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Deep Learning and Hybrid Time-Series Forecasting for Intelligent Traffic Management and Sustainable Urban Mobility

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Abstract: Urban traffic congestion is a major barrier to sustainable mobility because it increases travel delay, fuel consumption, emissions, crash exposure, and uncertainty in daily travel. Recent advances in connected vehicles, Internet of Things (IoT) infrastructure, urban sensing, navigation platforms, and deep learning have created new opportunities for intelligent traffic management systems that can forecast congestion before it spreads and respond through signal control, route guidance, and demand management. This paper presents a research-oriented review and conceptual framework for deep learning and hybrid time-series forecasting in intelligent traffic management and sustainable urban mobility. It uses the supplied reference papers on urban traffic management, connected and automated vehicle signal control, smart-city traffic optimization, anomaly-aware deep learning, hybrid CNN-LSTM, CNN-LSTM-GRU, GSA-LSTM, SDLSTM-ARIMA, attention-based GRU-LSTM, and CPO-CNN-LSTM-Attention models. The paper argues that future traffic systems should combine temporal learning, spatial network representation, anomaly detection, contextual data such as weather and holidays, optimization algorithms, and sustainability evaluation. For better presentation, the paper also includes comparative tables and conceptual figures that summarize model categories, architecture flow, and sustainability links.

Keywords: Deep Learning; Hybrid Forecasting; Time-Series Prediction; Intelligent Traffic Management; Sustainable Urban Mobility.

I. INTRODUCTION

Urban mobility systems are under pressure from rapid urbanization, increasing motorization, constrained road capacity, and rising expectations for reliable, low-emission travel. Congestion is no longer only an operational inconvenience; it is a sustainability problem that affects economic productivity, public health, air quality, road safety, fuel use, and quality of life. Traditional responses such as expanding road capacity are often expensive, land-intensive, and environmentally undesirable. As a result, many cities have turned toward intelligent traffic management approaches that use sensing, communication, computation, and control to make better use of existing infrastructure.

Early Urban Traffic Management (UTM) systems relied heavily on infrastructure-based detection, coordinated traffic signals, incident management, bus priority, parking information, and traveler information services. Hounsell et al. [1] describe the shift from road construction toward capacity management and show how UTM environments integrate multiple data sources and control applications. Their work also anticipates the growing influence of in-vehicle technologies such as navigation systems, driver support systems, and vehicle-based data.

Connected and automated vehicles further extend this landscape. Guo et al. [2] review urban signal control with connected and automated vehicles and emphasize mobile sensing, traffic state estimation, and signal timing optimization. Connected vehicles can provide trajectory, speed, acceleration, queue, and arrival information at a level of detail that fixed sensors alone cannot provide. However, CAV-based control depends on penetration rate, robust estimation under partial observability, communication reliability, and validation beyond simulation.

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Recent advances in artificial intelligence have improved the ability to model nonlinear and dynamic traffic patterns. Mihaita et al. [3] demonstrate that CNN, LSTM, and CNN-LSTM models can exploit spatial and temporal dependencies in traffic data, especially when combined with anomaly detection and data repair. Anjaneyulu and Kubendiran [4] propose a hybrid Xception-SVM model for short-term congestion prediction. Other studies emphasize IoT-based traffic optimization [5], AI-based vehicle routing [6], CNN-LSTM-GRU forecasting with weather and holiday variables [7], GSA-optimized LSTM [8], HCLM for traffic volume prediction [9], SDLSTM-ARIMA combination forecasting [10], attention-based GRU-LSTM forecasting for smart cities [11], and CPO-CNN-LSTM-Attention models for urban traffic flow prediction [12].

The objective of this paper is to synthesize these contributions into a coherent research paper on deep learning and hybrid time-series forecasting for intelligent traffic management and sustainable urban mobility. The paper is organized as follows. Section 2 reviews the literature. Section 3 presents comparison tables. Section 4 explains hybrid forecasting needs. Section 5 proposes an integrated framework. Section 6 discusses sustainability implications. Section 7 identifies challenges and research gaps. Section 8 concludes the paper.

II. LITERATURE REVIEW

A. Urban Traffic Management and In-Vehicle Technologies

UTM systems collect, process, and apply traffic information to improve network operation. Hounsell et al. [1] review advanced traffic control systems and wider UTM environments, noting that congestion has increasingly been addressed through management of existing capacity rather than new road construction. Their review discusses systems such as SCOOT, integrated traveler information, parking information, bus priority, automatic incident detection, and enforcement-related applications. A key insight is that UTM is not a single technology but an operational environment where detection, communication, information processing, control, and policy objectives must be aligned.

The same work highlights the potential interaction between infrastructure-based UTM and vehicle-based systems. Navigation systems, mobile phones, driver support systems, Adaptive Cruise Control, Intelligent Speed Adaptation, and floating car data can influence traffic behavior and provide additional information to traffic managers. This remains relevant because modern traffic management increasingly depends on connected data ecosystems.

B. Connected and Automated Vehicle Signal Control

Guo et al. [2] provide a comprehensive survey of urban traffic signal control with connected and automated vehicles. Their review focuses on how CAV data can support traffic state estimation and signal timing optimization. Conventional traffic signals often rely on loop detectors, cameras, or historical timing plans. CAVs can supplement these sources by reporting position, speed, trajectory, and estimated arrival information. This can improve queue length estimation, arrival flow prediction, platoon management, and adaptive signal control.

The review identifies multiple CAV-based control methods and emphasizes a mathematical framework based on state variables, control inputs, and environmental inputs. This is directly relevant to hybrid forecasting because signal control is only as effective as the traffic state representation used by the controller. If short-term forecasts estimate flow, speed, occupancy, queue formation, and shockwave propagation, signal timing can become proactive rather than reactive.

C. Smart-City Traffic Optimization and Vehicle Safety

Krishnan and Balasubramanian [5] propose a smart-city model for traffic flow optimization and vehicle safety using IoT & LiFi. Their paper frames congestion and road accidents as two linked urban problems and proposes that IoT data can be stored in the cloud and processed using machine learning algorithms to identify better routes. LiFi-based communication is proposed for vehicle-to-vehicle information exchange and accident prevention.

Although conceptual, the paper contributes an important smart-city perspective: traffic optimization and safety should be addressed together. A forecasting system that reduces travel time but encourages unsafe rerouting, abrupt speed changes, or excessive traffic through vulnerable streets may not support sustainable mobility.

D. Hybrid Deep Learning for Short-Term Congestion Prediction

Anjaneyulu and Kuben Diran [4] propose a hybrid Xception-SVM model for short-term traffic congestion prediction. Their method uses Google Maps snapshots from Bangalore and predicts congestion every five minutes over a one-hour horizon. The Xception architecture extracts deep features, while SVM performs classification through margin-based separation. The authors report 97.16 percent accuracy, showing the value of combining deep feature extraction with classical machine learning.

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This work is important because many cities may not have dense loop detector networks but may have map feeds, cameras, GPS traces, or mobile data. It also confirms that hybrid models can combine the representation power of deep learning with the stability of conventional classifiers.

E. AI-Based Vehicle Routing and Congestion Reduction

Dikshit et al. [6] examine artificial intelligence for optimizing vehicle routing and reducing traffic congestion. The study emphasizes real-time traffic data, road network characteristics, individual travel patterns, machine learning, optimization algorithms, travel time reduction, fuel consumption, emissions reduction, scalability, and economic viability. This focus links prediction to action. Forecasting alone does not improve mobility unless predictions are converted into operational decisions such as route guidance, signal timing, congestion pricing, public transport priority, or incident response.

AI routing also creates network-level challenges. If many drivers receive the same shortest route, congestion may shift rather than disappear. A sustainable routing system must consider system-optimal assignment, user compliance, fairness, emissions, safety, and local street impacts.

F. Anomaly Detection and Deep Spatio-Temporal Forecasting

Mihaita et al. [3] present a deep learning framework for traffic congestion anomaly detection and prediction using large-scale motorway data from Sydney. The study predicts traffic flow, speed, and occupancy across many monitoring stations and compares CNN, LSTM, BPNN, and CNN-LSTM architectures. The authors show that deep learning models outperform traditional methods and that anomaly detection and data repair improve forecasting performance.

This contribution is important because real-time traffic data are often noisy, missing, delayed, or distorted by detector faults, incidents, weather, special events, and communication failures. A forecasting model trained on uncorrected anomalies may learn false patterns or fail during the moments traffic managers most need reliable predictions.

G. Recent Hybrid Forecasting Models Added from the Additional Papers

Zhang et al. [7] propose a CNN-LSTM-GRU hybrid model for spatiotemporal highway traffic flow prediction. Their model builds a multidimensional feature matrix that includes temporal sequences, spatial correlations, and meteorological conditions. CNN captures spatial patterns, while LSTM and GRU jointly model temporal dependencies. The paper evaluates holiday and non-holiday patterns and the impact of weather data, showing that contextual variables can improve forecasting in real traffic conditions.

Naheliya et al. [8] develop GSA-LSTM, where the gravitational search algorithm optimizes LSTM parameters for short-term traffic flow forecasting. The model is compared with ARIMA, WNN, GRU, LSTM, GSA-GRU, ACO-LSTM, and PSO-LSTM using RMSE, MAE, MAPE, correlation coefficient, and average accuracy. The study concludes that GSA-LSTM performs better than the selected baseline models, showing the value of metaheuristic parameter optimization.

Mead and Refaat [9] propose the Hybrid CNN and LSTM Model (HCLM) for short-term traffic volume prediction. Their model predicts traffic volume using time-series traffic data at different intervals and is compared with ARIMA, CNN, and LSTM. The reported results show lower MAE and RMSE for HCLM, especially at 25-minute and 75-minute intervals, and the model also requires less build time than its nearest competitor.

Liu et al. [10] propose SDLSTM-ARIMA, a combination forecasting method based on improved LSTM and ARIMA. The method introduces a traffic data time singularity ratio in the dropout module and combines unequal time intervals to improve accuracy. This work is important because it explicitly integrates statistical time-series forecasting with deep learning, supporting the argument that hybrid models are more robust than single-method approaches.

Albalooshi [11] proposes a deep learning framework for smart-city traffic prediction that integrates GRU, LSTM, and an attention mechanism. The model is evaluated on PeMS-03, PeMS-04, PeMS-07, and PeMS-08 datasets and reports reductions of 3.75 percent in MAE, 2.00 percent in RMSE, and 4.17 percent in MAPE compared with baseline methods. This study strengthens the role of attention mechanisms in highlighting the most relevant temporal patterns.

Topilin et al. [12] design a CPO-CNN-LSTM-Attention architecture for urban traffic flow prediction using Paris road traffic data. The model combines the Crested Porcupine Optimizer with CNN, LSTM, and attention modules. Reported results include RMSE of 17.35-19.83, MAE of 13.98-14.04, and MAPE of 5.97-6.62 percent, outperforming

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comparison models. This paper shows that optimizer-assisted attention models are becoming important in smart-city traffic forecasting.

III. COMPARATIVE TABLES AND FIGURES

Table I. Summary of Reference Papers

No.	Study	Method	Data	Key Contribution
1	Hounsell et al. [1]	Urban Traffic Management review	UTM and in-vehicle systems	Establishes traffic management as integrated data-control-policy environment
2	Guo et al. [2]	CAV-based signal control survey	Connected and automated vehicles	Links traffic state estimation with adaptive signal optimization
3	Mihaita et al. [3]	CNN, LSTM, CNN-LSTM with anomaly repair	Sydney motorway data	Shows spatio-temporal forecasting improves with anomaly detection
4	Anjaneyulu and Kubendiran [4]	Xception-SVM	Google Maps snapshots, Bangalore	Demonstrates hybrid deep-feature and SVM congestion classification
5	Krishnan and Balasubramanian [5]	IoT and LiFi smart-city concept	Smart city traffic and safety	Connects optimization, cloud data, vehicle communication, and safety
6	Dikshit et al. [6]	AI vehicle routing	Urban routing and congestion	Links AI prediction with route optimization and sustainability outcomes
7	Zhang et al. [7]	CNN-LSTM-GRU	Highway traffic, weather, holidays	Integrates spatial, temporal, meteorological, and holiday effects
8	Naheliya et al. [8]	GSA-LSTM	Short-term traffic flow	Uses gravitational search to optimize LSTM parameters
9	Mead and Refaat [9]	HCLM: CNN-LSTM	California traffic volume data	Shows hybrid CNN-LSTM improves MAE/RMSE and build time
10	Liu et al. [10]	SDLSTM-ARIMA	Traffic flow time series	Combines improved LSTM with ARIMA for stability and accuracy
11	Albalooshi [11]	GRU-LSTM-Attention	PeMS-03/04/07/08	Uses attention for temporal relevance and smart-city planning
12	Topilin et al. [12]	CPO-CNN-LSTM-Attention	Paris urban road traffic	Combines optimizer, CNN, LSTM, and attention for urban forecasting

Table II. Comparison of Hybrid Forecasting Architectures

Model Type	Network Topology	Sequential learning	Optimization	Computational Efficiency	Limitation
ARIMA	No	Linear time-series	Statistical fitting	Simple and interpretable	Weak for nonlinear and incident-driven traffic
LSTM	Limited	Strong	Neural training	Captures long-term dependencies	Sensitive to parameters and data quality

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GRU	Limited	Strong	Neural training	Faster and simpler than LSTM	May miss some long-term patterns
CNN-LSTM	Yes	Strong	Neural training	Learns spatial and temporal features together	Needs careful architecture tuning
CNN-LSTM-GRU	Yes	Strong	Neural training	Combines CNN spatial learning with LSTM memory and GRU efficiency	Higher complexity and training demand
Xception-SVM	Image/deep feature based	Indirect	SVM classifier	Useful for congestion classification from map snapshots	Depends on labeled images/classes
GSA-LSTM	Limited	Strong	Gravitational search optimization	Improves parameter selection	Metaheuristic search can add computation
SDLSTM-ARIMA	No/limited	Strong plus statistical trend	Improved dropout and ARIMA	Combines deep nonlinear learning with statistical stability	Spatial network effects may be limited
GRU-LSTM-Attention	Limited	Strong	Attention mechanism	Highlights important time steps and improves accuracy	Attention interpretation still requires care
CPO-CNN-LSTM-Attention	Yes	Strong	CPO plus attention	Strong urban spatio-temporal prediction	More complex deployment pipeline

Table III. Reported Performance Evidence from Selected Papers

Study	**Published findings**	**Interpretation**
Anjaneyulu and Kubendiran [4]	97.16 percent accuracy	Hybrid Xception-SVM can classify short-term congestion effectively
Mead and Refaat [9]	HCLM gives lower MAE/RMSE than ARIMA, CNN, and LSTM; sample RMSE values around 9.4-10.08 versus ARIMA around 14.5	CNN-LSTM improves traffic volume prediction over single models
Albalooshi [11]	3.75 percent MAE reduction, 2.00 percent RMSE reduction, 4.17 percent MAPE reduction	Attention-enhanced GRU-LSTM improves public PeMS dataset forecasting
Topilin et al. [12]	RMSE 17.35-19.83, MAE 13.98-14.04, MAPE 5.97-6.62 percent	Optimizer-assisted CNN-LSTM-Attention improves urban road prediction
Zhang et al. [7]	Hybrid CNN-LSTM-GRU outperforms LSTM, GRU, CNN-LSTM, and CNN-GRU	Combining weather, holiday, spatial, and temporal features increases realism
Naheliya et al. [8]	GSA-LSTM outperforms ARIMA, WNN, GRU, LSTM, GSA-GRU, ACO-LSTM, and PSO-LSTM	Metaheuristic optimization improves LSTM parameter selection
Liu et al. [10]	SDLSTM-ARIMA has higher accuracy and stability than ARIMA-based comparison methods	Statistical-deep hybrid models can improve stability in time-series forecasting

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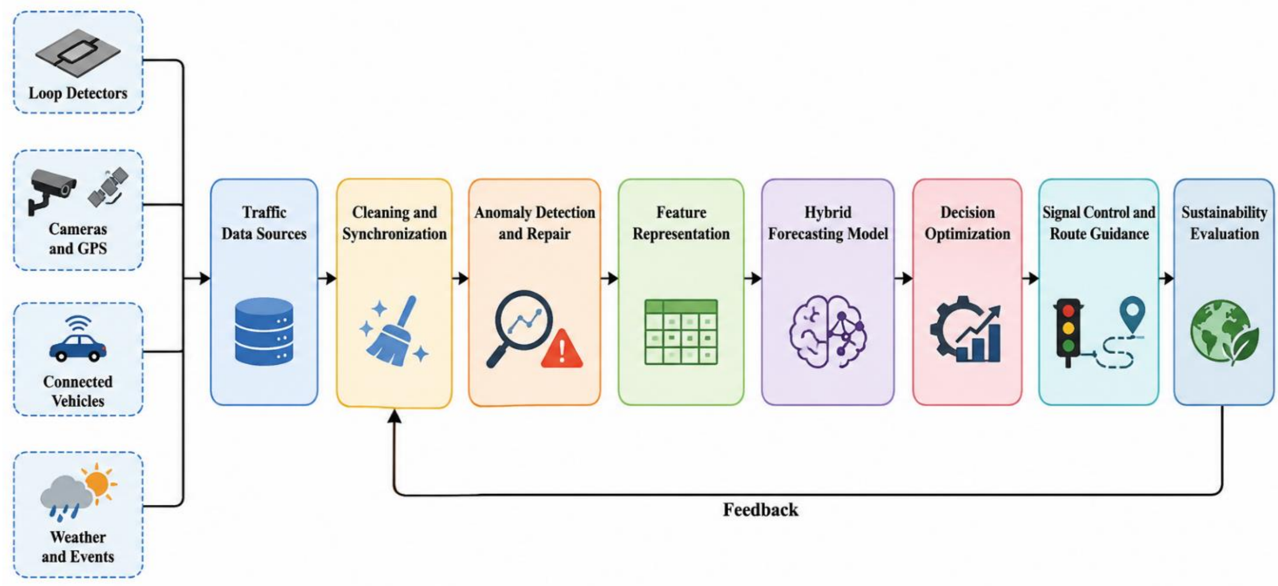

Figure 1. Proposed Intelligent Traffic Forecasting and Management Pipeline

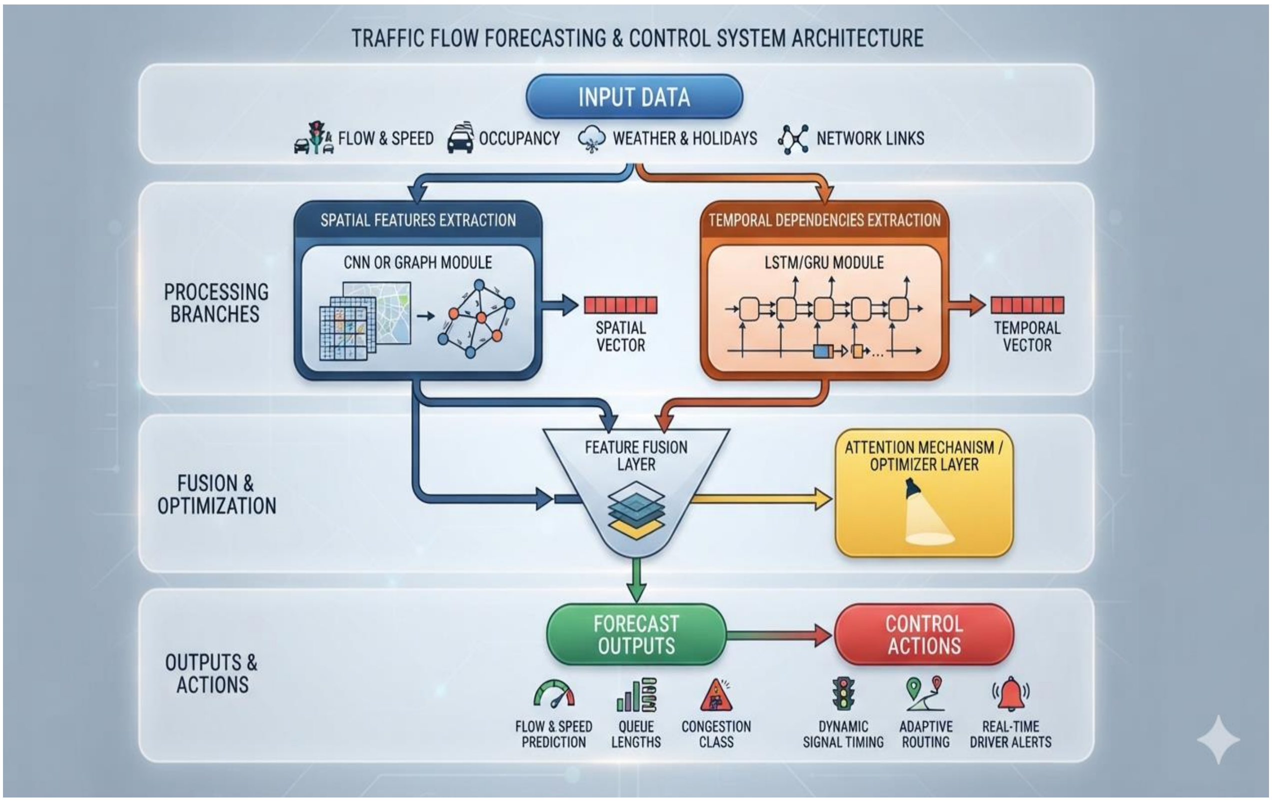

Figure 2. Traffic Flow Forecasting & Control System Architecture

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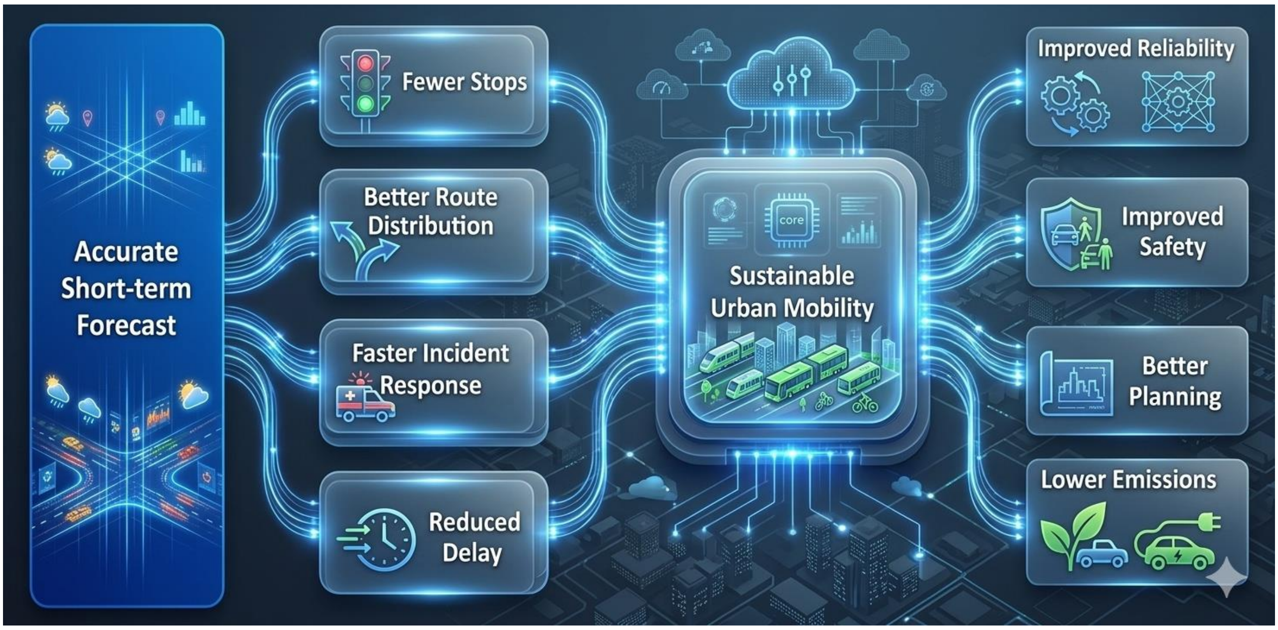

Figure 3. Sustainability Linkage of Forecasting Outputs

IV. NEED FOR DEEP LEARNING AND HYBRID TIME-SERIES FORECASTING

Traffic systems are dynamic, nonlinear, stochastic, and spatially interconnected. Congestion can emerge gradually through recurring demand patterns or suddenly through incidents, weather, bottlenecks, or signal failures. A traffic state observed at one road segment is influenced by upstream arrivals, downstream capacity, signal timing, turning movements, public transport operations, driver behavior, and route choice. These dependencies make traffic forecasting a difficult time-series problem.

Classical time-series methods such as ARIMA are useful when traffic patterns are relatively linear and stable. However, urban traffic often violates these assumptions. Machine learning models such as support vector machines can capture more complex relationships but may require careful feature engineering. Deep learning models, particularly CNN, LSTM, GRU, graph-based networks, and attention models, can learn richer representations from large-scale data.

Hybrid forecasting is valuable because different methods capture different aspects of traffic behavior. Statistical models capture trend and seasonality. CNN models capture spatial relationships. LSTM models capture long-term dependencies. GRU models offer efficient temporal learning. Attention mechanisms identify important time steps. Optimization algorithms such as GSA or CPO improve parameter selection. Classifiers such as SVM can improve congestion class separation. Together, these components can produce more reliable traffic forecasts than any single model.

V. PROPOSED INTELLIGENT TRAFFIC MANAGEMENT FRAMEWORK

The proposed framework contains six layers: data acquisition, preprocessing and anomaly management, feature representation, hybrid forecasting, decision optimization, and sustainability evaluation.

A. Data Acquisition Layer

The first layer collects heterogeneous traffic and mobility data. Potential sources include loop detectors, cameras, GPS traces, connected vehicles, mobile navigation platforms, public transport feeds, parking systems, weather services, incident reports, signal controller logs, and IoT devices. CAV data can provide high-resolution trajectories and arrival information, while UTM infrastructure can provide validated network-level measurements.

B. Preprocessing and Anomaly Management Layer

Raw traffic data require cleaning, synchronization, map matching, aggregation, and anomaly handling. Mihaita et al. [3] show that anomaly detection and repair can improve deep traffic prediction. In the proposed framework, anomaly management includes missing value detection, detector fault identification, outlier recognition, event labeling, and repair using historical and neighboring data.

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Anomalies should not always be removed. Some anomalies represent true incidents, sudden congestion, weather disruptions, or special events. The system must distinguish sensor errors from meaningful traffic disturbances.

C. Feature Representation Layer

Traffic forecasting requires temporal, spatial, and contextual features. Temporal features include recent flow, speed, occupancy, queue length, travel time, time of day, day of week, and seasonal demand. Spatial features include upstream and downstream states, intersection adjacency, corridor structure, and network bottlenecks. Contextual features include weather, holidays, incidents, road works, public events, parking availability, and public transport disruptions. The CNN-LSTM-GRU study [7] demonstrates the importance of including weather and holiday effects.

D. Hybrid Forecasting Layer

The hybrid forecasting layer predicts traffic states across multiple time horizons. Short horizons of 5 to 15 minutes support signal control and incident response. Medium horizons of 15 to 60 minutes support route guidance and demand management. Longer horizons support planning and infrastructure investment.

A practical hybrid model may include a statistical baseline, a spatio-temporal deep learning module, an attention or optimization module, and a classification layer. The model output should include predicted flow, speed, occupancy, queue length, travel time, congestion class, and uncertainty. Uncertainty is important because traffic managers need to know when predictions are reliable and when conservative control is required.

E. Decision Optimization Layer

The decision layer translates predictions into actions. Possible actions include adaptive signal timing, route guidance, ramp metering, public transport priority, variable speed advisories, incident response dispatch, parking guidance, freight scheduling, and demand management. AI routing can use predicted travel times to distribute demand across the network, while signal control can use predicted queues and arrivals to optimize green splits, offsets, and phase sequences.

F. Sustainability Evaluation Layer

A sustainable mobility system should be evaluated using multiple indicators, not only forecasting accuracy. Relevant metrics include travel time, delay, queue length, stop frequency, fuel consumption, emissions, public transport reliability, crash risk, access equity, and network resilience. A model that reduces average delay but shifts pollution or safety risks to vulnerable neighborhoods should not be considered fully successful.

VI. DISCUSSION: SUSTAINABLE URBAN MOBILITY IMPLICATIONS

Deep learning and hybrid forecasting support sustainable urban mobility in several ways. First, accurate short-term prediction enables proactive traffic management. If congestion can be forecast before queues block intersections, signal plans and route guidance can be adjusted early. Second, hybrid forecasting supports better use of existing infrastructure, reducing the need for land-intensive road expansion. Third, connected vehicle data can improve observability and enable better signal control. Fourth, AI routing can reduce congestion hotspots when implemented with network-level coordination. Fifth, anomaly-aware forecasting improves resilience during incidents and abnormal conditions.

The additional papers strengthen this argument by showing the importance of practical model design. CNN-LSTM-GRU models demonstrate that weather and holidays affect traffic volatility [7]. GSA-LSTM and CPO-CNN-LSTM-Attention show that optimization methods can improve neural network performance [8], [12]. HCLM and SDLSTM-ARIMA show that hybrid architectures can outperform single CNN, LSTM, and ARIMA approaches [9], [10]. Attention-based GRU-LSTM models show that temporal relevance can be learned directly from high-frequency PeMS datasets [11]. These findings support a shift from isolated forecasting models toward integrated, context-aware, and sustainability-oriented traffic intelligence.

VII. CHALLENGES AND RESEARCH GAPS

- Despite strong potential, several challenges limit deployment.
- Data quality and availability: Many cities do not have dense, reliable, standardized traffic data. Missing values, sensor faults, inconsistent sampling rates, and proprietary data restrictions complicate model development.
- Generalization: Models trained in one city, corridor, or season may not perform well elsewhere. Urban networks differ in geometry, driver behavior, land use, signal policy, and modal composition.

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- Interpretability: Deep learning models are often difficult to interpret. Traffic managers may hesitate to rely on black-box systems for real-time control unless predictions and decisions can be explained.
- Scalability: Citywide forecasting across thousands of links and intersections requires efficient computation, data storage, and communication infrastructure.
- Mixed traffic conditions: CAV-based methods must work during long transition periods when connected, automated, conventional, public transport, freight, two-wheelers, pedestrians, and cyclists share the network.
- Control integration: Forecasting accuracy does not automatically produce better traffic management. Prediction models must be integrated with signal controllers, routing platforms, policy constraints, and human operators.
- Privacy and cybersecurity: Connected vehicle and mobile data can reveal sensitive travel patterns. Systems must protect privacy and resist malicious data injection or control interference.
- Equity: AI routing and traffic control may unintentionally shift traffic, pollution, and safety risks to disadvantaged neighborhoods. Sustainability evaluation must include distributional impacts.

Future research should focus on explainable hybrid models, graph-based forecasting, transfer learning across cities, privacy-preserving data fusion, uncertainty-aware control, real-world field trials, and sustainability-centered performance evaluation.

VIII. CONCLUSION

This paper presented a research-oriented synthesis of deep learning and hybrid time-series forecasting for intelligent traffic management and sustainable urban mobility. The literature shows a clear evolution from infrastructure-based urban traffic management toward connected, AI-enabled, data-driven mobility systems. The original and additional reference papers show that hybrid models such as CNN-LSTM, CNN-LSTM-GRU, GSA-LSTM, SDLSTM-ARIMA, GRU-LSTM-Attention, Xception-SVM, and CPO-CNN-LSTM-Attention can improve traffic flow and congestion prediction by combining the strengths of spatial learning, temporal learning, statistical modeling, optimization, and classification.

The proposed framework integrates data acquisition, anomaly management, feature representation, hybrid forecasting, decision optimization, and sustainability evaluation. The main argument is that forecasting should not be treated as an isolated prediction task. It should be embedded in a complete intelligent traffic management cycle that senses, predicts, decides, acts, and evaluates outcomes against mobility, safety, environmental, and equity goals. For sustainable urban mobility, the next step is to move beyond simulation-centered evaluation toward explainable, privacy-preserving, real-world deployments that improve both traffic efficiency and urban quality of life.

REFERENCES

[1]. N. B. Hounsell, B. P. Shrestha, J. Piao, and M. McDonald, "Review of urban traffic management and the impacts of new vehicle technologies," IET Intelligent Transport Systems, vol. 3, no. 4, pp. 419-428, 2009, doi: 10.1049/iet-its.2009.0046.

[2]. Q. Guo, L. Li, and X. J. Ban, "Urban traffic signal control with connected and automated vehicles: A survey," Transportation Research Part C: Emerging Technologies, vol. 101, pp. 313-334, 2019, doi: 10.1016/j.trc.2019.01.026.

[3]. A.-S. Mihaita, H. Li, and M.-A. Rizoiu, "Traffic congestion anomaly detection and prediction using deep learning," arXiv:2006.13215, 2020.

[4]. M. Anjaneyulu and M. Kubendiran, "Short-term traffic congestion prediction using hybrid deep learning technique," Sustainability, vol. 15, no. 1, article 74, 2023, doi: 10.3390/su15010074.

[5]. S. Krishnan and T. Balasubramanian, "Traffic flow optimization and vehicle safety in smart cities," International Journal of Innovative Research in Science, Engineering and Technology, vol. 5, no. 5, pp. 7814-7820, 2016, doi: 10.15680/IJIRSET.2016.0505200.

[6]. S. Dikshit, A. Atiq, M. Shahid, V. Dwivedi, and A. Thusu, "The use of artificial intelligence to optimize the routing of vehicles and reduce traffic congestion in urban areas," EAI Endorsed Transactions on Energy Web, vol. 10, 2023, doi: 10.4108/ew.4613.

[7]. J. Zhang, J. Sha, C. Zhang, and Y. Zhang, "A CNN-LSTM-GRU hybrid model for spatiotemporal highway traffic flow prediction," Systems, vol. 13, article 765, 2025, doi: 10.3390/systems13090765.

[8]. B. Naheliya, P. Redhu, and K. Kumar, "A hybrid deep learning method for short-term traffic flow forecasting: GSA-LSTM," Indian Journal of Science and Technology, vol. 16, no. 46, pp. 4358-4368, 2023, doi: 10.17485/IJST/v16i46.2520.

DOI: 10.17148/IARJSET.2026.13719

[9]. M. A. Mead and H. E. Refaat, "Hybrid CNN and LSTM model (HCLM) for short-term traffic volume prediction," International Journal of Intelligent Computing and Information Sciences, vol. 22, no. 4, pp. 51-61, 2022, doi: 10.21608/ijicis.2022.142804.1189.

[10]. B. Liu, X. Tang, J. Cheng, and P. Shi, "Traffic flow combination forecasting method based on improved LSTM and ARIMA," International Journal of Embedded Systems, 2018.

[11]. F. A. Albalooshi, "Advancing urban planning with deep learning: Intelligent traffic flow prediction and optimization for smart cities," Future Transportation, vol. 5, article 133, 2025, doi: 10.3390/futuretransp5040133.

[12]. I. Topilin, J. Jiang, A. Feofilova, and N. Beskopylny, "Traffic flow prediction via a hybrid CPO-CNN-LSTM-Attention architecture," Smart Cities, vol. 8, article 148, 2025, doi: 10.3390/smartcities8050148.