LLM-Powered Framework for Interpretable Traffic Rule Processing in Autonomous Driving

Jean Douglas Carvalho[1], Felipe de Souza Forte[1], Hugo Kenji Taciro[1], **Glaucia Melo[2]**, Max Mauro Dias Santos[1]

[1]UTFPR-PG, Ponta Grossa, Brazil
[2]Toronto Metropolitan University, Toronto, Canada
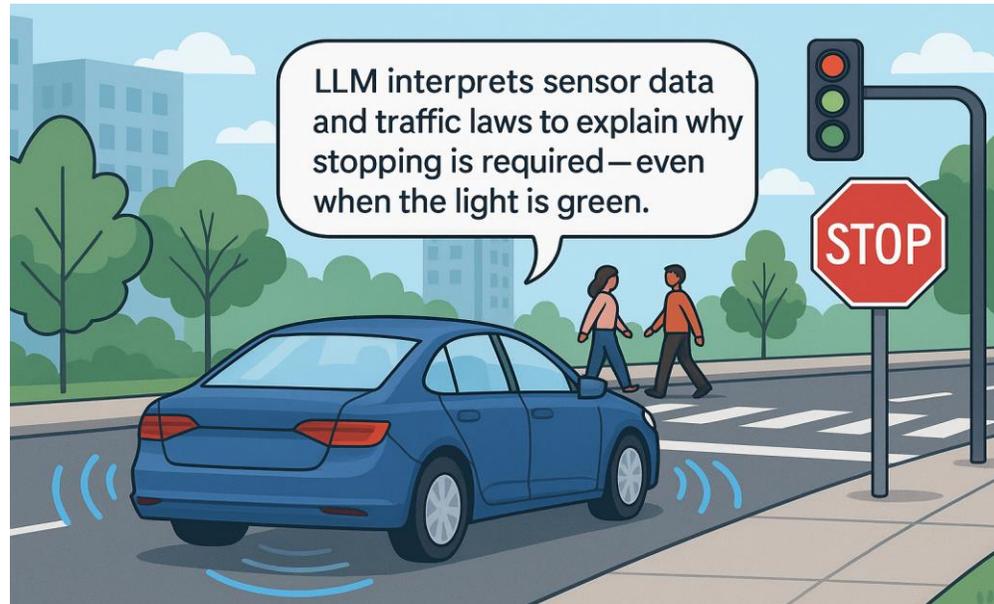
1. INTRODUCTION

Traffic rules are complex and require legal, contextual interpretation;
LLMs help autonomous vehicles make explainable, human-level decisions.

Example:

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Traffic rules are complex and require legal, contextual interpretation;
LLMs help autonomous vehicles make explainable, human-level decisions.

Objective:

✓ Translate multimodal data + legal rules into understandable actions.

1. INTRODUCTION

Solution:

- ✓ **AITR**: Automatic Interpretable Traffic Rules

A novel framework that uses Large Language Models (LLMs) to interpret, explain, and enforce traffic regulations for autonomous and assisted driving systems

Solution:

✓ **AITR**: Automatic Interpretable Traffic Rules

    ✓ **Key Features:**

        ✓ Processes real-time multimodal sensor data (GPS, IMU, Radar, YOLO, CAN)

        ✓ Translates legal texts into structured, machine-readable representations

        ✓ Provides explainable outputs: facts, legal interpretation, and recommended action

        ✓ Grounded in probabilistic LLM reasoning (GPT-3.5-turbo)

        ✓ Supports legal compliance across jurisdictions

    ✓ **Why It Matters:**

        ✓ Traditional systems lack interpretability and legal grounding

        ✓ AITR bridges the gap between sensor data and traffic law

        ✓ Enables transparent, compliant, and safe decision-making in autonomous navigation

Solution:

✓ **AITR**: Automatic Interpretable Traffic Rules

    ✓ **Why?:**

        ✓ Traffic rules are complex, inconsistent, and hard to code manually

        ✓ Traditional autonomous systems lack legal understanding

        ✓ Lack of transparency limits trust, safety, and adoption

        ✓ LLMs can bridge the gap

    ✓ **Our goal:**

        ✓ To enable autonomous and assisted driving systems to make decisions that are not only safe and intelligent but also legally explainable, jurisdiction-aware, and auditable.
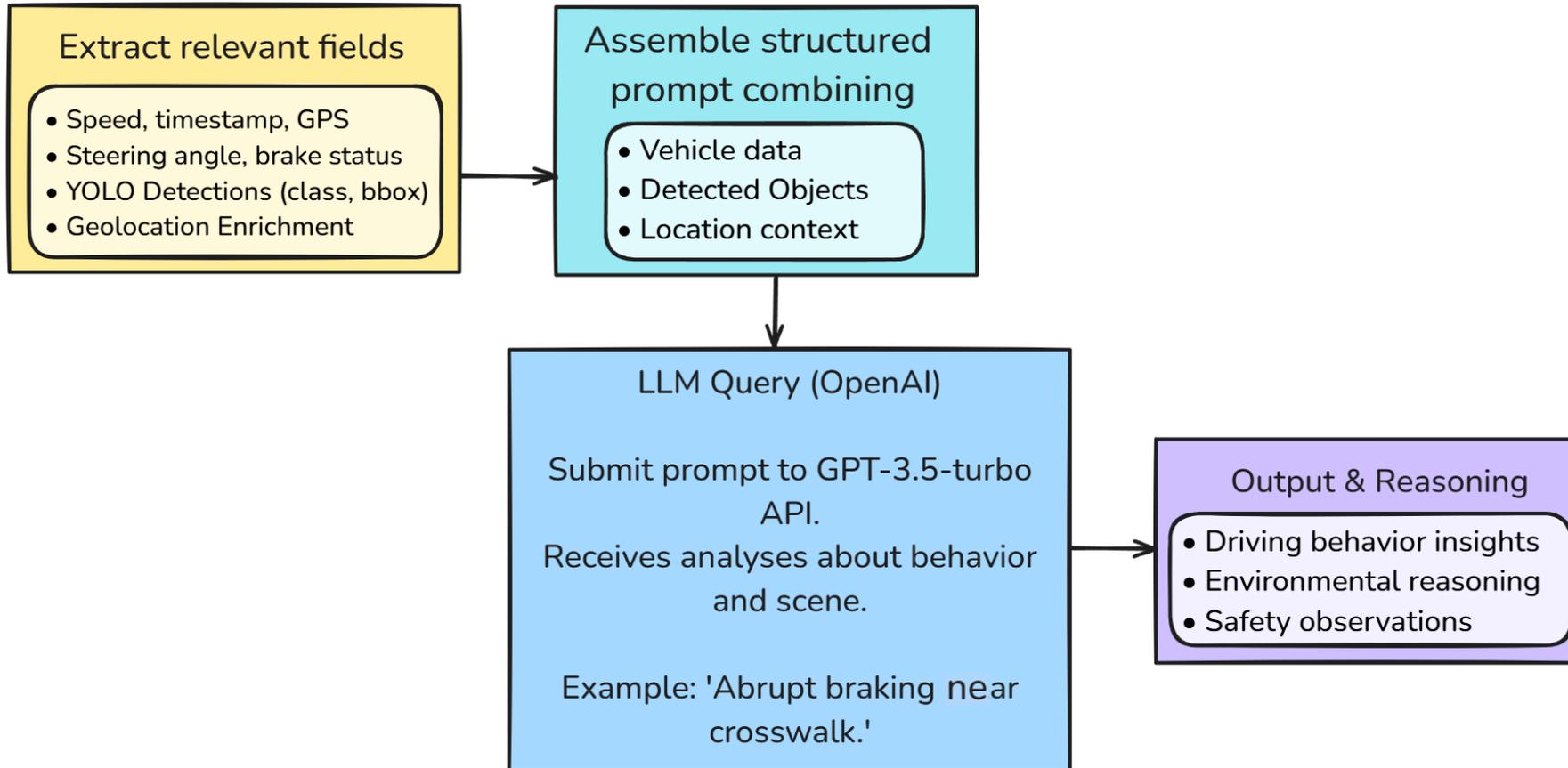
3. DATA ACQUISITION

Data collected via Carcara (a testbed vehicle equi...

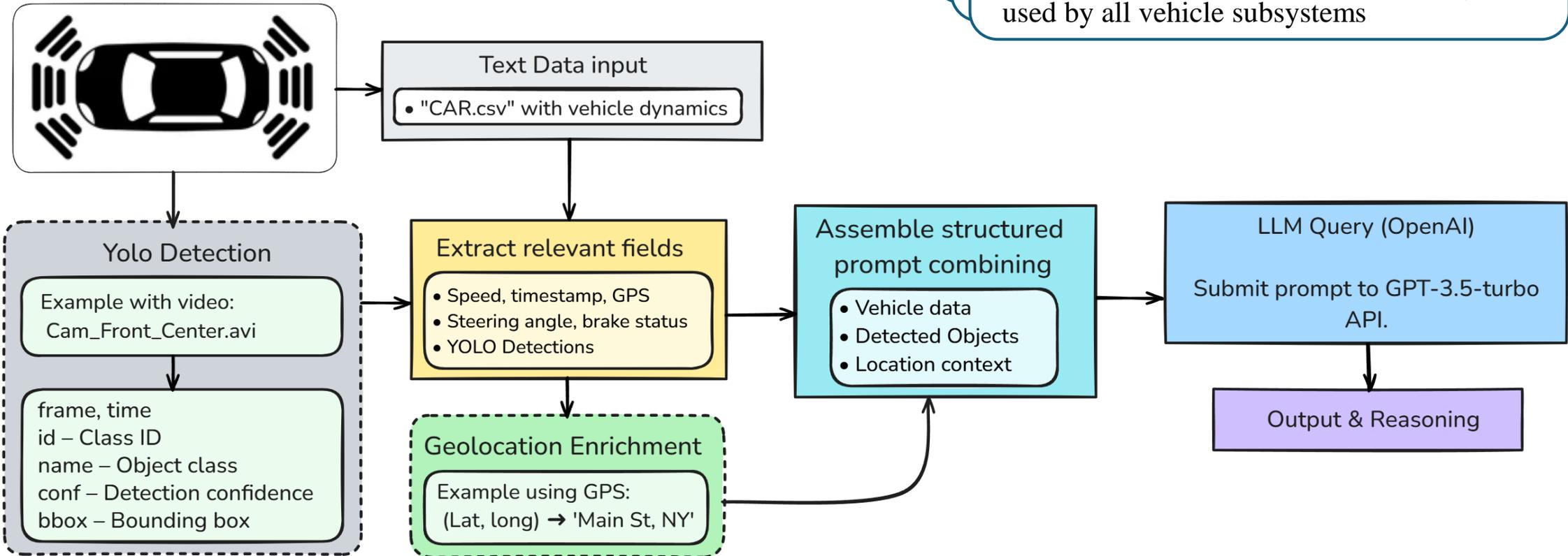✓ 5-minute blocks: GPS, IMU, Radar, YOLO, CAN;

GPS (Global Positioning System)
IMU (Inertial Measurement Unit)
Radar
YOLO (You Only Look Once – Obj Detection)

CAN (Controller Area Network)
- Collects internal vehicle telemetry (e.g., steering angle, brake pressure, gear status)
- This is the real-time communication layer used by all vehicle subsystems

Text Data input
- "CAR.csv" with vehicle dynamics

Yolo Detection

Example with video:
Cam_Front_Center.avi

frame, time
id – Class ID
name – Object class
conf – Detection confidence
bbox – Bounding box

Extract relevant fields
- Speed, timestamp, GPS
- Steering angle, brake status
- YOLO Detections

Geolocation Enrichment

Example using GPS:
(Lat, long) → 'Main St, NY'

Assemble structured prompt combining
- Vehicle data
- Detected Objects
- Location context

LLM Query (OpenAI)

Submit prompt to GPT-3.5-turbo API.

Output & Reasoning

4. EVALUATION – SCENARIO 1
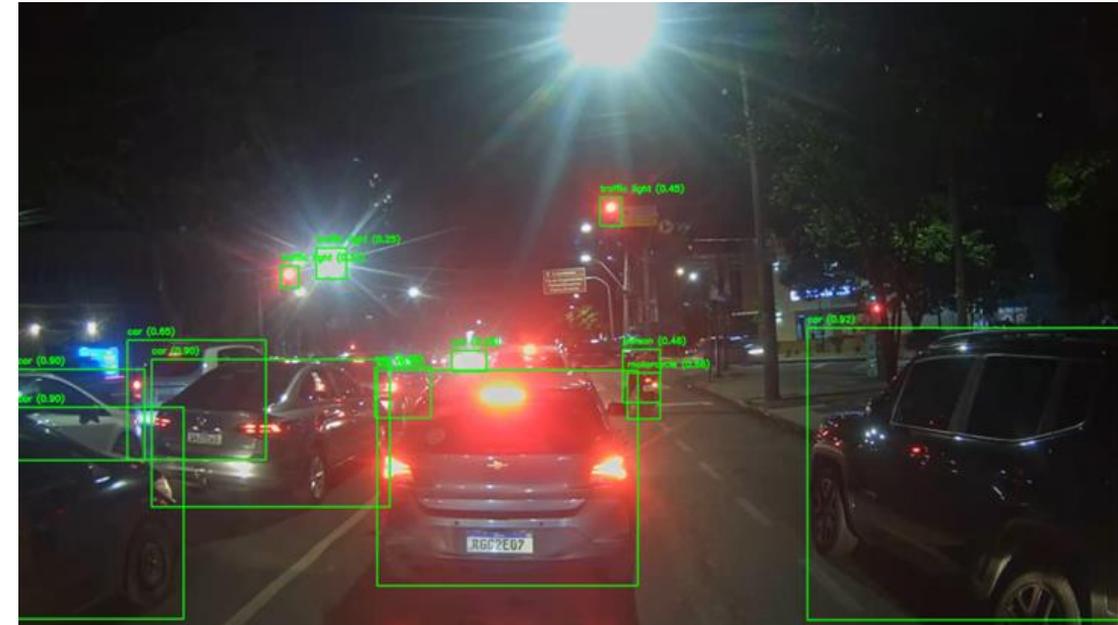
Scenario Input (5-min block):
– Highway, 0 km/h, steering 3.7°, brake pressed
– YOLO detections:
  • 6 nearby vehicles
  • 2 motorcycles
  • 3 traffic lights

LLM Role:
– Interprets telemetry + object detections
– Analyzes vehicle stoppage in a dense context
– Verifies compliance with CTB Article 192 (safe following distance)

Output (LLM Reasoning):
– "Stopped vehicle in dense traffic context"
– No violation, but situational awareness required
– Recommends maintaining safe distance and readiness to move

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Scenario Input (5-min block):
– Urban leisure zone – 17.16 km/h,
 steering 7.7°, no breaking
– YOLO detections:
  • 4 pedestrians
  • 1 vehicle
  • 1 static object (bench)

LLM Role:
– Analyzes perception + vehicle behavior
– Correlates objects with urban environment
– Assesses risks based on road type and proximity

Output (LLM Reasoning):
– "Pedestrian presence in leisure area = potential risk"
– Behavior acceptable but caution advised
– Recommends slowing down, refining object detection, and
staying ready for evasive action

5. COMPARATIVE EVALUATION

TABLE I
COMPARISON OF LLM CAPABILITIES ACROSS APPROACHES.

Solution / Criterion	LLM Output	Mathematical Basis	Explainability	Legal Rule
AITR (Ours)	Structured (facts, interpretation, actions)	Probabilistic model	Multi-layered, SHAP-based	Multi-jurisdiction, law-adaptable

AITR leverages GPT's probabilistic language modelling to interpret driving scenarios, infer likely legal outcomes, and generate structured, explainable decisions.

TABLE II
COMPARISON OF DECISION-MAKING BEFORE AND AFTER LLM
INTEGRATION.

Component	Traditional System (Before LLM)	AITR (After LLM)
Sensor Input	Detected pedestrian or vehicle via YOLO / LiDAR	Same
Decision	Stop	Stop
Interpretation	None	Pedestrian has legal right of way despite green light
Legal Reference	Not available	Brazilian Traffic Code – Article 70
Output Format	Binary action	Structured: facts + interpretation + action
User Explainability	Absent	Action justified and traceable

AITR enhances decision-making by adding legal interpretation and structured, explainable reasoning to traditional AV actions, transforming a binary stop into a legally justified and traceable response.

5. COMPARATIVE EVALUATION

TABLE III
COMPARISON OF DATA AND INPUT TYPES.

Solution / Criterion	Data Source	Input Modalities	Scenario Adaptability
AITR (Ours)	Real (5-min blocks), annotated CarCara data	Multimodal: GPS, IMU, Radar, YOLO, CAN, geolocation text	Semi-supervised loop, synthetic support

AITR processes rich, real-world multimodal data from the CarCara platform and supports adaptation through a semi-supervised feedback loop.

TABLE IV
DEPLOYMENT STATUS AND APPLICATION DOMAINS.

Solution / Criterion	Deployment	Main Application
AITR (Ours)	Online API + Website, GPT-3.5 turbo (prompts)	Legal-aware decisions, ADAS + human review

AITR moves beyond lab prototypes by offering a live API and web interface for legal-aware, human-reviewed driving decisions. Prior work focused on theory test assessment or V2X simulation.

What AITR delivers:
– Translates complex data + traffic law into explainable decisions
– Reduces legal ambiguity in autonomous driving
– Enables contextual, safe, and interpretable navigation

Future Work:
– Reinforcement Learning for adaptive rule processing
– Large-scale real-world validation
– Integration with automotive industry and regulatory agencies