Volume 10, Issue 5, May – 2025 International Journal of Innovative Science and Research Technology
ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may495

Trajectrack: Intelligent Trajectory Estimation, Speed Analysis, and Lane Detection for Autonomous Vehicles

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Publication Date: 2025/05/21

Abstract: Autonomous vehicles (AVs) need complex perception systems for safe operation under dynamic traffic scenes. We introduce TrajecTrack, a machine learning-based platform that integrates real-time trajectory estimation, velocity estimation and lane detection from LiDAR and vision inputs. We apply DBSCAN clustering and the constant velocity model for predicted trajectories, with our speed estimation based on YOLOv8 and ByteTrack, plus a new module for lane detection based on edge detection and the Hough transform. Compared to the NuScenes dataset and sample video input, TrajecTrack provides high-accuracy visualizations of the trajectories, velocities and road lane markings and therefore improves the situational awareness of AVs. This paper contributes significantly to the field of AV perception in that it supports a scalable single solution, with future implications being in traffic violative detection.

Keywords: *Trajectory Estimation, Speed Estimation, Lane Detection, Autonomous Driving, LiDAR, Camera-Based Perception, DBSCAN, YOLOv8, ByteTrack, Hough Transform, NuScenes Dataset, Real-Time Analysis.*

How to Cite: Himesh Chauhan; Varun Choudhary; Syed Faizan Haider; Dr. Gokulnath C (2025). Trajectrack: Intelligent Trajectory Estimation, Speed Analysis, and Lane Detection for Autonomous Vehicles. *International Journal of Innovative Science and Research Technology*, 10(5), 777-784. https://doi.org/10.38124/ijisrt/25may495

I. INTRODUCTION

The development of autonomous vehicles (AVs) is a powerful revolution in transportation that promises the potential for better safety, efficiency, and mobility. At its core is the perception system, which surveys the environment, enabling AVs to make decisions based on knowledge about what is in front of it. Three foundational tasks are central to this functionality which are trajectory estimation (which predicts the expected motion of nearby cars), speed estimation (which infers their velocities) and lane detection (which identifies road lanes to enable compliant navigation). Integrated, these activities make possible collision avoidance, route planning, and traffic rules following, which underlie safe autonomous driving.

But genuine real-time perception is difficult to attain. Sensor noise, occlusions, changing weather, and stochastic vehicle dynamics make these challenging. Conventional methods favor costly sensors such as radar and LiDAR for speed and trajectory estimation, or simple image processing for lane detection, but they may be computationally expensive or dependent on the environment. For example, Kalman filters, which are widely applied for trajectory estimation, need linear motion and have difficulty with rich dynamics, and conventional lane detection algorithms fail in bad lighting or road conditions. The advent of artificial intelligence (AI) and computer vision offers valid alternatives. Camera-based solutions, augmented with AI models, provide economically viable solutions with increasingly high accuracy. Most current frameworks, however, are poised to tackle these functionalities in a siloed fashion, with no integrated system that brings together trajectory, speed, and lane detection to offer complete perception. TrajecTrack fills this gap by combining LiDAR-based trajectory estimation, camera-based speed estimation, and a new real-time lane detection module through a single AI-based system. Our solution employs DBSCAN clustering, YOLOv8, ByteTrack and a custom lane detection pipeline to produce accurate and actionable outputs, such as trajectory visualizations, speed annotations, and lane markings. This paper builds on our previous work by adding lane detection and performing an in-depth analysis of our methodology, system architecture, and results to provide a complete overview of TrajecTrack's capability.

II. LITERATURE REVIEW

➢ *Overview*

The technology of autonomous driving has seen significant advances, especially for perception tasks such as trajectory and speed estimation. These tasks were traditionally performed using sensor fusion techniques, wherein LiDAR, radar, and camera data are fused to yield accurate results. These techniques, however, tend to have high computational overhead and are not quite efficient in

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may495

generalizing across varied settings. Recent advances in artificial intelligence and computer vision have recently provided cost-effective alternatives that enable real-time processing with low reliance on hardware resources. Despite these advances, long-term trajectory prediction and computation of speed with precision under dynamic settings remain a challenge.

Our approach improves upon these developments by combining LiDAR-based trajectory estimation with speed estimation from cameras. This overview summarizes existing techniques, their weaknesses, and how TrajecTrack exploits AI to overcome them.

➢ *Ai Integration*

Artificial Intelligence (AI) has revolutionized perception systems in AVs to enable automation and accuracy. AI powers trajectory and speed estimation with domain-specific algorithms and models in TrajecTrack.

➢ *AI in Trajectory Estimation*

Trajectory estimation involves monitoring vehicle motion and anticipating future trajectories. Older techniques such as Kalman filters are linear motion-based, which is not effective in complex situations. We use a multi-step AI-based approach:

- *DBSCAN Clustering:*

  We classify LiDAR points into vehicle-representing clusters using DBSCAN based on its density-based nature to efficiently deal with irregular shapes.

- *Individualized Tracking:*

  A dedicated algorithm uses the Hungarian method to establish correspondence between frames, thus ensuring consistent tracking.

- *Constant Velocity Prediction:*

  A basic predictive model predicts near-term trajectories based on current velocity, serving as a foundation for further refinements.

➢ *AI in Speed Estimation*

Accurate detection and distance estimation are required for camera speed estimation. Our system employs a combination of:

- *YOLOv8 Detection:*

  The latest, high-accuracy model detects vehicles in real time.

- *ByteTrack Tracking:*

  A robust tracker maintains vehicle identities across frames, handling occlusions well.

- *Perspective Transformation:*

  We transform image coordinates to bird's-eye view to enable us to compute real-world speed.

➢ *Limitations of Existing Systems*

Modern perception systems are full of defects:

- *Sensor Dependency:*

  Expensive sensor dependency constrains scalability.

- *Complexity:*

  Deep learning models are computationally intensive, making real-time deployment difficult.

- *Accuracy in Predictions:*

  Long-term route prediction is uncertain because of volatile traffic conditions.

- *Integration Gaps:*

  Not many systems integrate trajectory and speed estimation smoothly.

TrajecTrack meets these challenges with a light and modular system that combines both functions and therefore reduces dependency on special-purpose sensors and real-time performance enhancement.

III. METHODOLOGY

The TrajecTrack system integrates cutting-edge AI methods with sensor information to tackle trajectory estimation, speed analysis, and lane detection. In the following, we outline our extended methodology, highlighting the integration of the new lane detection module.

➢ *Data Collection and Preprocessing NuScenes Dataset:*

We utilize the NuScenes v1.0-mini dataset, comprising LiDAR point clouds and camera images with ground-truthed vehicle locations, for validation and estimation of trajectories. Video Inputs: Ordinary video recordings are used as an input for speed estimation and lane detection, preprocessed to achieve informative features such as vehicle tracks and road edges.

➢ *Trajectory Estimation Detection:*

DBSCAN clusters LiDAR points as car objects (eps=0.5, min_samples=10), height-filtered (0.5m–3.0m) for noise suppression. Tracking: A proprietary algorithm uses the Hungarian method (max_age=5, min_hits=2, dist_threshold=3.0) to associate detections across frames. Prediction: A constant velocity model generates predictions up to 10 steps (5 seconds), providing short-term trajectory estimates.

➢ *Speed Estimation Detection:*

YOLOv8n identifies cars with a confidence threshold of 0.3, optimized for real-time execution. Tracking: ByteTrack tracks vehicle identities across frames regardless of occlusion. Speed Calculation: Perspective transformation warps image coordinates to a 25x250-unit domain and calculates speeds in km/h from frame-to-frame displacement.

The new real-time lane detection module processes video frames to detect and show lane markings: Preprocessing: Grayscale and blur frames with a 5x5 Gaussian kernel to reduce noise. Edge Detection: Canny edge detection (low_t=50, high_t=150) extracts road edge features. Region Selection: Masks the road area with a trapezoidal

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may495

mask (bottom-left: 10%, 95%; top-left: 40%, 60%; top-right: 60%, 60%; bottom-right: 90%, 95%) via bitwise AND. Hough Transform: Detects line segments (rho=1, theta=π/180, threshold=20, minLineLength=20, maxLineGap=500) within the masked area. Lane Line Calculation: Calculates averages of slopes and intercepts, weighted by line length, to form left (negative slope) and right (positive slope) lanes, mapped from image bottom to 60% height. Visualization: Renders red lane lines (thickness=12) on the original frame via weighted blending.

➢ *System Integration:*

LiDAR module (trajectory) and camera module (speed and lane detection) run in parallel with combined outputs for visualization. Modularity allows scaling and ease of extension.

➢ *Evaluation Qualitative:*

Visual inspection of lane paths, speed labels, and lane lines. Quantitative: Verification of predicted trajectories against NuScenes ground truth and manual checking of speeds and lane correctness.

IV. SYSTEM DESIGN AND ARCHITECTURE

TrajecTrack is designed with modularity and real-time processing in mind and combines three core elements into one framework.

➢ *Architectural Overview*

- *Input Layer:*

Handles LiDAR point cloud and camera frames.

- *Processing Layer:*

Performs detection, tracking, prediction, speed calculation, and lane detection.

- *Output Layer:*

Generates labeled images using Matplotlib and OpenCV.

➢ *Component Details*

- *LiDAR Module:*

Manages trajectory estimation with DBSCAN, tracking, and prediction.

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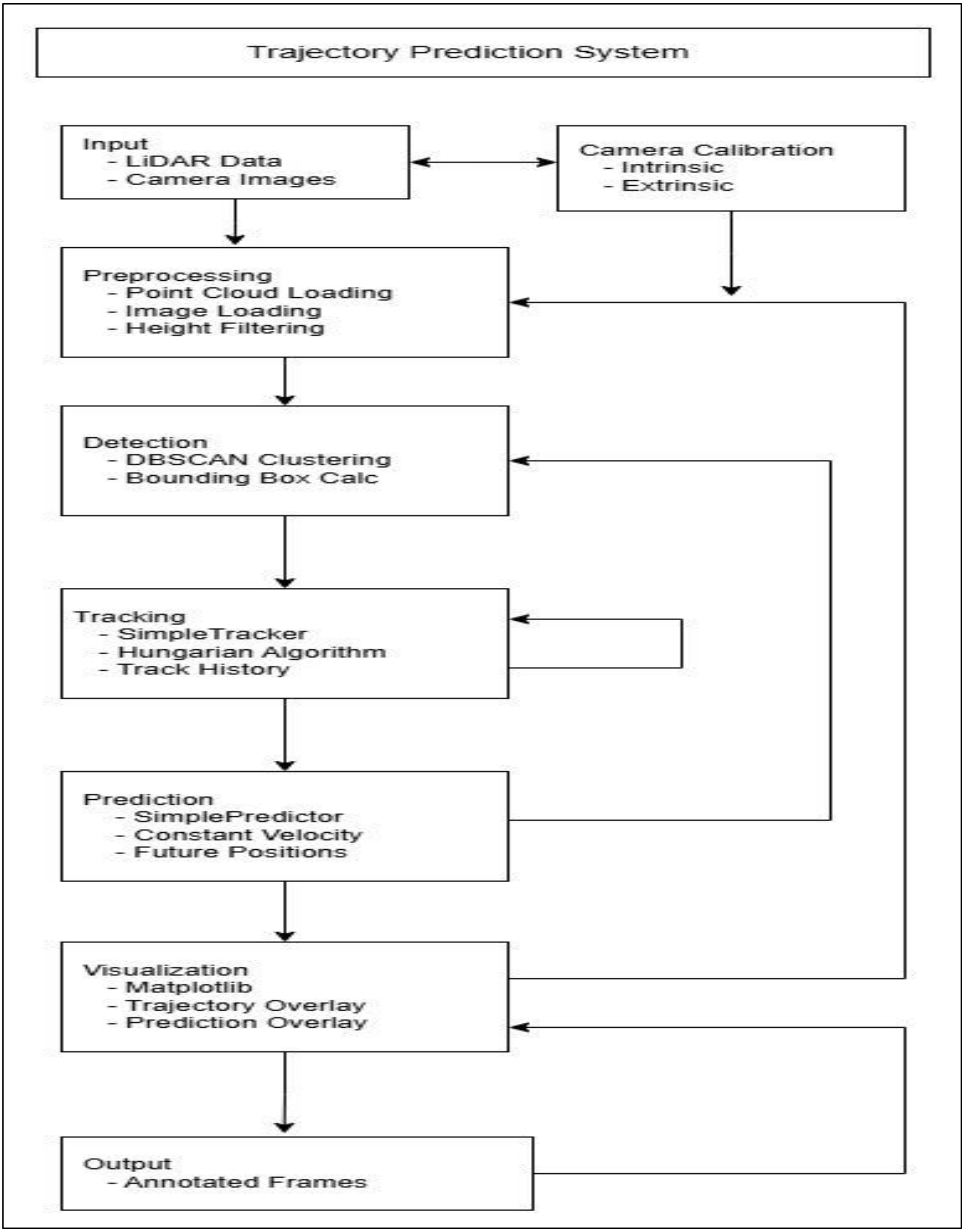

Fig 1 Architecture Diagram of Trajectory Prediction System

- *Camera Module:*

Controls speed estimation (YOLOv8, ByteTrack, perspective transformation) and lane detection (Canny, Hough, line averaging).

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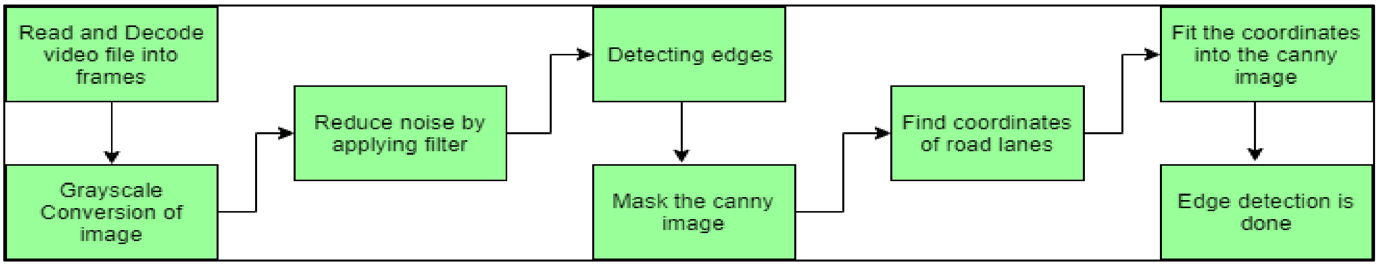

Fig 2 Architecture Diagram of Road Lane Detection System

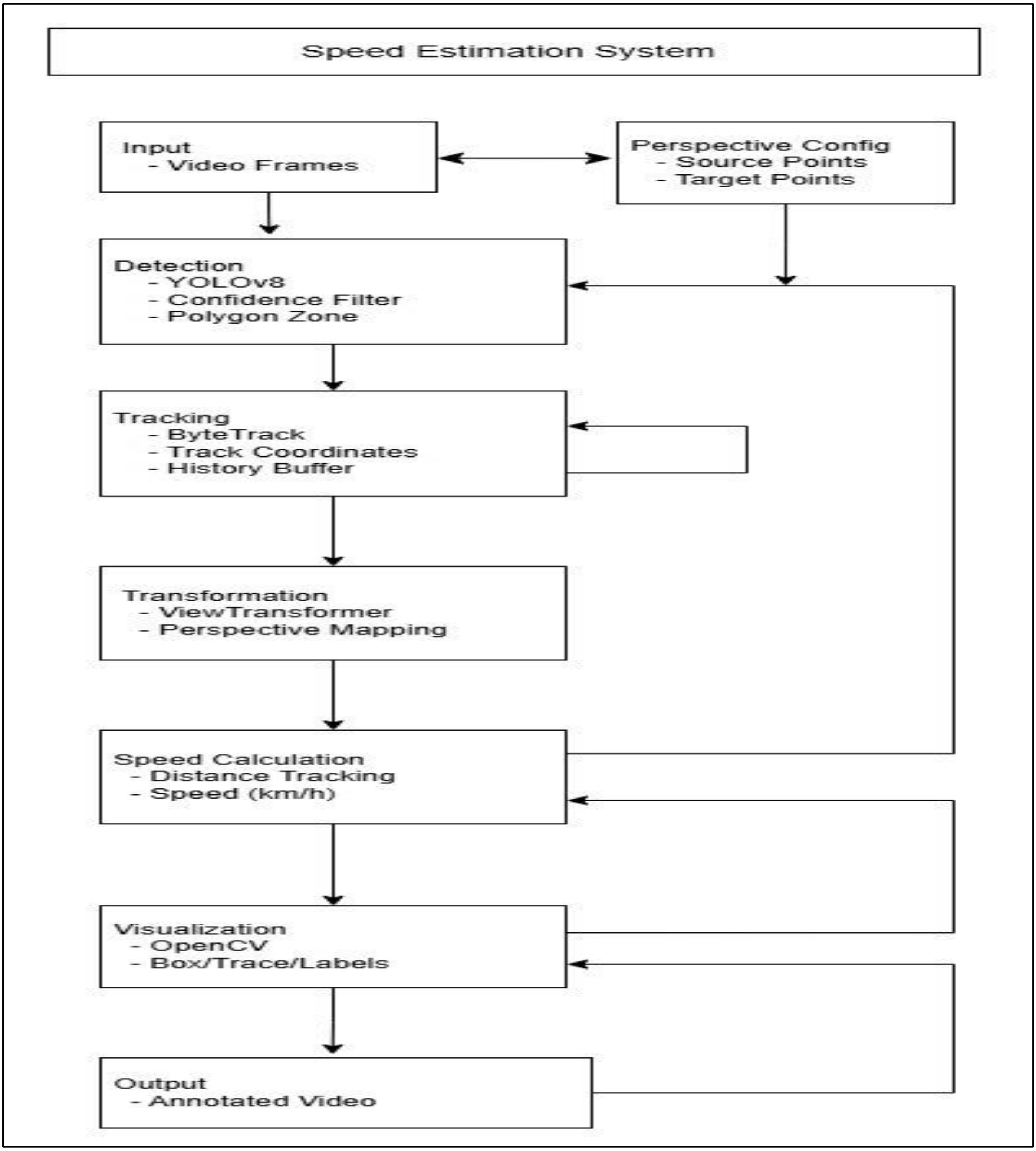

Fig 3 Architecture Diagram of Speed Estimation System

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may495

- *Visualization:*

Overlay trajectories, speed signals, and lane markings onto video frames.

➢ *Workflow*

LiDAR data are grouped and followed, forecasting car routes.

Camera frames are processed to determine vehicle speeds and identify lane markings.

Results are computed and displayed simultaneously.

➢ *Scalability*

The modular design of the system enables future upgrades like deep learning predictors or other sensor inputs to be provided with flexibility to changing AV requirements.

V. RESULTS AND OUTPUT

TrajecTrack produces practical outputs that enhance AV perception:

➢ *Trajectory Estimation*

- *Output:*

Graphical routes of automobiles with standard identifiers and live predictions.

- *Performance:*

Precise tracking and prediction in NuScenes test cases.

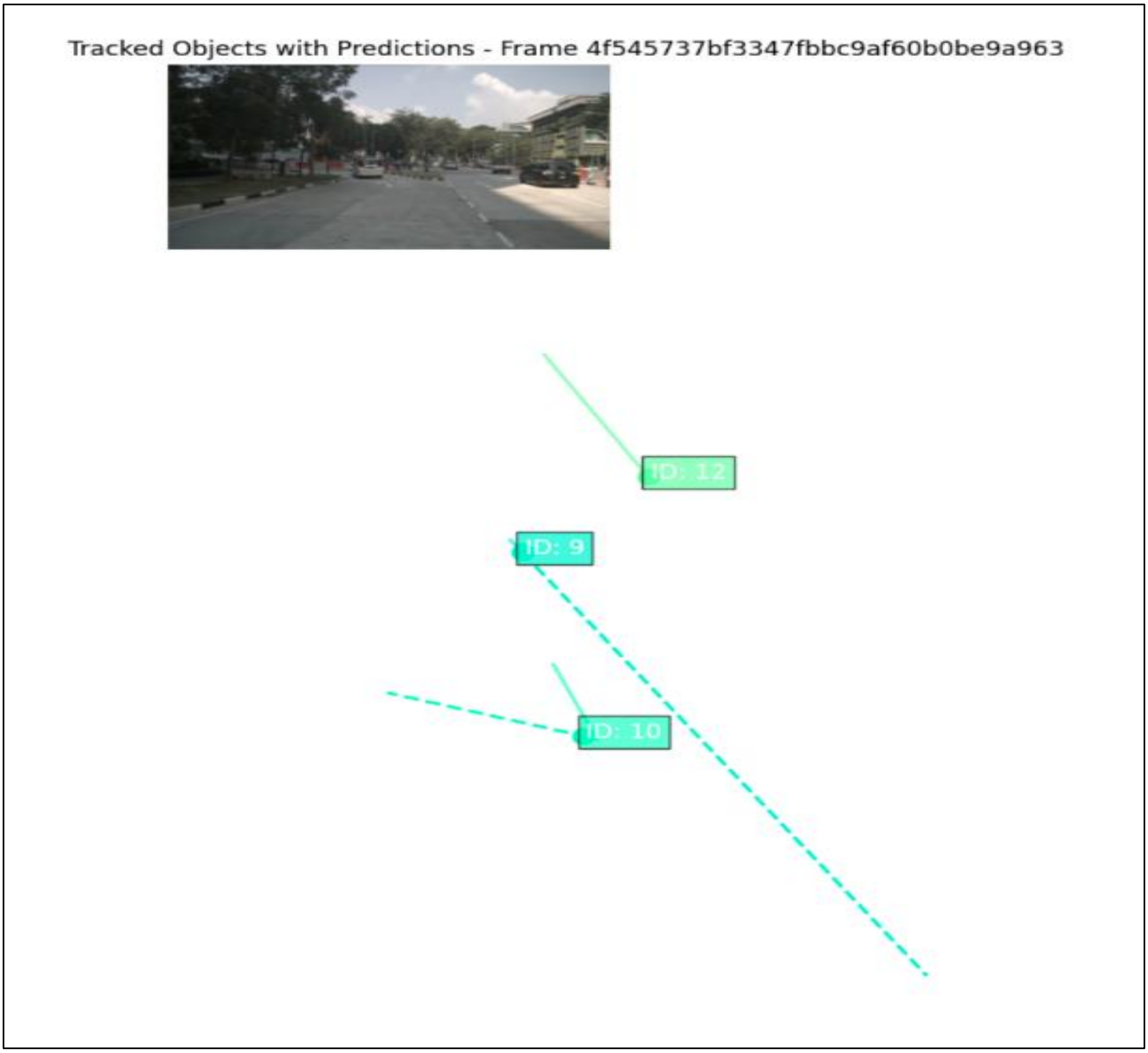

Fig 4 Output of Trajectory Prediction System

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may495

➢ *Speed Estimation*

- *Output:*
  Video frames labeled with vehicle IDs and velocities (km/h).

- *Performance:*
  Precise speed readings verified with expected values.

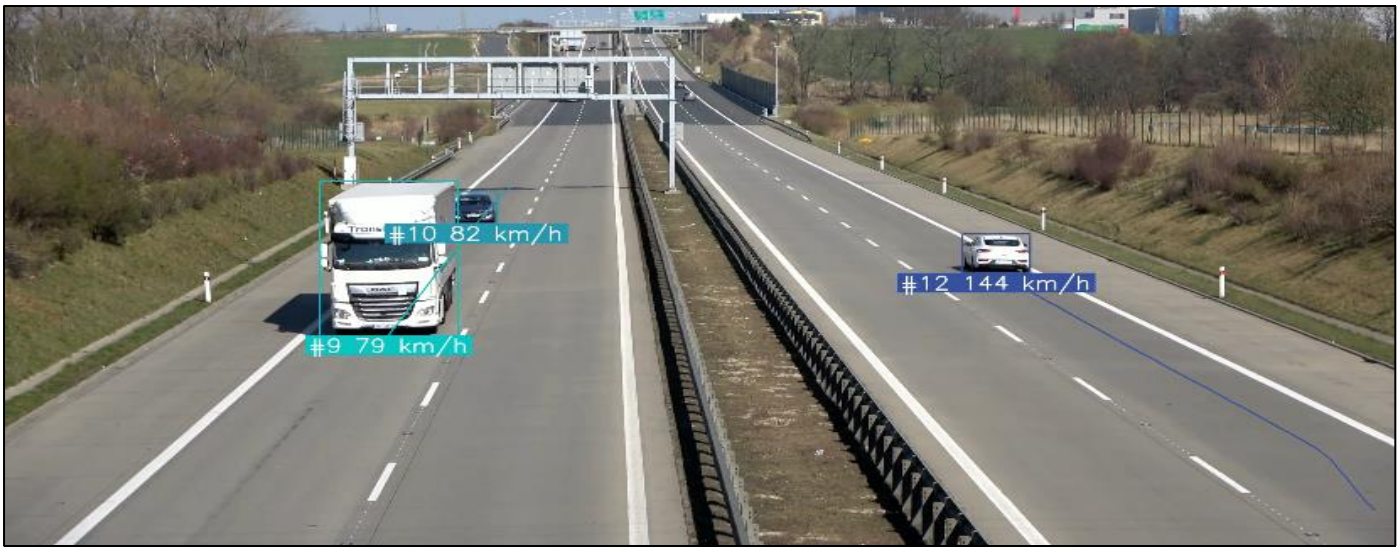

Fig 5 Output of Speed Estimation System

➢ *Lane Detection*

- *Output*:
  Red lane markings that establish the left and right boundaries on frames.

- *Performance:*
  Exceptional identification features observed under diverse lighting and road conditions during video testing.

Fig 6 Output of Road Lane Detection System

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VI. CONCLUSION

TrajecTrack pushes the boundaries of autonomous driving by combining trajectory estimation, speed analysis, and real-time lane detection into one AI-powered system. The inclusion of the lane detection module renders it more useful, with the added benefit of clear road boundary visualizations in addition to vehicle motion information. Although future research can include higher-level prediction models and traffic violation detection, the system provides a scalable platform for enhancing AV safety and navigation.

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