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Research

Machine Learning Strategies for Fusing Drone-Based Visual Data and Vehicle Telemetry in Congestion Mitigation

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Abstract: The integration of drone-based visual data and vehicle telemetry offers a promising approach to addressing urban traffic congestion. Machine learning (ML) provides an effective framework for processing and fusing these diverse data sources to generate actionable insights for congestion mitigation. This paper explores strategies for leveraging ML techniques to combine visual data from drones and telemetry data from vehicles, focusing on applications in traffic flow optimization, incident detection, and real-time rerouting. Key challenges, such as data heterogeneity, computational efficiency, and the need for robust models under dynamic conditions, are examined. We review existing ML methods, including deep learning for visual data analysis and ensemble techniques for telemetry fusion, and propose novel approaches that leverage spatiotemporal modeling and federated learning. Experimental results on simulated and real-world datasets demonstrate the potential of these strategies to improve traffic prediction accuracy and reduce congestion through proactive interventions. The paper concludes with recommendations for implementing scalable ML systems that integrate drone and vehicle data streams, addressing practical considerations such as edge computing, privacy, and adaptability to varying urban contexts.

Keywords: congestion mitigation, data fusion, drone data, machine learning, spatiotemporal modeling, traffic optimization, vehicle telemetry.

1. Introduction

Traffic congestion has become one of the most pressing challenges in modern urban transportation systems, exerting a profound influence on the daily lives of millions of commuters worldwide. Congestion not only increases travel times but also exacerbates fuel consumption and greenhouse gas emissions, leading to significant economic and environmental costs. The traditional approaches to traffic management, which often rely on static infrastructural solutions such as signal timing optimization and roadway expansion, have proven insufficient in accommodating the dynamic and complex nature of modern transportation systems. However, the proliferation of advanced sensing technologies, including drones equipped with high-resolution imaging capabilities and vehicles outfitted with telemetry sensors, has paved the way for innovative approaches centered around multimodal data fusion. This paradigm leverages diverse data streams to provide a holistic view of urban traffic dynamics, enabling more effective and adaptive traffic management strategies [1,2].

Drone-based visual data offer a macroscopic perspective of urban traffic, capturing real-time insights into traffic flow patterns, incident hotspots, and road conditions. These aerial platforms have the unique advantage of high spatial coverage, allowing for the monitoring of large urban areas with minimal obstructions. For example, drones can provide detailed images of traffic bottlenecks, detect road obstructions caused by accidents or

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construction, and monitor pedestrian activities at intersections. On the other hand, vehicle telemetry data provide complementary, granular insights into individual driving behaviors, including speed, acceleration, and location. Such data are typically captured through in-vehicle sensors and GPS systems, yielding a wealth of information on the dynamic state of individual vehicles [3]. The fusion of these two data modalities—macro-level visual data from drones and micro-level telemetry data from vehicles—has immense potential for transforming traffic management. However, the integration of such heterogeneous data streams is a non-trivial task, necessitating sophisticated machine learning (ML) techniques that can handle high-dimensional, noisy, and often incomplete data.

Recent advances in ML, particularly deep learning and spatiotemporal modeling, have demonstrated remarkable potential in addressing the complexities associated with traffic management. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have proven highly effective in processing and analyzing large-scale, high-dimensional data. For instance, CNNs can be used to extract spatial features from drone images, identifying regions of high congestion or hazardous conditions. RNNs, particularly those equipped with long short-term memory (LSTM) units, are well-suited for capturing temporal dependencies in telemetry data, enabling accurate predictions of traffic flow and vehicle trajectories. By combining these techniques within a unified framework, researchers can build predictive models capable of informing real-time traffic management decisions, such as dynamic signal control and rerouting strategies.

The fusion of drone-based visual data and vehicle telemetry data is fundamentally a multimodal learning problem, requiring the integration of data streams that differ not only in their dimensionality but also in their semantic representations. One promising approach to this challenge is the use of attention mechanisms within deep learning architectures. Attention mechanisms allow models to selectively focus on the most relevant features in each data stream, thereby enhancing the interpretability and accuracy of predictions. For example, a traffic management system could use attention-based models to prioritize data from areas with higher congestion levels, ensuring that limited computational resources are allocated efficiently [4].

Another critical aspect of multimodal data fusion is the alignment of spatial and temporal dimensions across data streams. This requires advanced spatiotemporal modeling techniques that can capture the intricate dependencies between drone and telemetry data. Graph neural networks (GNNs) have emerged as a powerful tool for this purpose, as they can model the relationships between spatially distributed entities, such as road segments and intersections. By representing the urban transportation network as a graph, with nodes corresponding to specific locations and edges representing traffic flow, GNNs can incorporate both drone and telemetry data to generate comprehensive insights into traffic dynamics [5].

The application of ML techniques to multimodal data fusion in traffic management also raises several practical considerations. One major challenge is the handling of noisy and incomplete data, which are common in real-world scenarios. For instance, drone imagery may be affected by weather conditions, such as rain or fog, while telemetry data may suffer from signal loss or sensor malfunctions. To address these issues, researchers have developed robust ML algorithms that incorporate data imputation and denoising techniques. Variational autoencoders (VAEs) and generative adversarial networks (GANs) are particularly effective in this regard, as they can generate realistic approximations of missing data while preserving the underlying patterns.

Another challenge is the computational scalability of ML models, particularly in the context of real-time traffic management. The high-dimensional nature of multimodal data, combined with the need for rapid processing, necessitates the use of efficient algorithms and hardware acceleration. Advances in distributed computing and cloud-based infrastructures have facilitated the deployment of ML models at scale, enabling the processing of massive data streams with minimal latency. Moreover, edge computing technologies, which allow

for localized data processing on devices such as drones and in-vehicle systems, have further enhanced the feasibility of real-time traffic management solutions.

The effectiveness of ML-based approaches to traffic management can be demonstrated through several case studies and experimental evaluations. For instance, researchers have shown that the integration of drone imagery and vehicle telemetry data can significantly improve the accuracy of traffic flow predictions. Table 1 summarizes the performance of different ML models in predicting traffic congestion levels based on multimodal data, highlighting the superiority of deep learning techniques over traditional statistical methods.

Table 1. Accuracy of Traffic Congestion Prediction Models Based on Multimodal Data

Model	Input Data Types	Prediction Accuracy (%)
Linear Regression	Telemetry Data Only	78.4
Random Forest	Drone Imagery and Telemetry Data	85.2
Convolutional Neural Network	Drone Imagery Only	88.7
Hybrid Deep Learning Model	Drone Imagery and Telemetry Data	94.1

In addition to improving prediction accuracy, ML models can facilitate more effective resource allocation in urban traffic management. For example, reinforcement learning algorithms have been employed to optimize traffic signal timings based on real-time data, resulting in significant reductions in congestion and fuel consumption. Table 2 provides a comparison of resource allocation strategies based on different traffic management approaches, illustrating the advantages of ML-driven methods [6,7].

Table 2. Comparison of Resource Allocation Strategies in Traffic Management

Approach	Resource Allocation Criterion	Reduction in Congestion (%)
Fixed Signal Timing	Predefined Schedules	15.3
Dynamic Programming	Traffic Volume Estimates	32.7
Reinforcement Learning	Real-Time Multimodal Data	48.9

While the potential benefits of multimodal data fusion and ML in traffic management are substantial, several challenges remain to be addressed. Privacy and security concerns are particularly significant, as the collection and processing of vehicle telemetry and drone data involve sensitive information about individuals' movements [8]. Ensuring data anonymization and secure transmission is essential to mitigate these risks and gain public trust. Furthermore, the deployment of ML models in real-world traffic systems requires close collaboration between researchers, policymakers, and industry stakeholders to ensure that the solutions are both technically feasible and socially acceptable.

In conclusion, the integration of drone-based visual data and vehicle telemetry data through advanced ML techniques represents a transformative approach to addressing urban traffic congestion. By leveraging the complementary strengths of these data modalities, researchers can develop more accurate and adaptive traffic management systems, ultimately reducing the economic and environmental costs of congestion. Continued advancements in ML algorithms, computational infrastructures, and data privacy measures will be critical in realizing the full potential of this paradigm. This paper investigates strategies for fusing drone-based visual data and vehicle telemetry using ML, emphasizing their application to congestion mitigation. The primary objectives are to enhance situational awareness, improve prediction accuracy, and support real-time decision-making for traffic management systems. We address key research questions, including: How can ML models effectively

combine visual and telemetry data? What are the computational and scalability challenges? And how can privacy concerns be mitigated in such systems?

The remainder of this paper is organized as follows. Section 2 reviews related work in data fusion and traffic management using ML. Section 3 details the proposed ML strategies, including data preprocessing, model architectures, and evaluation metrics. Section 4 presents experimental results, highlighting the effectiveness of the proposed approaches. Finally, Section 5 concludes with a discussion of findings and future research directions.

2. Related Work

The integration of visual and telemetry data for traffic management has gained significant traction in recent years, with research contributions spanning multiple dimensions, including data fusion methodologies, machine learning applications, and practical system implementations. Early research efforts predominantly focused on single-modal approaches, employing either computer vision techniques to analyze drone imagery or statistical models to process telemetry data. While these methods provided valuable insights into specific aspects of traffic dynamics, their limitations became apparent as urban traffic systems grew in complexity and scale. Consequently, the research focus has shifted toward multimodal data fusion, leveraging the complementary strengths of visual and telemetry data to develop more comprehensive and effective traffic management solutions.

2.1. Visual Data Analysis

Drone-based visual data provide a unique vantage point for observing and analyzing traffic systems. The ability to capture a bird's-eye view of road networks enables the identification of large-scale traffic flow patterns, congestion hotspots, and road hazards. Traditional computer vision techniques, such as optical flow analysis, edge detection, and feature-based object tracking, have been widely used to process drone imagery. These methods have been particularly effective in tasks like estimating vehicle speeds, detecting lane changes, and identifying stationary vehicles that may indicate accidents.

More recently, the advent of deep learning has revolutionized the analysis of visual data. Convolutional neural networks (CNNs), in particular, have demonstrated exceptional performance in tasks such as object detection, vehicle counting, and traffic density estimation. For example, CNN-based frameworks like YOLO (You Only Look Once) and Faster R-CNN have been successfully employed to detect and classify vehicles in drone footage with high accuracy and efficiency. Additionally, vision transformers (ViTs) have emerged as a promising alternative to CNNs, offering improved capabilities for capturing global contextual information in high-resolution images. While these deep learning methods excel at extracting spatial features, their ability to model temporal dependencies—crucial for understanding evolving traffic conditions—remains limited. To address this, researchers have explored hybrid architectures that combine CNNs with recurrent neural networks (RNNs) or attention mechanisms, enabling the integration of spatial and temporal information.

2.2. Telemetry Data Processing

Telemetry data collected from vehicles offer granular insights into individual driving behaviors and vehicle dynamics. These data are typically acquired through a combination of GPS, accelerometers, gyroscopes, and on-board diagnostic systems, providing information on variables such as speed, acceleration, fuel consumption, and engine performance. Statistical models and rule-based systems were initially employed to analyze telemetry data, but their inability to capture complex patterns and dependencies limited their utility in dynamic traffic environments.

Machine learning techniques have since emerged as a powerful tool for processing telemetry data. Decision trees, random forests, and support vector machines (SVMs) have been widely used to classify driving behaviors and detect anomalies. For example, random forests have been applied to identify instances of aggressive driving, such as sudden acceleration or harsh braking, based on accelerometer data. Recurrent neural

networks (RNNs), particularly those with long short-term memory (LSTM) units, have proven highly effective in modeling temporal dependencies in telemetry data, enabling accurate predictions of vehicle trajectories and travel times. Ensemble methods, such as gradient boosting frameworks like XGBoost and LightGBM, have also shown promise in handling the noise and heterogeneity inherent in telemetry data, improving the robustness and generalizability of predictive models.

2.3. Data Fusion Approaches

The fusion of visual and telemetry data has been extensively studied in the context of autonomous driving, intelligent transportation systems, and smart city applications. Data fusion approaches can generally be categorized into early fusion, late fusion, and hybrid fusion methods, each with distinct advantages and challenges.

Early fusion methods involve concatenating raw or preprocessed features from visual and telemetry data into a unified representation, which is then fed into a machine learning model for joint analysis. While this approach is conceptually straightforward, it often requires careful feature engineering to ensure compatibility between the heterogeneous data streams. Late fusion methods, on the other hand, involve training separate models for visual and telemetry data and combining their predictions at a later stage. This approach offers greater flexibility, as it allows for the independent optimization of models for each modality. However, it may fail to capture complex interactions between the data streams, limiting its effectiveness in scenarios where such interactions are critical.

Hybrid fusion methods aim to address the limitations of early and late fusion by incorporating advanced architectures that explicitly model the dependencies between visual and telemetry data. Spatiotemporal networks, for example, combine convolutional layers for spatial feature extraction with recurrent layers for temporal modeling, enabling the joint analysis of drone imagery and vehicle telemetry data. Graph neural networks (GNNs) have also emerged as a powerful tool for multimodal data fusion, particularly in applications involving spatially distributed entities, such as road networks. By representing the transportation network as a graph, with nodes corresponding to specific locations and edges representing traffic flow, GNNs can incorporate both visual and telemetry data to generate comprehensive insights into traffic dynamics.

Attention mechanisms have further enhanced the effectiveness of hybrid fusion methods by enabling models to selectively focus on the most relevant features in each data stream. For instance, a traffic management system might use attention-based models to prioritize telemetry data from areas with high congestion levels while simultaneously leveraging visual data to monitor surrounding road conditions. These approaches have demonstrated significant improvements in predictive accuracy and interpretability, making them a promising direction for future research.

Despite these advancements, several challenges remain in achieving robust and scalable data fusion for traffic management. One major challenge is the alignment of spatial and temporal dimensions across visual and telemetry data, particularly in dynamic traffic conditions. Ensuring that data from different modalities are synchronized and co-registered is essential for accurate analysis but can be difficult to achieve in practice. Additionally, the computational demands of multimodal data fusion, particularly in real-time applications, require efficient algorithms and hardware acceleration to ensure scalability.

The application of multimodal data fusion in traffic management has also raised important questions regarding data privacy and security. The collection and processing of telemetry and visual data involve sensitive information about individuals' movements, necessitating the development of robust anonymization and encryption techniques. Addressing these challenges will be critical for the widespread adoption of multimodal data fusion in real-world traffic systems.

3. Proposed Machine Learning Strategies

To effectively fuse drone-based visual data and vehicle telemetry data for mitigating urban traffic congestion, we propose a suite of advanced machine learning (ML) strategies. These strategies address key challenges in data integration, spatiotemporal modeling, and large-scale system deployment. Our proposed approaches include comprehensive preprocessing pipelines, hybrid model architectures for multimodal fusion, federated learning frameworks for scalability and privacy preservation, and rigorous evaluation metrics for benchmarking. This section details the technical methodologies underlying each of these components, supplemented by mathematical expressions and algorithmic formulations.

3.1. Data Preprocessing and Augmentation

Given the inherent heterogeneity and noise in drone-based visual data and vehicle telemetry data, preprocessing plays a critical role in ensuring the compatibility and quality of these datasets. The first step involves extracting meaningful features from each data modality. For visual data, object detection models, such as YOLO or Faster R-CNN, are employed to identify vehicles in aerial imagery. The outputs of these models include bounding box coordinates, class labels, and confidence scores. Mathematically, this detection process can be expressed as follows:

$$\mathcal{D}_v = \{(b_i, c_i, s_i) \mid i = 1, 2, \ldots, N\}, \tag{1}$$

where b_i represents the bounding box coordinates, c_i is the class label (e.g., car, truck, motorcycle), and s_i is the confidence score for the i-th detected object. Here, $\mathcal{D}_v$ denotes the set of detected objects in a given drone image, and N is the total number of objects.

Telemetry data, on the other hand, consist of time-series measurements, including vehicle speed, acceleration, and GPS coordinates. These data are denoted as $\mathcal{T} = \{(t_k, x_k, y_k, v_k, a_k) \mid k = 1, 2, \ldots, M\}$, where t_k is the timestamp, (x_k, y_k) are the GPS coordinates, v_k is the velocity, and a_k is the acceleration of the k-th vehicle. Temporal alignment and spatial mapping techniques are then employed to synchronize telemetry data with the visual data. A spatial mapping function $\mathcal{M}$ transforms GPS coordinates into the pixel space of the drone imagery:

$$\mathcal{M}(x_k, y_k) = (u_k, v_k), \tag{2}$$

where (u_k, v_k) are the pixel coordinates corresponding to the GPS location (x_k, y_k).

To enhance the robustness of the ML models, data augmentation techniques are applied. For visual data, augmentation methods such as rotation, scaling, and synthetic imagery generation using generative adversarial networks (GANs) are utilized. For telemetry data, trajectory interpolation is performed to handle missing values, leveraging cubic splines or Kalman filters.

3.2. Hybrid Model Architectures

To fully exploit the complementary strengths of drone-based visual data and vehicle telemetry data, we propose a hybrid model architecture that integrates convolutional neural networks (CNNs) for spatial analysis of visual data and recurrent neural networks (RNNs) or transformer models for temporal analysis of telemetry data. The architecture incorporates a fusion layer that combines the extracted features, enabling the model to capture spatiotemporal dependencies effectively.

The overall architecture consists of three primary components: the visual feature extractor, the telemetry feature extractor, and the fusion module. Let $\mathbf{X}_v$ and $\mathbf{X}_t$ represent the features extracted from the visual and telemetry data, respectively. The CNN-based visual feature extractor computes:

$$\mathbf{X}_v = f_{\text{CNN}}(\mathcal{D}_v; \Theta_v), \tag{3}$$

where f_{CNN} denotes the convolutional neural network, and Θ_v represents the learnable parameters. Similarly, the telemetry feature extractor, which can be an RNN or transformer model, computes:

$$\mathbf{X}_t = f_{\text{RNN}}(\mathcal{T}; \Theta_t), \tag{4}$$

where f_{RNN} represents the temporal modeling network, and Θ_t represents its parameters.

The fusion module integrates these features using attention mechanisms or graph neural networks (GNNs). An attention-based fusion mechanism computes the fused representation $\mathbf{X}_f$ as:

$$\mathbf{X}_f = \text{softmax}(\mathbf{Q}\mathbf{K}^\top / \sqrt{d})\mathbf{V}, \tag{5}$$

where $\mathbf{Q}$, $\mathbf{K}$, and $\mathbf{V}$ are query, key, and value matrices derived from $\mathbf{X}_v$ and $\mathbf{X}_t$, and d is the feature dimension. The fused representation is then used for downstream tasks, such as traffic density prediction, congestion classification, and incident detection.

The training process leverages a multi-task learning framework with a joint loss function:

$$\mathcal{L} = \alpha \mathcal{L}_{\text{density}} + \beta \mathcal{L}_{\text{congestion}} + \gamma \mathcal{L}_{\text{incident}}, \tag{6}$$

where $\mathcal{L}_{\text{density}}$, $\mathcal{L}_{\text{congestion}}$, and $\mathcal{L}_{\text{incident}}$ are loss terms corresponding to different tasks, and α, β, and γ are weighting factors.

3.3. Federated Learning for Scalability

To address privacy and scalability concerns in large-scale urban deployments, we propose a federated learning framework that enables decentralized model training across edge devices, such as drones and vehicles. Federated learning minimizes data transmission by training models locally and aggregating updates on a central server. The training process is governed by the following optimization problem:

$$\min_{\Theta} \frac{1}{K} \sum_{k=1}^{K} \mathcal{L}_k(\Theta), \tag{7}$$

where Θ represents the global model parameters, K is the number of edge devices, and $\mathcal{L}_k(\Theta)$ is the local loss function for the k-th device. The Federated Averaging (FedAvg) algorithm is used to aggregate local updates:

$$\Theta^{(t+1)} = \sum_{k=1}^{K} \frac{n_k}{n} \Theta_k^{(t)}, \tag{8}$$

where $\Theta^{(t+1)}$ is the updated global model, n_k is the number of data points on the k-th device, and n is the total number of data points across all devices.

To enhance privacy and security, techniques such as differential privacy and homomorphic encryption are integrated into the federated learning framework. Differential privacy adds noise to model updates to obscure individual contributions, while homomorphic encryption ensures that data remain encrypted during computations.

3.4. Evaluation Metrics and Benchmarking

The proposed methods are evaluated using a comprehensive set of metrics that reflect both predictive accuracy and computational efficiency. For traffic density prediction, metrics such as mean absolute error (MAE) and root mean square error (RMSE) are used:

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |\hat{y}_i - y_i|, \tag{9}$$

Algorithm 1: Federated Learning with Differential Privacy

Input: Initial model parameters $\Theta^{(0)}$, learning rate η, number of communication rounds T.

Output: Trained global model parameters $\Theta^{(T)}$. [1] $t = 1, \ldots, T$ Broadcast $\Theta^{(t)}$ to all devices. each device k in parallel Compute local gradient $\mathbf{g}_k = \nabla \mathcal{L}_k(\Theta^{(t)})$. Add noise for differential privacy: $\mathbf{g}_k \leftarrow \mathbf{g}_k + \mathcal{N}(0, \sigma^2)$. Send $\mathbf{g}_k$ to the server. Aggregate gradients: $\mathbf{g} \leftarrow \frac{1}{K} \sum_{k=1}^{K} \mathbf{g}_k$. Update global model: $\Theta^{(t+1)} \leftarrow \Theta^{(t)} - \eta \mathbf{g}$.

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_i)^2}, \tag{10}$$

where $\hat{y}_i$ and y_i are the predicted and true values, respectively. For incident detection, precision, recall, and F1-score are employed:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{11}$$

$$\text{F1-score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}, \tag{12}$$

where TP, FP, and FN represent true positives, false positives, and false negatives, respectively. Computational efficiency is measured in terms of inference latency and memory usage, ensuring that the proposed methods are suitable for real-time deployment.

Benchmarking is performed on real-world datasets, such as drone video footage and vehicle telemetry records, as well as synthetic datasets generated for controlled experiments. Comparative analyses against baseline models demonstrate the superiority of the proposed hybrid architecture and federated learning framework, highlighting their potential for large-scale traffic management applications.

4. Experimental Results

To evaluate the efficacy of the proposed machine learning strategies, extensive experiments were conducted on a combination of real-world and simulated datasets. The experiments were designed to assess the performance of the hybrid model architecture, the impact of federated learning on scalability and privacy, and the overall benefits of multi-modal data fusion for traffic congestion mitigation. This section details the experimental setup, results, and key insights obtained from the analysis [9,10].

4.1. Datasets and Experimental Setup

The experiments utilized two primary datasets: (1) a real-world dataset comprising drone video footage and telemetry records from urban traffic networks, and (2) a synthetic dataset generated to simulate controlled traffic conditions, enabling benchmarking under various scenarios. The real-world dataset included high-resolution drone imagery captured at 30 frames per second, annotated with bounding boxes and class labels for detected vehicles. The telemetry data consisted of GPS trajectories [11], speed measurements, and acceleration profiles collected from over 1,000 vehicles equipped with on-board sensors. The synthetic dataset was generated using a traffic simulation platform, which provided ground truth annotations for vehicle movements and congestion levels.

For the hybrid model architecture, the visual feature extractor utilized a ResNet-50-based convolutional neural network, while the telemetry feature extractor employed an LSTM network. The fusion layer incorporated an attention mechanism to integrate features from the two modalities. The models were trained using the Adam optimizer with a learning rate of 0.001 and a batch size of 64. Federated learning experiments

were conducted on a simulated edge computing environment, where local updates were aggregated using the Federated Averaging (FedAvg) algorithm.

4.2. Traffic Flow Prediction

The first set of experiments evaluated the accuracy of traffic flow prediction, comparing the proposed hybrid model to single-modal models that relied solely on visual or telemetry data. Table 3 summarizes the results, highlighting the superiority of the hybrid architecture. The proposed model achieved a mean absolute error (MAE) of 2.45 vehicles per minute, representing a 15% improvement over the best-performing single-modal model. The attention mechanism in the fusion layer played a critical role in enhancing predictive accuracy by prioritizing relevant features from each data modality.

Table 3. Performance of Traffic Flow Prediction Models

Model	**Input Data Types**	**MAE (vehicles/min)**
Telemetry-Only Model	Telemetry Data	2.91
Visual-Only Model	Drone Imagery	2.78
Proposed Hybrid Model	Visual and Telemetry Data	**2.45**

4.3. Incident Detection Performance

The second set of experiments focused on incident detection, such as accidents or sudden traffic bottlenecks. Precision, recall, and F1-score were used as evaluation metrics. Table 4 presents the results, showing that the proposed multimodal fusion approach achieved a 10% improvement in precision and a 12% increase in F1-score compared to baseline methods. This improvement can be attributed to the enhanced ability of the hybrid model to capture spatiotemporal dependencies, enabling more accurate identification of anomalous events.

Table 4. Incident Detection Performance Metrics

Model	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Baseline Model (SVM)	85.1	83.7	84.4
Telemetry-Only Model	87.3	85.9	86.6
Proposed Hybrid Model	**95.6**	**92.1**	**93.8**

4.4. Impact of Federated Learning

Federated learning experiments demonstrated significant benefits in terms of scalability and privacy preservation. By enabling decentralized training across edge devices, federated learning reduced data transmission by 60%, as measured by the total volume of data exchanged between devices and the central server. Despite this reduction, the global model's performance remained comparable to that of a centrally trained model, with only a 0.8% decrease in traffic flow prediction accuracy. This result underscores the viability of federated learning for large-scale urban traffic systems.

To further evaluate privacy protection, differential privacy was integrated into the federated learning framework. The added noise ensured that individual contributions from local devices were obscured, achieving an average privacy loss of $\epsilon = 1.2$ (small values indicate stronger privacy guarantees).

4.5. Computational Efficiency

The proposed strategies were also evaluated for computational efficiency, focusing on inference latency and memory usage. The hybrid model achieved an average inference latency of 42 milliseconds per frame for traffic flow prediction and incident detection tasks, making it suitable for real-time applications. Memory usage was optimized through model

pruning and quantization techniques, reducing the total memory footprint by 35% without significant loss in accuracy.

4.6. Key Insights

The experimental results highlight several key insights:

1. Multimodal Fusion: The integration of visual and telemetry data significantly enhances predictive accuracy and incident detection performance, leveraging the complementary strengths of the two modalities.

2. Attention Mechanisms: Incorporating attention mechanisms into the fusion layer improves the model's ability to prioritize relevant features, particularly in scenarios involving complex spatiotemporal dependencie]s.

3. Scalability with Federated Learning: Federated learning enables efficient and privacy-preserving training across distributed edge devices, making it a practical solution for large-scale urban deployments.

4. Computational Feasibility: The proposed strategies achieve low latency and memory usage, ensuring their suitability for real-time traffic management systems.

In conclusion, the experimental evaluation demonstrates the efficacy and practicality of the proposed ML strategies for addressing urban traffic congestion. Future work will focus on extending the framework to incorporate additional data sources, such as pedestrian movement and weather conditions, further enhancing the robustness and versatility of the system.

5. Conclusion

This paper presented a comprehensive suite of machine learning (ML) strategies designed to fuse drone-based visual data and vehicle telemetry for mitigating urban traffic congestion. The proposed framework leveraged hybrid model architectures to effectively integrate heterogeneous data modalities, enabling the capture of complex spatiotemporal dependencies inherent in urban traffic systems. Advanced preprocessing pipelines ensured the compatibility and quality of input data, addressing challenges related to noise, heterogeneity, and temporal alignment. By incorporating attention mechanisms and graph-based fusion techniques, the models achieved enhanced accuracy in traffic flow prediction and incident detection, surpassing the performance of single-modal approaches.

The adoption of federated learning demonstrated the feasibility of decentralized model training across edge devices, significantly reducing data transmission by 60% while maintaining model performance. This approach not only enhanced scalability but also preserved user privacy, integrating techniques such as differential privacy and homomorphic encryption to address security concerns. The experimental results validated the effectiveness of the proposed strategies, showing substantial improvements in predictive accuracy, computational efficiency, and resource scalability. For example, traffic flow prediction accuracy improved by 15%, and incident detection precision increased by 10% compared to baseline models [12].

The findings underscore the transformative potential of ML in enabling smarter and more efficient traffic management systems. The integration of multimodal data sources provides a more holistic view of traffic dynamics, facilitating real-time decision-making and adaptive resource allocation. Such systems hold promise for reducing congestion, lowering fuel consumption, and minimizing greenhouse gas emissions, ultimately enhancing urban mobility and sustainability.

Future work will focus on several directions to further advance the proposed methodologies. One key area is the extension of the framework to dynamic and complex traffic scenarios, including those influenced by unpredictable factors such as weather conditions, road construction, and special events. Real-time implementation of the proposed models will also be a priority, requiring optimization of computational pipelines and hardware compatibility for deployment in live urban environments [13]. Additionally, addressing emerging challenges in multimodal data fusion, such as handling extreme data imbalance

or incorporating novel data types like pedestrian movement and public transportation schedules, will be critical for broadening the applicability and robustness of the system [14,15].

The research presented in this paper provides a significant step toward leveraging ML and multimodal data fusion for intelligent traffic management. By demonstrating the practical benefits of integrating drone-based visual data and vehicle telemetry, this work highlights the potential for advanced analytics and AI-driven solutions to revolutionize urban transportation systems. The continued development and refinement of these strategies will be essential for achieving the vision of smarter, more sustainable cities.

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