Secure Federated Data Fusion Model for Traffic Violation Detection using Rule Based Supervision

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***Abstract*—Most existing traffic violation detection systems rely on centralized processing where large-scale vehicle images and video streams are collected and analyzed on a single server. Although effective, the design introduces serious privacy concerns and increases the risk of sensitive data exposure. In addition, many conventional approaches are trained using only one modality (either images or videos), while ignoring important scene-level cues such as weather, road layout, lane structure, and geographic location. Another major limitation is the heavy dependence on manual annotation, which is costly and difficult to scale for real-world deployments. To address these challenges, this work presents a privacy-aware federated multimodal learning framework for traffic violation detection. The proposed method jointly uses dashcam/CCTV visual inputs along with map-driven contextual information to improve reliability under diverse driving conditions. Since training is performed locally on edge devices, raw video data never leaves the client side; only encrypted model updates are transmitted for aggregation, thereby supporting privacy-preserving learning. Furthermore, the labelling burden is reduced using a rule-based supervision strategy that generates weak labels automatically, significantly minimizing human effort while maintaining effective training signals.**

***Index Terms*—Federated learning, intelligent transportation systems, privacy-preserving learning, multimodal fusion, weak supervision, traffic violation detection, cross-attention**

I. INTRODUCTION

Road safety has become a critical challenge for modern transportation systems, as traffic violations such as red-light running, unsafe lane changes, and pedestrian-related conflicts continue to contribute to a large number of accidents every year [9]. Automated traffic violation detection is therefore an essential component for intelligent transportation systems, supporting applications such as autonomous driving, smart surveillance, and post-incident insurance assessment[3]. However, many deep learning–based detection pipelines still depend on large-scale, manually labelled datasets, which are expensive and difficult to obtain for violation-specific scenarios [16]. In addition, violation recognition is not purely visual; it often requires contextual understanding of the road environment, including lane structure, intersection geometry, and location-dependent constraints [12]. To address these limitations, this work proposes a weakly supervised multimodal learning pipeline for traffic violation detection. First, a YOLO based detector is used to identify key road entities such as vehicles, pedestrians, and traffic lights [11]. Next, a rule-driven supervision module aligns these detections with OpenStreetMap (OSM) lane geometry and contextual metadata to automatically generate violation labels, eliminating the need for manual annotation [15]. Finally, a transformer-based fusion network integrates visual features, map priors, and contextual tokens to perform violation classification. This design enables scalable training while supporting privacy-aware deployment, making it suitable for distributed learning settings such as federated learning used in intelligent transportation systems [1] .The key contributions of this work are summarized as follows:

Rule-Based Weak Supervision: A programmatic labelling strategy that derives traffic violation classes without requiring human annotation, reducing labelling cost and improving scalability. Multimodal Fusion Framework: A transformer-based architecture that jointly models camera features, contextual metadata, and OSM-derived lane geometry using attention-based fusion. Feasibility Validation: An experimental study demonstrating that weak supervision combined with multimodal fusion can support effective traffic violation classification in privacy-aware intelligent transportation pipelines [8].

II. RELATED WORKS

Modern traffic scene understanding has progressed rapidly due to improvements in privacy-preserving distributed training, multimodal fusion architectures, attention-based alignment, and scalable labelling techniques [2]. This section summarises related research across four key directions: (i) federated learning for distributed perception, (ii) cross-attention mechanisms for modality alignment, (iii) multimodal fusion in driving environments, and (iv) weak supervision and rule-based labelling.

A. Federated Learning for Distributed Perception

Federated learning (FL) has become an important paradigm for collaborative model training across multiple clients without requiring centralized access to raw data. Instead of collecting datasets on a single server, FL relies on periodic sharing of local model updates, which improves privacy while enabling large-scale learning [6]. Foundational approaches such as Federated Averaging (FedAvg) introduced efficient aggregation for

distributed optimization, and have motivated a wide range of extensions to handle real-world constraints [4].

In intelligent transportation systems, FL is particularly suitable because driving data often contains sensitive visual content, such as faces, license plates, and private locations. Recent surveys highlight that federated learning is increasingly explored for connected vehicles, roadside units, and smart-city infrastructures where privacy and regulatory compliance are essential [2]. However, despite its advantages, FL does not directly address the labeling problem, since clients still require annotated samples for supervised training [7]. This limitation motivates research directions that reduce human labeling effort, such as weak supervision strategies used in the proposed framework.

B. Cross-Attention for Modality Alignment

Transformer-based models have popularized attention mechanisms for learning relationships between tokens in high-dimensional feature spaces [10]. Cross-attention extends this concept by enabling one modality to attend to another, which supports selective alignment between heterogeneous representations. This mechanism has been successfully applied in multimodal learning tasks such as vision-language modeling, trajectory prediction, and structured scene reasoning. In driving-related perception, cross-attention has been adopted to connect dynamic agents (vehicles and pedestrians) with static priors such as lane graphs and map topology. This enables models to reason not only about object appearance, but also about the surrounding road structure and constraints. Such attention-based fusion is particularly valuable for traffic violation detection, since violations often depend on geometric relationships (e.g., lane departure) and contextual conditions rather than raw pixels alone.

C. Multimodal Fusion for Driving Scene Understanding

Driving environments naturally involve multiple complementary data sources, including camera images, GPS, lane maps, traffic signals, and contextual metadata. Earlier multimodal fusion approaches typically relied on feature concatenation or late decision fusion. In contrast, more recent architectures integrate modalities using tokenization and transformer attention, enabling deeper cross-modality interaction. Prior studies show that multimodal fusion improves performance in safety-related driving tasks [5], including anomaly detection, traffic prediction, and accident severity estimation [13]. These approaches demonstrate that combining visual cues with contextual signals leads to stronger generalization [14], particularly under challenging conditions such as occlusions or poor weather. However, many multimodal driving systems still depend on strongly labeled datasets, which are costly to produce at scale. The proposed work differs by using weakly generated labels, while still exploiting multimodal fusion for improved violation reasoning.

D. Weak Labeling and Rule-Based Supervision

Weak supervision is a scalable alternative to manual annotation, where training labels are produced using indirect sources such as heuristics, rules, programmatic labeling functions, or external knowledge [15]. Frameworks such as Snorkel demonstrated that noisy labels generated from multiple rules can be sufficient to train competitive models when large-scale ground truth is unavailable. In the transportation domain, weak labeling has been explored using signals such as GPS traces, traffic rules, and vehicle telemetry. Rule-based labeling is especially effective in structured environments where violations can be expressed through explicit constraints, such as lane boundaries, pedestrian crossings, and intersection signal logic [16]. Motivated by this observation, the proposed framework combines YOLO-based detections with contextual metadata and OpenStreetMap lane polygons to infer violation labels automatically. These weak labels are then used to supervise a multimodal transformer classifier, enabling scalable learning even when strongly annotated violation datasets are limited or unavailable.

III. PROPOSED SYSTEM

The proposed traffic violation classification framework is designed as a distributed client–server pipeline that supports privacy-aware learning while reducing the need for manual annotation. In this architecture, each client performs local perception and generates supervision signals automatically using rule-based logic. The server acts as a coordinator that aggregates client updates and trains a multimodal transformer model for violation classification. This design aligns well with federated learning principles, where raw data remains local and only model parameters are exchanged.

A. Client-Side Processing

The client module runs on edge devices or local data acquisition nodes (e.g., dashcam units, roadside cameras, or dataset partitions). Its main role is to process visual frames, extract contextual cues, and generate weak labels without requiring human annotation. Since all perception and labeling steps are executed locally, raw images and sensitive content are not shared externally, improving privacy and supporting scalable deployment.

1) Object Detection: A pretrained YOLO detector is deployed at the client to identify key road entities, including vehicles, pedestrians, and traffic lights. For each frame, the detector produces bounding boxes and semantic class predictions. YOLO is selected due to its efficiency and suitability for real-time inference on embedded hardware.

2) Contextual Metadata Retrieval: Along with visual input, the client retrieves lightweight context signals such as scene category (intersection/highway), weather conditions, and time-of-day. These attributes are loaded from locally stored metadata files (e.g., JSON format). Such context features provide strong semantic priors for traffic violation reasoning, since violations often depend on environmental conditions rather than appearance alone.

3) Lane Geometry Extraction: To incorporate road structure, lane polygons and drivable regions are extracted using OpenStreetMap (OSM) vector data. Unlike pixel-based lane

segmentation, OSM provides a consistent topological description of road boundaries and lane connectivity. The extracted polygons are indexed per frame and stored as structured geometry for downstream processing.

4) Rule-Based Weak Label Generation: Weak supervision is generated using a rule engine that combines detection outputs, contextual metadata, and OSM-based geometry. In this work, three primary violation categories are inferred:

- Traffic Light Violation: triggered when a traffic light is detected under intersection context.
- Lane Violation: triggered when a vehicle centroid lies outside valid lane polygons.
- Pedestrian Hazard: triggered when vehicle and pedestrian bounding boxes overlap, indicating potential conflict.

If none of the above rules are satisfied, the sample is assigned a Normal class. The generated labels are stored locally and transmitted only as lightweight training targets, avoiding manual labeling effort.

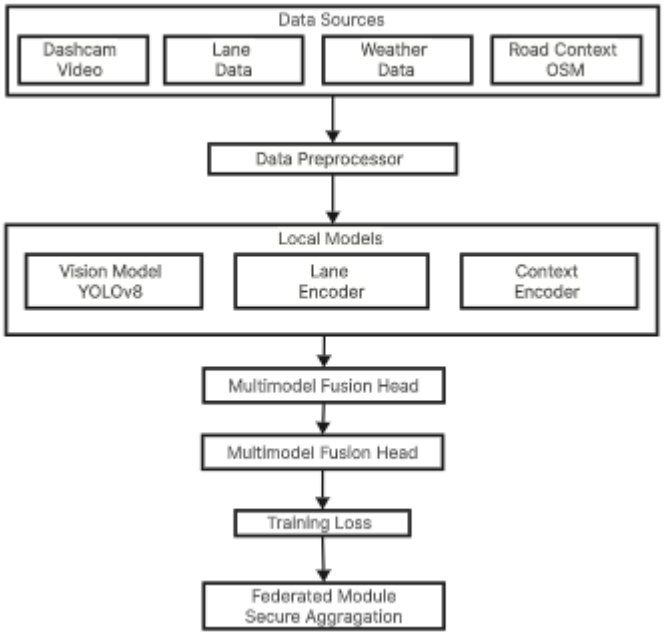

Fig. 1. Client Architecture

B. Server-Side Processing

The server module operates as the global coordination and analytics layer. It communicates with multiple heterogeneous clients and performs federated aggregation, model updates, and higher-level analysis. The server responsibilities are organized into the following major subsystems.

1) Secure Aggregation and Communication Layer: The server receives periodic client updates such as gradients, weight differences, or compressed feature representations. To prevent leakage of sensitive information, updates are protected using secure aggregation strategies, including encryption-based communication or secure multi-party computation (SMPC). This ensures that individual client contributions cannot be directly reconstructed, while still enabling global optimization.

2) Federated Learning Module: The federated learning subsystem acts as the central optimizer that integrates model updates from participating clients. Multiple aggregation strategies are supported:

- FedAvg standard weighted averaging of client parameters.
- FedProx: FedAvg extension that improves stability under non-IID client distributions.
- FedOpt: optimizer-based federated variants supporting adaptive updates.

After aggregation, the server produces updated global weights for the multimodal fusion model. The updated model may then be redistributed to clients for the next training round or deployed for inference.

3) Prediction and Hotspot Inference Engine: Once a stable global model is obtained, the server performs inference to identify violation patterns over space and time. This subsystem may include: Temporal forecasting models (Transformer/LSTM-based) for predicting future violation trends. Geospatial hotspot scoring, where regions are ranked by predicted risk intensity. Visualization and alert generation, enabling real-time monitoring through heatmaps and event triggers. This stage transforms sample-level violation predictions into actionable intelligence for traffic authorities and analysts.

4) Validation and Analytics Layer: A dedicated analytics layer evaluates global performance and provides training diagnostics. Key measurements include: overall accuracy, ROC-AUC, confusion matrix, and per-class F1-score, convergence monitoring and participation tracking, client-side fairness analysis and update variance monitoring. These metrics quantify both model effectiveness and system-level stability across distributed clients.

5) Dashboard and Visualization Frontend: Finally, the server provides a web-based dashboard for presenting aggregated insights such as predicted violations, spatio-temporal hotspots, and training metrics. Importantly, the dashboard only consumes non-sensitive outputs rather than raw client data, maintaining privacy compliance.

IV. SYSTEM IMPLEMENTATION

The proposed framework is implemented as a decentralized and privacy-preserving training pipeline, where multiple clients collaboratively learn a multimodal traffic violation classifier under the federated learning (FL) setting. Each client independently performs data preparation, weak supervision, multimodal fusion, and local model optimization. The server acts as a global coordinator by aggregating client updates and redistributing the updated model parameters. Throughout the training process, raw images, metadata, and map geometry remain local to each client, which aligns with privacy and data governance requirements in intelligent transportation systems.

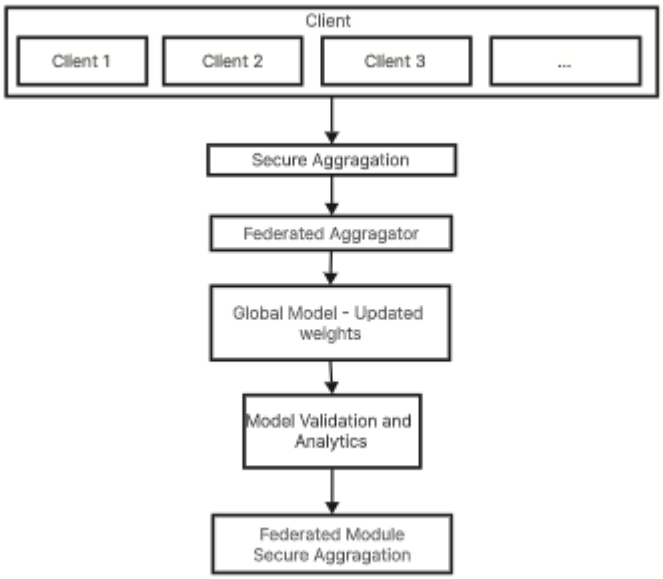

Fig. 2. Server Architecture

A. Client-Side Implementation

1) Data Ingestion and Preprocessing: Each client maintains a local dataset consisting of three synchronized components: visual frames, contextual metadata, and OpenStreetMap (OSM) lane geometry. For a given time step t, the input is represented as:

$$X_t = \{I_t, C_t, M_t\} \tag{1}$$

where I_t is the raw image, C_t contains categorical scene descriptors (e.g., weather, time-of-day, and scene type), and M_t denotes the lane/crosswalk polygon geometry derived from OSM vector maps.

During preprocessing, images are resized and normalized to match the detector input requirements. Context values are converted into numeric representations using dictionary encoding, allowing them to be used as learnable embeddings during training.

2) Weak Supervision and Rule-Based Labeling: Since large-scale manually annotated violation datasets are limited, the client generates supervision signals using a rule-based weak labeling strategy. A frozen YOLO detector extracts bounding boxes for key agents such as vehicles, pedestrians, and traffic lights. Based on these detections, violation labels are inferred as:

$$y_t \in \{0, 1, 2, 3\} \tag{2}$$

where the classes correspond to Normal, Traffic Light Violation, Lane Violation, and Pedestrian Conflict.

The label assignment follows geometric and contextual rules:

- Traffic light violation: inferred when the scene corresponds to an intersection and a traffic light is detected.
- Lane violation: inferred when a vehicle centroid lies outside valid lane polygons.
- Pedestrian conflict: inferred when vehicle and pedestrian bounding boxes overlap.

This approach transforms raw perception data into usable training labels without human annotation, significantly reducing cost while enabling scalable supervision.

3) Multimodal Tokenization and Fusion: The client model integrates three modalities: (i) visual features, (ii) context embeddings, and (iii) lane geometry tokens.

Multi-scale visual representations are extracted from intermediate YOLO feature maps (e.g., P3,P4,P5) and tokenized into a shared embedding space:

$$V = Tokenize(P3, P4, P5) \in \mathbb{R}^{(HW)\times d} \tag{3}$$

Contextual metadata is embedded as:

$$C = f_{ctx}(C_t) \in \mathbb{R}^{1\times d} \tag{4}$$

Lane polygons are encoded into lane tokens using pooled geometry embeddings:

$$L = f_{lane}(M_t) \in \mathbb{R}^{K\times d} \tag{5}$$

where K is the number of lane segments in the current frame.

To enable structured reasoning, a cross-attention fusion block combines the three modalities:

$$Z = Fusion(V, L, C) \tag{6}$$

This fusion step allows the model to reason jointly over appearance, road geometry, and contextual priors, which is critical for violation classification.

4) Local Optimization and Client Update: The fused representation is passed through a classification head:

$$y = f_{head}(Z) \tag{7}$$

The model is trained using cross-entropy loss:

$$L^{(i)} = -\sum y_t \log(y_t) \tag{8}$$

The YOLO backbone remains frozen, while only the multimodal fusion and classification layers are updated. After completing E_{local} epochs, each client computes its parameter update:

$$\Delta\theta_i = \theta_i^t - \theta^{t-1} \tag{9}$$

and transmits $\Delta\theta_i$ to the federated server. Importantly, no raw images, contextual metadata, lane geometry, or weak labels are uploaded.

B. Server-Side Implementation

1) Global Aggregation and Coordination: The server aggregates client updates $\{\Delta\theta_i\}_{i=1}^N$ received from N clients. In the default configuration, the server applies FedAvg aggregation:

$$\theta^{t+1} = \sum_{i=1}^{N} \frac{n_i}{\sum_{j=1}^{N} n_j} \Delta\theta_i \tag{10}$$

where n_i denotes the number of training samples available on client i. For vehicular datasets with strong distribution shifts across clients, FedProx can be used to stabilize training under non-IID conditions.

TABLE I
COMPARATIVE PERFORMANCE OF CLIENT-WISE TRAINING MODELS

Client	Precision (P)	Recall (R)	mAP@50	mAP@50–95
Client 1	0.457	0.308	0.326	0.169
Client 2	0.44–0.46	0.29–0.31	0.31–0.32	0.16–0.17
Client 3	0.43–0.45	0.28–0.30	0.30–0.32	0.15–0.16

TABLE II
CLASS-WISE ROC-AUC COMPARISON

Class	Client 1	Client 2	Client 3
Class 0	0.775	0.763	0.751
Class 1	NaN	NaN	NaN
Class 2	0.757	0.759	0.75
Class 3	0.467	0.633	0.456

2) Global Model Distribution: After aggregation, the updated global model θ^{t+1} is redistributed to clients for the next communication round. The iterative FL cycle continues until convergence or until validation metrics stabilize. The server does not require access to any raw client-side data.

3) Privacy and Deployment Considerations: The federated design satisfies key constraints in real-world ITS deployment:

- Data locality: city- or fleet-specific driving data remains on-premise.
- Regulatory compliance: sensitive driving footage is not centralized.
- Bandwidth efficiency: parameter updates are significantly smaller than raw sensor streams.

C. End-to-End Client - Server Workflow

The overall training workflow can be summarized as follows: Clients ingest multimodal inputs and generate weak labels locally, Clients train the multimodal fusion model for E epochs, Clients send updates $\Delta\theta_i$ to the server, The server aggregates updates to produce a new global model and The updated model is redistributed for the next FL round.

This end-to-end protocol enables collaborative multimodal safety learning across multiple regions without centralizing raw sensor data, supporting scalable and privacy-aware traffic violation analytics.

V. RESULTS AND DISCUSSION

This section evaluates the proposed weakly supervised multimodal traffic violation classifier trained in a federated setting. The goal of the experiments is to examine whether combining visual cues with contextual metadata and OSM-based lane geometry improves violation recognition when strong ground-truth annotations are unavailable.

A. Evaluation Metrics

Model performance is evaluated using standard multi-class classification metrics widely adopted in intelligent transportation and safety-critical perception research: Overall Accuracy, Class-wise Precision, Recall, and F1-score, Confusion Matrix, Receiver Operating Characteristic (ROC) Curves, Area Under the ROC Curve (AUC) and Mean Average Precision (mAP)

B. Quantitative Results

Accuracy reflects global predictive correctness, whereas precision and recall provide class-sensitive insights, particularly important under class imbalance (e.g., rare pedestrian conflicts). F1-score balances precision and recall, offering robustness to skewed distributions. ROC-AUC evaluates the separability of predicted probabilities, while mAP measures ranking quality across categories.

The experimental results indicate that the proposed multimodal fusion model performs effectively despite relying on weak supervision rather than manually curated labels. The achieved validation accuracy suggests that the learned representations generalize beyond the training distribution and are able to separate normal driving from violation events.

Analysis of the confusion matrix shows that the Normal and Traffic Light Violation categories obtain the highest true positive rates. This behavior is expected because these classes benefit strongly from contextual cues (e.g., intersection metadata) and object-level evidence such as traffic light detections. In contrast, Lane Violation and Pedestrian Conflict show comparatively reduced recall. These categories occur less frequently and require more precise geometric reasoning, making them harder to learn under weak labeling. The macro-averaged ROC-AUC values remain well above random chance across all four classes, indicating that the classifier produces meaningful posterior probabilities rather than relying on biased decision boundaries. Similarly, macro mAP confirms that the model maintains reliable ranking quality across violation categories, even under noisy supervision.

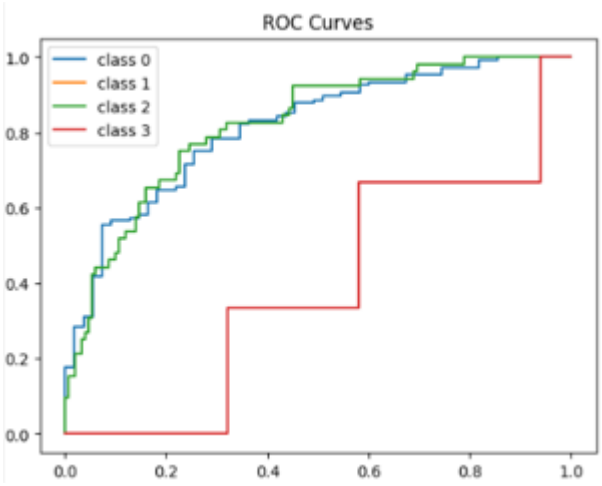

Fig. 3. ROC-AUC Curves

C. Ablation on Multimodal Inputs

To measure the impact of each modality, qualitative ablation experiments were conducted by selectively disabling specific inputs during inference. When contextual metadata

TABLE III
COMPARABLE MULTIMODAL RESULTS (CLIENT-WISE)

Metric	Client 1	Client 2	Client 3
Epochs	10	5	5
Final Train Accuracy	0.746	0.742	0.72
Validation Accuracy	0.764	0.754	0.768
mAP (Macro)	0.3773	0.3756	0.3671

tokens were removed, the model showed reduced sensitivity to traffic-light-related violations, indicating that scene-level priors contribute strongly to signal-related reasoning. When lane geometry embeddings were removed, lane violation recognition degraded noticeably, confirming that map-derived structure provides essential information for lane-level constraint enforcement.

Overall, these ablations support the conclusion that traffic violations are inherently multimodal events and cannot be robustly identified using visual appearance alone.

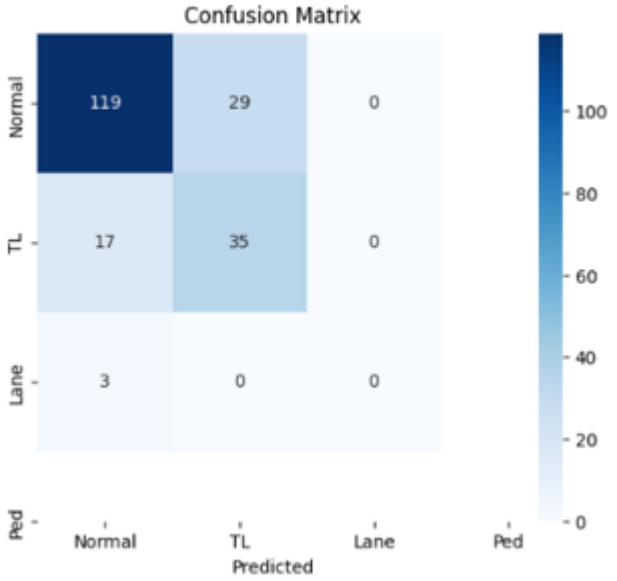

Fig. 4. Confusion Matrix- Server

D. Discussion

The results demonstrate that weakly supervised multimodal fusion can support practical traffic violation classification without requiring expensive manual annotation. The improvement observed over visual-only configurations highlights the importance of three factors: Scene-level contextual cues, Scene-level contextual, Map-based geometric Priors and Actor-object interactions cues.

From a deployment perspective, the framework aligns with real-world ITS requirements. Training is executed locally on clients, and only federated model updates are exchanged, which reduces privacy risks and supports regulatory compliance . This makes the approach suitable for integration into distributed surveillance systems, connected vehicle platforms, and insurance-driven risk assessment pipelines.In future extensions, the predicted violation outputs can be aggregated over time and space to derive higher-level safety indicators, supporting hotspot forecasting and city-scale policy evaluation.

CONCLUSION AND FUTURE SCOPE

This paper presents a federated, multimodal, and weakly supervised framework for traffic safety violation classification within intelligent transportation systems (ITS). The proposed approach integrates visual perception features with contextual metadata and OpenStreetMap (OSM)-derived road geometry information to enable accurate violation reasoning without depending on expensive manual annotations or centralized data storage. A client-side pipeline is designed to perform rule-based weak label generation, multimodal feature fusion, and local model optimization, while a centralized server coordinates global model aggregation and redistribution in a privacy-preserving federated learning environment. Experimental results demonstrate that the framework achieves reliable violation discrimination even in the absence of strong ground-truth supervision, underscoring the effectiveness of multimodal fusion in safety-critical perception tasks. In addition to its classification capability, the framework provides practical deployment benefits for real-world ITS applications. Since model training occurs locally and only encrypted model updates are shared with the server, sensitive driving footage remains decentralized, thereby supporting data locality, regulatory compliance, and bandwidth-efficient collaborative learning. These characteristics make the system well-suited for municipal traffic monitoring, fleet analytics, and distributed autonomous vehicle ecosystems where strict privacy requirements must be maintained.

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