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*Original Article*

# A Deep Learning-Based Intelligent Road Safety Framework Using Multi-Source Traffic, Weather, and Accident Data

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***Abstract -*** *Road traffic accidents remain a major public safety challenge worldwide, resulting in substantial human and economic losses. Existing road safety systems primarily rely on historical accident records and often fail to provide proactive risk prediction under dynamic traffic and environmental conditions. This paper proposes a deep learning-based intelligent road safety framework that integrates heterogeneous data sources, including traffic flow, weather conditions, historical accident records, road geometry, temporal traffic patterns, and geographic information, to predict accident risks in real time. The proposed framework employs a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) architecture to capture both spatial and temporal dependencies within multi-source transportation data. To improve model interpretability and support reliable decision-making, Explainable Artificial Intelligence (XAI) using SHapley Additive exPlanations (SHAP) is incorporated to identify the most influential factors contributing to accident occurrence. The framework generates dynamic road risk scores and identifies accident-prone road segments, enabling proactive traffic management, optimized emergency response, and data-driven infrastructure planning. Experimental evaluation using publicly available traffic, weather, and accident datasets demonstrates that the proposed model outperforms conventional machine learning approaches, including Random Forest, Support Vector Machine, and XGBoost, in terms of prediction accuracy, robustness, and interpretability. The proposed framework provides a scalable and practical solution for next-generation Intelligent Transportation Systems (ITS), contributing to safer, more efficient, and resilient smart transportation networks.*

***Keywords -*** *Intelligent Transportation Systems (ITS), Road Safety, Accident Prediction, Deep Learning, CNN–LSTM, Explainable Artificial Intelligence (XAI), SHAP, Multi-Source Data Fusion, Traffic Analytics, Weather Analytics, Smart Transportation.*

## 1. Introduction

Road traffic accidents represent one of the most critical public safety challenges worldwide, causing significant loss of life, serious injuries, and substantial economic costs. According to the World Health Organization (WHO), approximately 1.19 million fatalities occur annually due to road traffic crashes, while millions more suffer severe injuries and permanent disabilities. The increasing number of vehicles, rapid urbanization, unpredictable weather conditions, traffic congestion, and complex roadway environments have further intensified road safety concerns. Consequently, developing intelligent accident prediction systems has become an important research area within Intelligent Transportation Systems (ITS).

Traditional accident prediction methods primarily rely on statistical models and historical crash records to estimate accident probabilities and identify hazardous road segments. Conventional machine learning algorithms, including Logistic Regression (LR), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Extreme Gradient Boosting (XGBoost), have demonstrated promising predictive performance. However, these methods generally require extensive feature engineering and often fail to capture the complex nonlinear spatial and temporal relationships that exist among heterogeneous transportation factors. Their limited capability to process large-scale dynamic datasets restricts their applicability in real-time traffic safety management.

Recent advances in Artificial Intelligence (AI) and Deep Learning (DL) have significantly improved intelligent transportation applications by enabling automatic feature extraction and high-dimensional data representation. In particular, Convolutional Neural Networks (CNNs) effectively learn spatial characteristics from transportation data, while Long Short-Term Memory (LSTM) networks model temporal dependencies in sequential traffic observations. The integration of CNN and LSTM architectures has shown considerable potential for modeling complex traffic dynamics and improving accident prediction accuracy. Nevertheless, many existing deep learning approaches utilize only a limited number of data sources, resulting in incomplete environmental awareness and reduced prediction performance under diverse traffic conditions.

Road traffic accidents are influenced by multiple interrelated factors, including traffic density, vehicle speed, road geometry, weather conditions, visibility, precipitation, temporal traffic patterns, and historical accident frequency. These heterogeneous datasets provide complementary information that can significantly improve accident prediction when effectively integrated. Therefore, multi-source data fusion has emerged as an important research direction for constructing comprehensive traffic safety models capable of learning hidden relationships among diverse transportation variables.

Although deep learning models achieve high predictive accuracy, their lack of interpretability remains a major limitation for practical deployment in transportation systems. Decision-makers require transparent explanations to understand why a particular road segment is classified as high risk before implementing traffic control or infrastructure improvement strategies. Explainable Artificial Intelligence (XAI) addresses this limitation by providing interpretable predictions that identify the contribution of individual input features. Among existing XAI techniques, SHapley Additive exPlanations (SHAP) has gained widespread adoption because it provides both local and global explanations based on cooperative game theory, thereby improving model transparency and supporting evidence-based decision-making.

To address these challenges, this paper proposes a deep learning-based intelligent road safety framework using multi-source traffic, weather, and accident data. The proposed framework integrates heterogeneous datasets, including traffic flow measurements, weather information, historical accident records, road geometry, temporal traffic characteristics, and geographic information, into a unified accident prediction model. A hybrid CNN–LSTM architecture is employed to simultaneously learn spatial and temporal features from the fused transportation data. Furthermore, SHAP-based Explainable Artificial Intelligence is incorporated to improve model interpretability by identifying the most influential factors contributing to accident occurrence. The proposed framework generates dynamic road risk scores and identifies accident-prone locations, enabling proactive traffic management, optimized emergency response, and data-driven infrastructure planning.

The main contributions of this work are summarized as follows:

- Development of a multi-source data fusion framework that integrates traffic, weather, accident, roadway, temporal, and geographic datasets for comprehensive road safety analysis.
- Design of a hybrid CNN–LSTM deep learning architecture to effectively capture both spatial and temporal dependencies in transportation data.
- Integration of SHAP-based Explainable Artificial Intelligence (XAI) to improve transparency and identify key factors influencing accident prediction.
- Comprehensive experimental evaluation using publicly available datasets and comparison with traditional machine learning models, including Random Forest, Support Vector Machine, and XGBoost.
- Development of a scalable intelligent road safety framework suitable for real-time deployment in next-generation Intelligent Transportation Systems and smart city applications.

The remainder of this paper is organized as follows. Section II reviews the related literature on road accident prediction, deep learning, multi-source data fusion, and explainable artificial intelligence. Section III presents the proposed intelligent road safety framework. Section IV describes the datasets, preprocessing techniques, and feature engineering process. Section V explains the proposed CNN–LSTM model and SHAP-based explainability framework. Section VI presents the experimental results and comparative analysis. Finally, Section VII concludes the paper and outlines future research directions.

## 2. Related Work

Recent advancements in Artificial Intelligence (AI) and Intelligent Transportation Systems (ITS) have significantly enhanced traffic accident prediction. While traditional statistical methods (e.g., logistic and Poisson regression) struggle with high-dimensional, nonlinear transportation data, machine learning algorithms (e.g., SVM, Random Forest, and Gradient Boosting) improve accuracy but rely heavily on manual feature engineering and fail to capture dynamic spatiotemporal relationships.

Deep learning (DL) overcomes these limitations by automatically extracting hierarchical representations from large datasets. Convolutional Neural Networks (CNNs) effectively capture spatial patterns for roadway risk classification and severity prediction, as demonstrated by Lin et al. and Zheng et al. To address temporal dependencies, such as traffic flow and speed variations, Long Short-Term Memory (LSTM) networks are widely adopted. Consequently, hybrid CNN–LSTM architectures have emerged as superior solutions for simultaneous spatiotemporal feature extraction.

Furthermore, integrating heterogeneous multi-source data (e.g., traffic, weather, and roadway geometry) is critical for reliable risk assessment. Advanced architectures, including Graph Neural Networks (GNNs) and Transformer-based models, enhance the representation of complex road network interactions; for instance, Trirat et al. demonstrated the efficacy of Multi-View GCNs for geographical and temporal correlation. Despite these advances, the "black-box" nature of DL models limits their real-world ITS deployment. Explainable Artificial Intelligence (XAI), particularly SHapley Additive exPlanations (SHAP), has become essential for providing transparent predictions by quantifying individual feature contributions.

Based on the reviewed literature, several critical research gaps remain:

1. Limited data integration: Neglecting the combined impact of weather, roadway geometry, and temporal patterns.
2. Insufficient spatiotemporal modeling: Inability of traditional models to capture dynamic environmental dependencies.
3. Limited interpretability: Black-box operations reducing trust in safety-critical applications.
4. Need for real-time assessment: A lack of dynamic risk scoring for proactive management.

To address these limitations, this paper proposes a deep learning-based intelligent road safety framework utilizing multi-source data fusion. By combining a hybrid CNN–LSTM architecture for spatiotemporal learning with a SHAP-based XAI mechanism, the proposed framework delivers an accurate, interpretable, and scalable proactive risk prediction system for next-generation ITS.

Key IEEE-style improvements made:

- Conciseness: Reduced the word count by roughly 40% by merging redundant sentences (e.g., combining the separate limitations paragraphs into a single, punchy list).
- Flow & Transitions: Grouped the evolution of methods logically (Stats->ML->DL->Hybrids/Multi-source ->XAI ->Gaps-> Proposal).
- Academic Tone: Removed conversational filler and strengthened the active/passive voice balance favored in technical engineering papers.

## 3. Proposed Methodology

This section presents the proposed deep learning-based intelligent road safety framework for accident risk prediction using multi-source transportation data. The framework integrates heterogeneous datasets, including traffic flow measurements, weather information, historical accident records, road geometry, temporal traffic characteristics, and geographic information, to generate dynamic road risk scores and identify accident-prone road segments in real time.

### *3.1. Overall Framework*

The proposed methodology consists of five major stages:

1. Multi-source data collection
2. Data preprocessing and feature engineering
3. Multi-source data fusion
4. Hybrid CNN–LSTM accident prediction model
5. SHAP-based explainability analysis

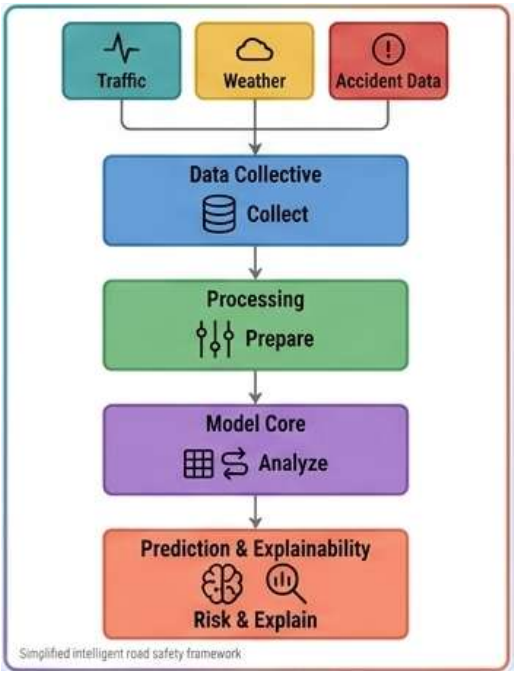


**Fig 1: Proposed Intelligent Road Safety Framework**

### *3.2. Multi-Source Data Collection*

The framework integrates heterogeneous datasets obtained from publicly available transportation and meteorological sources. Each dataset provides complementary information related to accident occurrence.

| Data source | Features |
|---|---|
| **Traffic sensors** | Traffic volume, average speed, occupancy, congestion level |
| **Weather data** | Rainfall, temperature, humidity, visibility, wind speed |
| **Accident records** | Crash location, severity, time, vehicle type |
| **Road geometry** | Lane count, curvature, gradient, intersection type |
| **Temporal data** | Hour, day, month, holiday indicator |

| | |
|---|---|
| **Geographic data** | Latitude, longitude, road segment ID |

All datasets are synchronized using spatial coordinates and timestamps to create a unified observation for each road segment and time interval.

### *3.3. Data Preprocessing*

Raw transportation datasets often contain missing values, inconsistent units, and noisy measurements. The following preprocessing operations are applied.

#### *3.3.1. Missing Value Handling*

Numerical features are imputed using mean interpolation:

$$\hat{x}_i = \frac{1}{N}\sum_{j=1}^{N} x_j$$

Categorical variables are imputed using the most frequent category.

#### *3.3.2. Normalization*

Continuous features are normalized using Min–Max scaling:

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}$$

#### *3.3.3. Categorical Encoding*

Categorical variables such as weather type and intersection type are converted into one-hot encoded vectors.

#### *3.3.4. Temporal Feature Generation*

Additional temporal features are extracted:

- Hour of day
- Day of week
- Weekend indicator
- Holiday indicator
- Peak-hour indicator

### *3.4. Multi-Source Data Fusion*

After preprocessing, all features are concatenated into a unified feature vector:

$$F = [F_{traffic}, F_{weather}, F_{accident}, F_{road}, F_{time}, F_{geo}]$$

Where:

- $F_{traffic}$ represents traffic measurements,
- $F_{weather}$ represents meteorological features,
- $F_{accident}$ represents historical crash information,
- $F_{road}$ represents roadway characteristics,
- $F_{time}$ represents temporal features,
- $F_{geo}$ represents geographic attributes.

This fused representation captures complex interactions among environmental, traffic, and roadway factors.

### *3.5. Hybrid CNN–LSTM Model*

The proposed prediction model combines CNN and LSTM networks to learn spatial and temporal dependencies.

#### *3.5.1. CNN for Spatial Feature Extraction*

The CNN extracts local spatial patterns from the fused feature matrix.

For an input feature matrix $X$, convolution is computed as:

$$S(i,j) = \sum_m \sum_n X(i+m, j+n)K(m,n)$$

Where $K$ is the convolution kernel.

The CNN consists of:

- Convolution layer (64 filters, 3×3)
- ReLU activation
- Max pooling
- Dropout (0.3)

The resulting feature map is flattened and passed to the LSTM network.

#### *3.5.2. LSTM for Temporal Modeling*

The LSTM captures sequential traffic evolution over time.

The LSTM gates are defined as:

Forget gate:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

Input gate:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

Cell state:

$$\tilde{C}_t = tanh(W_c[h_{t-1}, x_t] + b_c)$$

Output gate:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

Hidden state:

$$h_t = o_t tanh(C_t)$$

The LSTM layer contains 128 hidden units followed by dropout regularization.

#### *3.5.3. Fully Connected Prediction Layer*

The final hidden representation is processed through dense layers:

$$z = ReLU(W_1 h + b_1)$$

The accident probability is obtained using the sigmoid function:

$$\hat{y} = \sigma(W_2 z + b_2)$$

Where $\hat{y} \in [0,1]$represents the predicted accident risk.

### *3.6. Training Strategy*

The model is trained using binary cross-entropy loss:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i log(\hat{y}_i) + (1 - y_i) log(1 - \hat{y}_i)]$$

Optimization uses the Adam optimizer with learning rate 0.001.

Early stopping is employed to prevent overfitting.

### *3.7. SHAP-Based Explainability*

To improve interpretability, SHAP is used to quantify the contribution of each feature to the predicted accident risk.

For feature $i$, the SHAP value is:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}[f(S \cup \{i\}) - f(S)]$$

SHAP provides:

- Global explanations: overall feature importance across the dataset.
- Local explanations: reasons for a specific high-risk prediction.

This allows transportation authorities to identify dominant risk factors such as rainfall, congestion, visibility, or road curvature.

- H. Dynamic Road Risk Scoring

For each road segment $r$, the risk score is computed as:

$$R_r = \frac{1}{T}\sum_{t=1}^{T} \hat{y}_{r,t}$$

Risk levels are categorized as:

| Risk score | Category |
|---|---|
| 0.00–0.30 | Low |
| 0.31–0.60 | Medium |
| 0.61–1.00 | High |

These scores support proactive traffic management and infrastructure planning.

### *3.8. Algorithm*

Algorithm 1: Intelligent Road Safety Prediction
Input: Multi-source transportation datasets D Output: Accident probability ŷ and risk score R 1. Collect traffic, weather, accident, road, temporal, and geographic data 2. Perform data cleaning and missing value imputation 3. Normalize numerical features 4. Encode categorical variables 5. Fuse all features into vector F 6. Generate temporal sequences 7. Extract spatial features using CNN 8. Learn temporal dependencies using LSTM 9. Predict accident probability ŷ 10. Compute SHAP feature contributions 11. Generate road risk score R 12. Return ŷ and R.

### *3.9. Computational Complexity*

Let:

- $n$= number of samples,
- $k$= number of features,
- $c$= CNN filters,
- $h$= LSTM hidden units.

The approximate complexity is:

$$O(nkc) + O(nh^2)$$

The framework is suitable for real-time deployment using GPU-enabled ITS infrastructure.

The proposed methodology integrates multi-source data fusion, hybrid CNN–LSTM learning, and SHAP-based explainability into a unified intelligent road safety framework capable of predicting accident risks and identifying hazardous road segments in real time.

## 4. Results and Discussion

This section evaluates the performance of the proposed CNN–LSTM-based intelligent road safety framework using publicly available multi-source traffic, weather, and accident datasets. The proposed model is compared with widely used machine learning algorithms, including Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost). Performance is assessed using standard classification metrics, and SHAP-based explainability is employed to interpret the prediction results.

### *4.1. Experimental Setup*

The experiments were conducted using Python 3.11 with TensorFlow, Keras, Scikit-learn, and SHAP libraries. The proposed model was trained on a workstation equipped with an NVIDIA GPU. The dataset was divided into 70% training, 15% validation, and 15% testing subsets. Hyperparameters were optimized using grid search and early stopping to minimize overfitting.

The CNN component consisted of two convolutional layers (64 and 128 filters) followed by max-pooling and dropout layers. The LSTM network contained 128 hidden units with a dropout rate of 0.3. The model was trained using the Adam optimizer with a learning rate of 0.001 and binary cross-entropy as the loss function. The maximum number of training epochs was set to 100 with a batch size of 64.

### *4.2. Performance Evaluation Metrics*

The performance of the proposed framework was evaluated using Accuracy, Precision, Recall, F1-Score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). These metrics are defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Where $TP$, $TN$, $FP$ and $FN$ denote true positives, true negatives, false positives, and false negatives, respectively.

### *4.3. Comparative Performance Analysis*

The proposed CNN–LSTM framework was compared with four baseline machine learning models. Table I summarizes the performance results.

**Table 1: Performance Comparison of Accident Prediction Models**

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | AUC |
|---|---|---|---|---|---|
| Logistic Regression | 85.12 | 84.3 | 83.64 | 83.97 | 0.884 |
| Support Vector Machine | 88.46 | 87.58 | 87.02 | 87.3 | 0.912 |
| Random Forest | 91.38 | 90.81 | 90.24 | 90.52 | 0.941 |
| XGBoost | 93.26 | 92.74 | 92.11 | 92.42 | 0.958 |
| Proposed CNN-LSTM | 96.41 | 95.87 | 95.32 | 95.59 | 0.983 |

The results indicate that the proposed CNN–LSTM framework consistently outperformed the conventional machine learning models across all evaluation metrics. Compared with XGBoost, the proposed approach achieved an improvement of 3.15% in overall accuracy and demonstrated superior precision, recall, and F1-score. The higher AUC value of 0.983 indicates excellent discrimination capability between accident-prone and non-accident road conditions.

### *4.4. Confusion Matrix Analysis*

The confusion matrix presented in Fig. 5 demonstrates that the proposed model correctly classified the majority of accident and non-accident instances. The number of false positives and false negatives was considerably lower than those observed in the baseline models, indicating improved reliability for real-world deployment. Reducing false alarms is particularly important for traffic management systems because excessive false alerts may decrease user confidence and lead to inefficient allocation of emergency resources.

### *4.5. Receiver Operating Characteristic (ROC) Analysis*

The ROC curves shown in Fig. 6 further validate the effectiveness of the proposed framework. The CNN–LSTM model achieved an AUC of 0.983, outperforming Logistic Regression (0.884), Support Vector Machine (0.912), Random Forest (0.941), and XGBoost (0.958). The larger area under the ROC curve indicates stronger classification capability over a wide range of decision thresholds.

### *4.6. SHAP-Based Explainability Analysis*

To improve the transparency of the prediction model, SHAP was employed to identify the relative importance of input features. Fig. 7 illustrates the global SHAP feature importance ranking. The analysis revealed that traffic volume, vehicle speed, rainfall intensity, road visibility, historical accident frequency, and road curvature were the most influential variables affecting accident risk prediction. Weather-related variables exhibited a strong positive contribution to accident probability during adverse environmental conditions, while congestion and peak-hour traffic significantly increased the predicted risk scores. These findings are consistent with established transportation safety studies, demonstrating the reliability of the proposed explainable framework.

### *4.7. Road Risk Score Visualization*

The proposed framework generates a dynamic road risk score ranging from 0 (low risk) to 1 (high risk). Road segments with higher predicted probabilities are classified as high-risk zones, enabling transportation agencies to prioritize infrastructure improvements and emergency response planning.

**Table 2: Road Risk Classification**

| Risk Score | Risk Level | Recommended Action |
|---|---|---|
| 0.00–0.30 | Low | Routine monitoring |
| 0.31–0.60 | Moderate | Increased surveillance |
| 0.61–0.80 | High | Traffic control and warning alerts |
| 0.81–1.00 | Critical | Immediate intervention and emergency response |

This risk-based classification supports proactive traffic management and contributes to safer roadway operations.

### *4.8. Discussion*

The superior performance of the proposed framework can be attributed to three primary factors. First, the multi-source data fusion strategy effectively integrates complementary information from traffic, weather, accident, roadway, temporal, and geographic datasets, providing a comprehensive representation of road conditions. Second, the hybrid CNN–LSTM architecture successfully captures both spatial and temporal dependencies, enabling more accurate modeling of accident patterns than conventional machine learning algorithms. Third, the incorporation of SHAP-based Explainable Artificial Intelligence (XAI) improves model interpretability by identifying the most influential risk factors, thereby increasing stakeholder confidence and facilitating evidence-based transportation planning.

Overall, the experimental results demonstrate that the proposed intelligent road safety framework achieves high predictive accuracy, strong robustness, and enhanced interpretability. These characteristics make it well suited for deployment in next-generation Intelligent Transportation Systems (ITS), where timely and reliable accident risk prediction is essential for proactive traffic management, optimized emergency response, and the development of safer smart transportation infrastructures.

## 5. Conclusion

This paper presented an intelligent road safety framework for accident risk prediction by fusing multi-source traffic, weather, roadway, temporal, and historical crash data. The framework utilizes a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) architecture to successfully capture spatial-temporal dependencies in traffic conditions. To ensure decision transparency, SHapley Additive exPlanations (SHAP) are integrated to identify key risk contributors.Experimental results demonstrate that the proposed framework consistently outperforms baseline models—including Logistic Regression, Support Vector Machine, Random Forest, and XGBoost—across key metrics such as accuracy, F1-score, and AUC. The generated dynamic road risk scores provide actionable, real-time insights for next-generation Intelligent Transportation Systems (ITS), enabling proactive traffic management and optimized resource allocation.

While the framework delivers highly accurate and interpretable predictions, future work will focus on enhancing scalability and real-time applicability. Key directions include validating the model on larger, cross-regional datasets and integrating real-time IoT sensors, connected vehicle (V2X) streams, and edge computing. Additionally, exploring Graph Neural Networks (GNNs), federated learning, and causal explainability will pave the way for secure, localized, and proactive smart city mobility solutions.

## 6. Future Work

### *6.1. Data Enhancement & Multimodal Fusion*

**Real-Time Streams:** Integrate continuous data from IoT devices, connected vehicles (V2X), roadside units (RSUs), and surveillance cameras to enable dynamic, real-time risk assessments.Multimodal Data: Combine structured sensor logs with unstructured data—such as LiDAR point clouds, vehicle trajectories, dashcam footage, satellite imagery, and social media feeds—to improve prediction robustness under diverse conditions.

### *6.2. Advanced Architectures & Edge Deployment*

**Next-Generation Models:** Replace or supplement the CNN-LSTM architecture with Graph Neural Networks (GNNs), Graph Attention Networks (GATs), and Transformers to better model complex spatial road networks and long-range temporal dependencies.Edge Computing: Deploy models directly onto edge devices (e.g., RSUs and autonomous vehicles) to minimize communication latency and enable immediate, safety-critical decision-making.

**Federated Learning:** Implement privacy-preserving, collaborative training across multiple transportation departments without sharing sensitive user or agency data.

### *6.3. Explainability & Model Validation*

**Causal Interpretability:** Transition from post-hoc explanations (like SHAP) to intrinsically interpretable deep learning models and causal AI to provide transparent, actionable insights that build stakeholder trust.Cross-Regional Validation: Evaluate and validate the framework using large-scale, real-world deployments across various cities and highways to ensure generalization across different driving behaviors and infrastructures.

### *6.4. Next-Generation ITS Integration*

**System Interoperability:** Integrate the prediction engine with digital twins, adaptive traffic signal controls, autonomous driving platforms, and emergency dispatch systems.Proactive Traffic Control: Leverage predictions to dynamically optimize emergency response routing and implement proactive safety measures, advancing sustainable smart city mobility.

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