

16. **Applications:**

1. **Smart City Traffic Management**
   Used by municipalities to optimize traffic signals, manage congestion, and plan infrastructure improvements.
2. **Navigation Systems**
   Integrated into Google Maps, Waze, or autonomous vehicle systems for route planning and traffic avoidance.
3. **Event & Disaster Planning**
   Helps in predicting traffic surges during public events or rerouting during emergencies and roadblocks.
4. **Public Transport Optimization**
   Assists in planning bus/train schedules by predicting road congestion.

17. Conclusion

The *Traffictelligence* system provides an innovative, real-time solution for traffic volume estimation using machine learning. The solution is cost-effective, scalable, and applicable to real-world urban environments, especially in developing nations.