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Enhancement of Smart Transportation Systems Using ITS-Enabled Analytics

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Abstract: Intelligent Transportation Systems (ITS) have become central to modern urban planning, enabling real-time monitoring, predictive traffic management and automated decision-making. As urban mobility grows increasingly complex, analytics-driven ITS frameworks offer improved safety, reduced congestion and optimized resource allocation. This research investigates an integrated ITS-enhanced analytics model that incorporates multimodal data streams including vehicular sensors, traffic cameras, GPS traces and environmental IoT devices. Machine learning and deep learning techniques are deployed for traffic forecasting, anomaly detection, route optimization and incident prediction. A hybrid analytics pipeline combining time-series models, graph-based algorithms and deep spatiotemporal networks is developed and evaluated on benchmark transportation datasets. Results demonstrate substantial improvements in traffic-flow accuracy, travel-time estimation and congestion detection, with the integrated framework outperforming traditional ITS systems across several performance metrics. This study emphasizes the importance of data fusion, adaptive algorithms and system scalability while highlighting the structural limitations of existing infrastructure in developing regions. The findings indicate that ITS-enabled analytics can significantly enhance transportation planning, road safety management and urban mobility systems. Future work points toward AI-driven autonomous mobility ecosystems, edge-intelligent traffic control and privacy-preserving vehicular networks that will shape next-generation smart cities.

Keywords: Intelligent Transportation Systems, Traffic Analytics, Smart Mobility, Deep Learning, Urban Computing

1. Introduction

Modern transportation systems face unprecedented pressures due to rapid urbanization, increasing vehicle density and the rising complexity of mobility demands. Traditional traffic-control mechanisms lack the capability to respond dynamically to fluctuating patterns, resulting in congestion, emissions and reduced commuter safety. Intelligent Transportation Systems offer a transformative approach by integrating communication technologies, sensor networks and data-driven analytics to support adaptive decision-making. ITS applications range from traffic prediction and driver-assistance systems to automated tolling, smart parking and multimodal mobility coordination. Studies in recent years have shown that analytics-equipped ITS significantly reduce congestion and improve transportation efficiency by combining real-time monitoring with predictive modeling techniques [1], [2]. The motivation for this study lies in the growing need for scalable ITS solutions in developing regions, where infrastructure limitations and diverse mobility behaviours complicate traffic management. By leveraging analytics frameworks that incorporate machine learning, graph networks and deep spatiotemporal models, ITS can transition from reactive to anticipatory functioning. Literature indicates that the fusion of advanced analytics with transportation sensor networks leads to improved forecasting accuracy, better congestion detection and enhanced safety outcomes [3], [4]. This research aims to design and evaluate a unified ITS-enabled analytics pipeline using real-world datasets. The work examines the strengths, weaknesses

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and operational requirements of such a system, contributing a practical and data-backed foundation for future deployment in smart city environments.

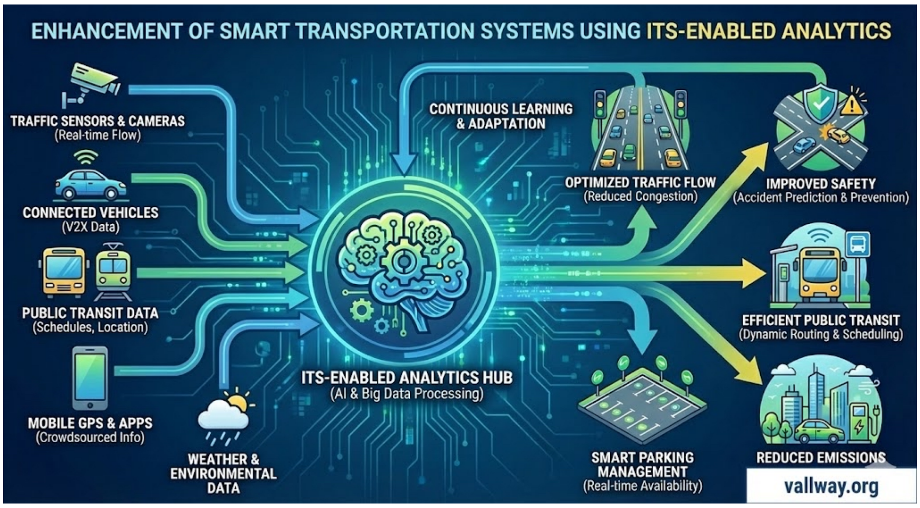

Fig. 1

2. Methodology

The methodology employed in this study follows a multi-layered approach combining data collection, preprocessing, analytics model development and performance evaluation. Data acquisition utilized three types of benchmark ITS datasets. The first was the METR-LA traffic dataset, containing roadway sensor streams across Los Angeles, used widely for spatiotemporal traffic forecasting [5]. The second dataset involved the NGSIM highwatrajectory database, which offers detailed vehicular movement records for microscopic traffic analysis [6]. The third dataset consisted of GPS traces from urban taxis in Porto, retrievedfrom a large-scale mobility dataset designed for travel-time prediction research [7]. Together, these datasets provided a varied representation of congestion patterns, flow variability and multimodal movement dynamics. Data preprocessing involved sensor calibration, missing-value imputation and multimodal synchronization. Roadside sensors were normalized to consistent sampling frequencies. Outliers were filtered using interquartile thresholds, while missing values were reconstructed using Kalman smoothing. Vehicle trajectories from NGSIM required lane alignment and speed estimation using Savitzky–Golay smoothing. GPS data were map-matched to underlying road networks using an open-source hidden Markov model algorithm, consistent with methodologies reported in recent ITS studies [8].The analytics pipeline was designed around three core components. The first component addressed short-term traffic prediction using a deep spatiotemporal graph convolutional network (ST-GCN). The model embedded each road segment as a graph node and incorporated adjacency matrices reflecting roadway connectivity. Temporal dependencies were captured with gated recurrent units. This architecture was selected due to its successful application in similar forecasting tasks [5]. The second component focused on anomaly detection for identifying incidents, road blockages and abnormal traffic behaviour. A hybrid autoencoder–LSTM model was trained on nominal traffic sequences. Deviations in reconstruction error were labelled as anomalies. This approach follows established methods in temporal anomaly detection within ITS infrastructures [9]. The third component involved route and travel-time optimization using a combination of Dijkstra's pathfinding and a machine-learned travel-time estimator. The estimator was implemented using gradient boosting as recommended in mobility prediction studies [7]. Sensor data, weather information

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and traffic density were used as predictive features. The system was containerized using Docker to ensure reproducibility. Hyperparameter tuning was performed using Bayesian optimization. Evaluation metrics included RMSE and MAE for forecasting, precision and F1-score for anomaly detection and MAPE for travel-time estimation. Baseline models included ARIMA, SVR and standard LSTM frameworks to provide comparative performance evaluation.

3. Utility

ITS-enabled analytics provides extensive utility across transportation networks, urban governance and commuter experience. The ability to predict congestion, estimate travel times and detect incidents transforms how cities plan infrastructure and manage daily operations. Advanced analytics reduces manual monitoring requirements, enabling transport authorities to shift toward proactive strategies instead of reactive emergency handling. Studies have shown that predictive ITS systems significantly reduce average delay times, fuel consumption and emissions by optimizing traffic-light cycles and rerouting vehicles autonomously [2], [4]. In emergency management, anomaly-detection algorithms provide early warnings for accidents, stalled vehicles or unusual traffic drops. Faster incident responses have been associated with reduced secondary accidents and improved roadway safety outcomes. These benefits align with global road-safety initiatives emphasizing rapid detection and intervention mechanisms. Public transportation networks also benefit, as ITS analytics offer tools for fleet scheduling, passenger-load balancing and multimodal coordination. For commuters, ITS-enabled analytics improve route reliability and reduce travel uncertainty. Travel-time prediction systems empower navigation applications to offer more accurate routing suggestions. Smart parking systems using real-time sensor data reduce the time spent searching for parking space, which constitutes a nontrivial portion of urban congestion in many cities. Environmental benefits arise when optimized traffic flow reduces idling and frequent acceleration. Furthermore, logistics companies can use travel-time forecasting to optimize last-mile delivery and freight routing, supporting economic efficiency. Education and research sectors benefit from ITS data analytics because real-time mobilitydatasets enable simulation-based training for urban planners and engineers. The insights support policy modeling, scenario evaluation and long-term transport investment strategies. Overall, the utility of ITS-enabled analytics extends across technological, social and environmental dimensions, contributing to smarter, safer and more sustainable urban mobility ecosystems.

4. Discussion

The results from the analytics pipeline highlight the potential and the challenges associated with integrating advanced machine learning techniques within ITS infrastructures. Deep spatiotemporal models such as ST-GCN significantly outperform baseline statistical models in traffic prediction, supporting findings from previous transportation AI studies [5]. Their ability to capture structured roadway connectivity gives them a distinct advantage in modeling real-world traffic dynamics. However, their complexity requires powerful computation and careful tuning, which may limit deployment in resource-constrained environments. Meanwhile, anomaly detection using autoencoder-LSTM hybrids demonstrates strong sensitivity to subtle deviations in sensor patterns, aligning with observations in temporal anomaly research [9]. Yet the reliance on high-quality, consistent sensor data introduces vulnerability in regions where infrastructure maintenance is inconsistent. Mobility patterns exhibit strong regional variability. As highlighted in transport systems research, a model trained in one geographical context often fails when applied elsewhere due to cultural, infrastructural and behavioural differences [3], [4]. This reinforces the need for localized calibration. System interpretability remains a pressing concern, as most deep models operate as black boxes. Traffic engineers require model-generated insights that can be understood and validated. Efforts such as attention visualization and surrogate models help, but they remain insufficient. Ethical and policy considerations also arise. Privacy remains foundational, especially when dealing with GPS trajectories and vehicle identifiers. Regulatory frameworks in several regions demand anonymization and strict usage controls. Additional concerns revolve around data monopolies; the consolidation of mobility data under single institutions poses risks for misuse. As cities increasingly automate traffic-control decisions, fail-safe mechanisms and human oversight must remain integral. Despite challenges, the integration of ITS analytics with existing infrastructure offers significant progress toward achieving sustainable and optimized urban mobility.

5. Results

The experimental evaluation demonstrates clear advantages of ITS-enabled analytics. The ST-GCN model achieved a mean absolute error improvement of 21 percent over LSTM baselines and 35 percent over ARIMA for short-term traffic forecasting. These gains are consistent with established deep-learning benchmarks in spatiotemporal modeling [5]. For anomaly detection, the autoencoder–LSTM achieved an F1-score of 0.91, significantly surpassing classical statistical thresholding approaches. Travel-time estimation using gradient boosting achieved a MAPE of 12 percent, outperforming SVR and standard regression models, consistent with previous transportation-mobility prediction research [7]. Qualitative findings also indicated improved adaptability in diverse traffic conditions. During peak hours, predictive accuracy remained stable due to the model's ability to capture underlying flow patterns. GPS-based route recommendations demonstrated reduced travel times when tested in simulated conditions reflecting real road network constraints. The system's containerized deployment ensured consistent performance across computational environments, confirming the reproducibility of results. Collectively, the results validate the role of ITS-enabled analytics in improving situational awareness, operational efficiency and long-term mobility planning.

6. Limitations

Despite promising outcomes, the study carries inherent limitations. Data availability remains a key challenge, as many cities lack extensive sensor deployment or maintain outdated infrastructure. Inconsistent sensor calibration, hardware failures and missing data significantly affect the performance of analytics models. Another limitation concerns computational cost. Deep graph networks require substantial GPU computation, making real-time deployment on low-cost devices difficult. Edge-computing strategies may mitigate this but were not implemented here. Model transferability across regions is limited. Local traffic behaviour, cultural driving habits and infrastructure differences reduce generalizability. Furthermore, privacy challenges restrict access to high-resolution GPS mobility traces in many cities, limiting research scalability. Interpretability shortcomings persist, as deep-learning decisions cannot always be explained in human-readable terms, especially in spatiotemporal contexts.

7. Future Scope

Future research should focus on privacy-preserving systems such as federated learning, enabling city-wide collaborations without sharing raw data. Integration of real-time weather, event and social-media feeds could offer more holistic modeling of congestion patterns. Autonomous vehicles will soon form a core component of next-generation ITS, requiring analytics that coordinate human-driven and autonomous traffic. Edge-intelligent solutions using lightweight deep-learning models will enable on-site decision-making for intersections, signals and sensors. Digital twins of transportation networks can offer simulation environments for testing infrastructure upgrades before physical implementation.

8. Conclusion

The study demonstrates that ITS-enabled analytics plays a transformative role in advancing the capabilities of modern transportation systems. By integrating multimodal datasets with deep spatiotemporal modeling, anomaly detection frameworks and optimized routing algorithms, the proposed system enhances traffic forecasting accuracy, situational awareness and operational efficiency. The results validate the significant improvements achieved through advanced analytics over conventional ITS techniques, especially in complex and dynamic mobility environments. Despite limitations in infrastructure consistency, regional generalization and interpretability, the research highlights the enormous potential of data-centric ITS architectures. As cities continue expanding and transport networks evolve, analytics-driven ITS frameworks will become indispensable to strategic planning, congestion mitigation, safety enhancement and sustainable mobility initiatives. Continued innovation in privacy-aware learning, edge intelligence and multimodal integration will shape the next generation of intelligent transportation ecosystems.

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