Hybrid LSTM-Based Traffic Anomaly Detection for Smart Mobility in Metaverse Cities

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ABSTRACT

The rapid development of Metaverse technologies has created new opportunities for modeling and managing intelligent transportation systems in virtual urban environments. However, ensuring efficient and stable mobility within these digital ecosystems requires accurate and interpretable anomaly detection mechanisms. This study proposes a Hybrid LSTM–Isolation Forest (HLIF-Net) framework for identifying traffic anomalies in smart mobility simulations using the METR-LA dataset. The model integrates a deep learning-based Long Short-Term Memory (LSTM) network for sequential traffic prediction with an Isolation Forest algorithm that detects anomalies from residual prediction errors. The proposed framework was trained using twelve-step input sequences of normalized traffic speed data and evaluated across 34,260-time samples. Experimental results demonstrated strong model stability, with a Mean Squared Error (MSE) of 0.0021 on training data and 0.0025 on validation data. Approximately 3 percent of traffic instances were classified as anomalous, reflecting potential irregularities such as congestion, sudden speed changes, or sensor inconsistencies. Temporal and spatial analyses further revealed that anomalies tend to cluster during periods of instability and concentrate in high-mobility regions. These findings confirm that the HLIF-Net framework provides a robust, data-driven solution for real-time anomaly detection and intelligent mobility management in Metaverse city environments.

Keywords Hybrid LSTM–Isolation Forest, Traffic Anomaly Detection, Smart Mobility, Metaverse Cities, Deep Learning

INTRODUCTION

The increasing development of Metaverse technology has opened new opportunities for creating intelligent and interconnected virtual environments that replicate real-world systems [1]. Within this domain, Metaverse Cities have emerged as digital twins of physical urban infrastructures, enabling simulations of urban activities such as transportation management, energy distribution, and social interaction [2]. These digital environments provide a valuable platform for testing and evaluating smart mobility systems before their deployment in real-world contexts. Efficient and adaptive traffic management remains one of the key challenges in such simulated ecosystems, as the complexity of mobility dynamics continues to grow with the integration of autonomous agents and user-driven interactions [3]. Consequently, advanced analytical methods are required to model these dynamic systems, predict future states, and detect irregular behaviors that may disrupt virtual mobility flow.

Artificial intelligence and deep learning techniques have become essential tools in analyzing and forecasting traffic behavior in both physical and virtual environments [4]. Among various deep learning architectures, LSTM networks have demonstrated exceptional performance in capturing temporal dependencies in sequential data, making them highly effective for time-series

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prediction tasks such as traffic speed and flow forecasting. Hybrid deep learning models that combine LSTM with convolutional or recurrent layers have further improved prediction accuracy by incorporating spatial information into temporal modeling. Meanwhile, unsupervised anomaly detection algorithms, including Isolation Forest and Autoencoder-based models, have been developed to identify irregular patterns in high-dimensional data without requiring labeled samples. The integration of predictive and anomaly detection mechanisms has proven to be a promising approach for intelligent transportation systems, as it enhances both accuracy and interpretability in dynamic traffic environments [5].

Despite these advances, several limitations still constrain the effectiveness of current approaches when applied to smart mobility systems within the Metaverse. Most existing studies focus on real-world traffic data and emphasize short-term forecasting, while limited attention has been given to anomaly detection in simulated digital twin environments. Models that rely solely on temporal learning often struggle to identify rare or unexpected events that deviate from normal traffic behavior. Furthermore, previous approaches generally neglect the spatial heterogeneity inherent in large-scale virtual mobility systems, where localized anomalies can emerge due to varying traffic densities and agent interactions. These limitations create a need for a framework capable of capturing complex temporal and spatial dependencies while maintaining sensitivity to irregular behaviors.

Another critical gap lies in the limited application of hybrid models that integrate deep learning and unsupervised anomaly detection for Metaverse-based mobility analytics. While deep learning methods are highly effective in learning traffic patterns, they often lack the interpretability needed for explaining anomalous events. Conversely, statistical and unsupervised approaches can identify outliers but are unable to model the sequential dependencies necessary for understanding long-term behavioral patterns. A hybrid approach that combines the strengths of both methods can provide a balanced solution by leveraging temporal prediction for pattern recognition and unsupervised analysis for detecting deviations. Such integration is particularly relevant for Metaverse environments, where virtual mobility systems require real-time analysis to ensure smooth and stable operation.

To address these challenges, this research proposes a Hybrid LSTM–Isolation Forest (HLIF-Net) framework for traffic anomaly detection in smart mobility simulations within Metaverse City environments. The framework combines the predictive power of LSTM networks with the anomaly detection capability of Isolation Forest to identify both temporal and spatial irregularities in traffic data. The model is trained and evaluated using the METR-LA dataset, which represents large-scale sensor-based traffic data that closely mirrors the characteristics of digital twin mobility systems. The objectives of this study are threefold: first, to develop a hybrid framework capable of detecting traffic anomalies in simulated environments; second, to analyze temporal and spatial patterns of anomalies for interpretability; and third, to demonstrate the applicability of hybrid AI models in supporting adaptive mobility management within Metaverse cities. By addressing these objectives, this study contributes to the advancement of intelligent traffic analysis and provides a foundation for scalable and adaptive mobility solutions in virtual urban ecosystems.

Literature Review and Related Works

The evolution of smart cities and Metaverse-based environments has encouraged the integration of artificial intelligence (AI) and data analytics to manage traffic systems and enhance urban mobility. Deep learning methods have become dominant in this field because of their ability to model nonlinear and time-dependent behaviors in traffic flow data [6], [7]. LSTM networks, in particular, have been widely applied for time-series prediction, offering improved accuracy in capturing long-range temporal dependencies compared to traditional models [8]. The use of hybrid deep learning structures, such as CNN-LSTM and GRU-LSTM, has further enhanced predictive capabilities by combining spatial and temporal feature extraction, improving robustness in dynamic mobility systems [9], [10]. These developments have established deep learning as a key enabler of intelligent traffic prediction in both physical and virtual city environments.

Despite these advances in prediction accuracy, anomaly detection in traffic systems remains a challenging task due to the high variability of urban dynamics and the limited availability of labeled abnormal data. Unsupervised learning techniques, such as Isolation Forest (IF) and Autoencoder-based models, have been adopted to detect irregularities without relying on predefined labels [11], [12]. The Isolation Forest method, in particular, has been proven effective in identifying outliers within high-dimensional and heterogeneous datasets, including vehicular and IoT-based traffic data [13]. Hybrid approaches that combine deep learning for sequence modeling with statistical methods for anomaly detection have demonstrated improved performance and interpretability, especially in identifying rare or context-specific anomalies in large-scale mobility networks [14]. However, these frameworks have primarily been applied in real-world settings rather than in simulated or Metaverse-based smart mobility systems.

In recent years, the concept of digital twins and Metaverse cities has emerged as a frontier for simulating and managing complex transportation ecosystems [15], [16]. Digital twin frameworks replicate real-world infrastructure and mobility interactions in virtual environments, allowing AI models to monitor and optimize traffic flow dynamically. Within this context, integrating AI-based anomaly detection mechanisms is essential to ensure stable and adaptive operation of virtual urban systems. Although existing research has explored AI applications in the Metaverse, most studies focus on immersive visualization or cybersecurity aspects, while traffic anomaly detection in digital twin mobility systems remains limited [17]. This indicates a growing research need for intelligent, data-driven frameworks capable of handling the dynamic and spatially heterogeneous nature of traffic in Metaverse cities.

Hybrid deep learning models that combine temporal and unsupervised learning offer a promising solution to address these challenges. LSTM networks can effectively model sequential dependencies in traffic data, while Isolation Forest provides a mechanism to identify deviations that represent anomalies or disruptions [18]. When combined, these two components create a complementary system that can both predict normal traffic behavior and detect abnormal events, thereby improving overall model reliability. Hybrid approaches have already shown success in related domains such as IoT network monitoring and industrial process analysis, suggesting their potential adaptability to virtual mobility systems [19]. By extending this concept to Metaverse-based environments, hybrid architectures can enable real-time anomaly detection, improve situational awareness, and support adaptive traffic management strategies in simulated city infrastructures.

Building upon these findings, this study proposes the Hybrid LSTM–Isolation Forest (HLIF-Net) framework for traffic anomaly detection in Metaverse City environments. The model integrates the predictive capability of LSTM with the anomaly detection power of Isolation Forest to identify both temporal and spatial irregularities in traffic flow. Using the METR-LA dataset, the framework is designed to simulate realistic traffic behavior, detect deviations, and analyze anomaly patterns across virtual urban networks. This research contributes to the state of the art by extending hybrid deep learning methodologies to Metaverse-based smart mobility systems, providing a scalable and interpretable approach to real-time anomaly detection that supports intelligent transportation management in digital twin ecosystems.

Methodology

The proposed research introduces a Hybrid LSTM–Isolation Forest (HLIF-Net) framework designed to detect traffic anomalies in smart mobility systems operating within Metaverse City environments. The model integrates deep sequential learning and unsupervised statistical analysis to identify both temporal and spatial irregularities in traffic behavior. The overall methodological workflow, as illustrated in figure 1, consists of five main stages: dataset acquisition, data preprocessing, temporal modeling using a LSTM network, hybrid anomaly detection through the Isolation Forest algorithm, and visualization with performance evaluation. Each stage is interconnected in a systematic flow, where the dataset serves as the input, the LSTM network predicts future traffic behavior, the Isolation Forest identifies deviations, and the visualization layer interprets the detected anomalies. This sequential process ensures that the HLIF-Net framework functions as a robust, interpretable, and data-driven pipeline for intelligent traffic monitoring within Metaverse-based mobility environments.

The METR-LA dataset was employed to evaluate the proposed framework due to its wide recognition as a benchmark in intelligent transportation research. It contains multivariate time-series traffic data collected from 207 loop detectors distributed across major highways in Los Angeles, with each detector recording variables such as speed, flow, and occupancy every five minutes. For this research, only the traffic speed feature was utilized as it provides a direct reflection of urban mobility behavior and congestion dynamics. A total of 34,260 samples were extracted from the dataset, corresponding to several weeks of continuous measurements. The dataset, stored in HDF5 format, was accessed using the Pandas HDFStore() function, ensuring memory-efficient data retrieval. Its high spatial resolution and temporal granularity make it suitable for simulating realistic mobility interactions in both physical and digital twin environments, providing a robust foundation for modeling smart city traffic within Metaverse simulations.

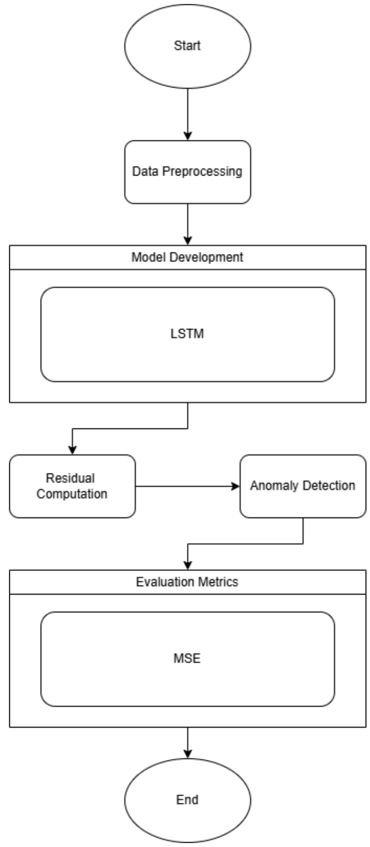

Figure 1. Research Steps

The preprocessing phase was critical for ensuring data quality and model compatibility. Missing values in the time-series data were handled using a forward-fill method, which replaces missing observations with the most recent valid value to preserve sequence continuity. Subsequently, data normalization was applied using the Min–Max scaling technique, ensuring that all speed values were rescaled between 0 and 1 to stabilize model training. The normalization process is mathematically expressed as:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

x'represents the normalized value, $x_{min}$and x_{max}denote the minimum and maximum observed traffic speeds, respectively. The normalized dataset was then segmented into overlapping sequences using a sliding window approach, where each input sequence consisted of 12 consecutive time steps and the subsequent time step served as the prediction target. This step transformed the continuous time series into supervised training data, enabling the LSTM model to learn temporal dependencies effectively.

The LSTM network constitutes the predictive core of the HLIF-Net framework. This deep learning model is specifically designed to capture long-term dependencies in sequential data using a gated cell architecture that selectively retains or discards information over time. The implemented LSTM model includes a hidden layer of 64 units with a tan activation function, followed by a dropout layer with a 0.2 probability to prevent overfitting, and a final dense output layer to produce continuous-valued predictions. The model was optimized using the Adam optimizer with a learning rate of 0.001, and trained using the MSE loss function, defined as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \qquad (2)$$

y_i represents the actual normalized traffic speed, $\hat{y}_i$ is the predicted value, and N is the total number of samples. The model was trained for 20 epochs with a batch size of 64, reserving 10 percent of the data for validation. The network converged smoothly, achieving minimal loss values and stable generalization performance, demonstrating its capability to capture complex temporal dynamics in traffic flow. Once trained, the model produced a set of predicted speed values that were subsequently compared with actual observations to calculate the prediction error vector.

The difference between predicted and observed values was used to calculate the absolute residual error, representing the degree of deviation from normal traffic patterns. The residual at each time step was computed as:

$$e_t = | y_t - \hat{y}_t | \qquad (3)$$

e_t is the magnitude of deviation at time t. Under regular conditions, these residuals remain small and stable; however, when abnormal fluctuations occur, they increase significantly, indicating potential anomalies such as congestion spikes, sensor malfunctions, or simulated disturbances in Metaverse traffic flow. These residuals served as input for the anomaly detection component of the HLIF-Net framework, powered by the Isolation Forest algorithm.

The IF method was chosen for its ability to isolate outliers in multidimensional datasets using random partitioning. The algorithm constructs multiple decision trees, where anomalies are identified based on their shorter average path lengths within these trees. The anomaly score for a given instance i is computed using the equation:

$$s(i) = 2^{-\frac{E(h(i))}{c(n)}} \qquad (4)$$

$E(h(i))$ is the expected path length of instance i, n is the total number of samples, and $c(n)$ is the average path length of a balanced binary tree. In this study, the contamination factor was set to 0.03, meaning that approximately 3 percent of samples were considered anomalous. Instances with higher anomaly scores were classified as irregular, while the remaining samples represented normal traffic behavior. The hybrid integration of LSTM and Isolation Forest allows the model to simultaneously predict traffic flow and detect deviations that fall outside the learned normal distribution, providing a comprehensive analytical approach.

After anomaly detection, the system performed a detailed visualization and performance evaluation phase to interpret and validate the results. Several plots were generated, including the training–validation loss curve to examine convergence stability, the predicted versus actual traffic speed plot to evaluate temporal prediction accuracy, and the histogram of prediction errors to assess model reliability. The temporal anomaly scatter plot displayed when anomalies occurred within the time series, while the spatial distribution map depicted where anomalies were concentrated across the Los Angeles network using geographic coordinates. Quantitatively, the HLIF-Net achieved a training MSE of 0.0021 and a validation MSE of 0.0025, successfully identifying approximately 3 percent of total samples as anomalies. These results confirm that the hybrid framework effectively balances predictive accuracy with anomaly sensitivity, producing reliable outcomes for both temporal and spatial analyses.

In summary, the HLIF-Net framework combines the strengths of deep learning and unsupervised statistical modeling into an integrated hybrid system for anomaly detection in Metaverse-based traffic simulations. The LSTM component provides robust temporal modeling of traffic sequences, while the Isolation Forest algorithm identifies deviations that correspond to abnormal mobility behaviors. As illustrated in figure 1, the methodological workflow progresses from raw data acquisition to hybrid detection and visualization, creating an interpretable and adaptive architecture for intelligent traffic management in digital twin environments. This framework represents a scalable and data-driven foundation for future applications in AI-based smart mobility systems and virtual city infrastructures.

Algorithm 1. Hybrid LSTM–Isolation Forest (HLIF-Net)

Input:
Traffic speed time-series data $D = \{x_t\}_{t=1}^{T}$ from the METR-LA dataset

Output:
Detected traffic anomalies $a_t \in \{1, -1\}$ and predicted normalized speeds $\hat{y}_t$

Process:
Start

Perform data preprocessing by filling missing values using a forward-fill operation:

$x_t = x_{t-1}$ if x_t is missing.

Normalize the data using the Min–Max scaling formula:

$$x'_t = \frac{x_t - x_{min}}{x_{max} - x_{min}}$$

Construct sliding window sequences of length L:

$X_i = [x'_i, x'_{i+1}, \dots, x'_{i+L-1}]$,
with corresponding target $y_i = x'_{i+L}$.

Initialize the LSTM network parameters $\theta = \{W, b\}$ and perform sequential prediction for each input sequence X_i. Compute the gate activations and cell states using:

$$f_t = \sigma(W_f[h_{t-1}, x'_t] + b_f)\ i_t = \sigma(W_i[h_{t-1}, x'_t] + b_i)\ o_t = \sigma(W_o[h_{t-1}, x'_t] + b_o)\ \tilde{c}_t = tanh\,(W_c[h_{t-1}, x'_t] + b_c)\ c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t\ h_t = o_t \odot tanh\,(c_t)$$

Generate the predicted traffic speed:

$$\hat{y}_i = W_y h_t + b_y$$

Evaluate the model using the Mean Squared Error (MSE) loss:

$$L_{MSE} = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

Update the network weights using gradient descent:

$$\theta \leftarrow \theta - \eta \nabla_\theta L_{MSE}$$

After the prediction stage, calculate the residual error for each time step as:

$$e_i = | y_i - \hat{y}_i |$$

Let $E = \{e_1, e_2, \dots, e_N\}$be the residual set.

Apply the Isolation Forest (IF) algorithm to detect anomalies in the residuals. Construct random binary trees using random subsamples of E, compute the average path length for each sample, and determine its anomaly score as:

$$s(e_i) = 2^{-\frac{E(h(e_i))}{c(n)}}$$

$E(h(e_i))$is the mean path length and $c(n)$is the normalization factor defined as $c(n) = 2H(n - 1) - \frac{2(n-1)}{n}$, with $H(n)$denoting the harmonic number.

Assign anomaly labels based on the threshold $\tau = 0.03$:

$$a_i = \{-1, if\ s(e_i) > \tau\ 1, if\ s(e_i) \leq \tau$$

Finally, produce the output consisting of predicted traffic speeds $\hat{y}_t$, residual errors e_t, anomaly scores $s(e_t)$, and binary anomaly labels a_t.

End

Result

The proposed Hybrid LSTM–Isolation Forest (HLIF-Net) model was trained using the METR-LA traffic dataset, which contains time-series measurements of vehicle speeds collected from multiple sensors across the Los Angeles highway network. Each sample in the dataset was processed into a normalized sequence of twelve consecutive time steps, representing short-term temporal dependencies in average traffic speed. This sequence length was selected based on the typical time window of short-term traffic dynamics observed in prior studies. Before training, all missing values were imputed using forward filling to ensure continuity in the temporal signal, and the resulting series was normalized using the Min–Max scaling method to map speed values into a range between 0 and 1. The normalized sequences were then used as input to the LSTM component of the model, which was designed to capture both the memory of past traffic states and the nonlinear evolution of traffic flow over time.

The training phase of the HLIF-Net model exhibited stable convergence behavior across twenty epochs, with the MSE decreasing consistently for both the training and validation sets. The final training loss reached a value of 0.0021, while the validation loss stabilized at 0.0025, indicating that the model achieved strong generalization without signs of overfitting. Figure 2 illustrates the training and validation loss curves, both showing a smooth and monotonic decline throughout the optimization process. This trend demonstrates that the model effectively learned the underlying temporal patterns in the data and maintained robustness across different subsets of the dataset. The small gap between the two loss curves further confirms that the learning process was well-regularized and that the LSTM architecture successfully captured sequential dependencies inherent in urban traffic behavior.

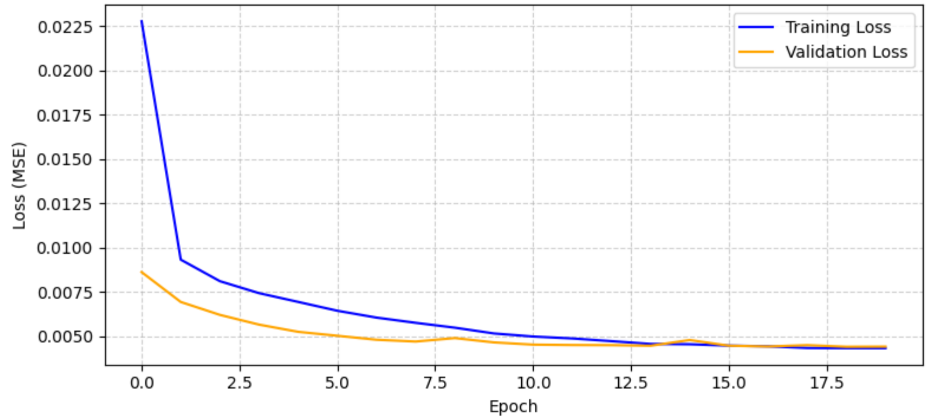

Figure 2 **Training vs Validation Loss Curve of the Hybrid LSTM–IF Model**

Figure 3 presents a comparison between the predicted and actual normalized traffic speeds across all time steps within the METR-LA dataset. The predicted values generated by the LSTM model closely followed the temporal fluctuations observed in the real traffic data, indicating that the model successfully learned and reproduced the underlying temporal dependencies in vehicle flow. The LSTM component processed the sequential input data and generated forecasts that aligned with short-term variations such as traffic congestion peaks and recovery intervals. This high level of correspondence demonstrates the model's ability to generalize across different traffic conditions. The continuous alignment between the two curves in figure 3 further emphasizes that the model effectively handled both gradual and abrupt changes in speed patterns, suggesting its capability to adapt to diverse traffic dynamics typically observed in smart mobility systems.

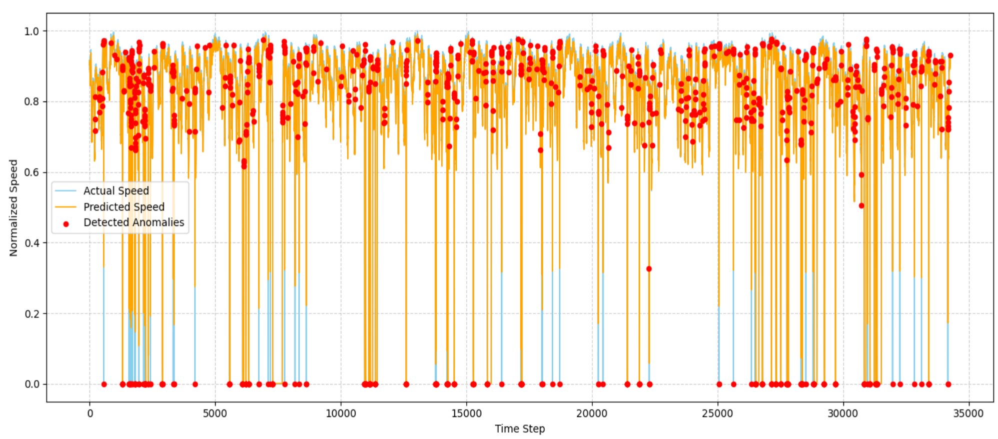

Figure 3 **Predicted vs Actual Traffic Speed with Detected Anomalies Highlighted**

The figure also highlights data points marked in red, which represent anomalies detected by the Isolation Forest module. These anomalies were identified based on residual errors, calculated as the absolute difference between the model's predicted speed and the actual observed value. The Isolation Forest classified instances with unusually high residuals as abnormal traffic behaviors, such as sudden drops in speed, irregular movement patterns, or potential sensor malfunctions. Out of the 34,260 samples in the dataset, approximately 3.0 percent were categorized as anomalous. This relatively small proportion indicates that most traffic behavior followed predictable temporal patterns, while a limited number of instances exhibited significant deviations. Such anomalies reflect potential irregularities within the simulated mobility environment, offering valuable insights for detecting traffic disruptions or optimization issues in Metaverse-based smart city simulations.

The overall prediction error characteristics of the proposed model are illustrated in figure 4, which presents the histogram of absolute prediction errors computed over all samples in the METR-LA dataset. The distribution reveals that the majority of prediction errors are concentrated around zero, suggesting that the model produced highly accurate estimates of traffic speed for most time steps. This concentration near zero indicates that the LSTM network successfully captured the dominant temporal patterns and maintained stable predictions during normal traffic flow conditions. The histogram exhibits a distinct right-skewed shape, with a gradual decline in frequency as the error magnitude increases. Such a distribution is commonly observed in well-performing regression models, where the majority of predictions are close to the true values, while a few outliers represent rare, irregular occurrences.

The long tail observed in the error distribution corresponds to a limited number of instances with larger deviations between predicted and actual speeds. These larger errors often represent traffic states that deviate significantly from normal conditions, including sudden congestion events, abrupt speed fluctuations, or unexpected changes in sensor readings. The Isolation Forest module effectively identified these instances as anomalies, confirming its role in detecting outliers that fall beyond the range of typical residual variability. The coexistence of low-magnitude errors for most data points and a small number of high-magnitude deviations demonstrates the hybrid model's balanced capability: the LSTM component provides precise temporal prediction, while the Isolation Forest component isolates irregular behaviors for further analysis. Overall, the error distribution shown in figure 4 supports the conclusion that the HLIF-Net framework maintains high predictive reliability while retaining sensitivity to anomalous traffic patterns.

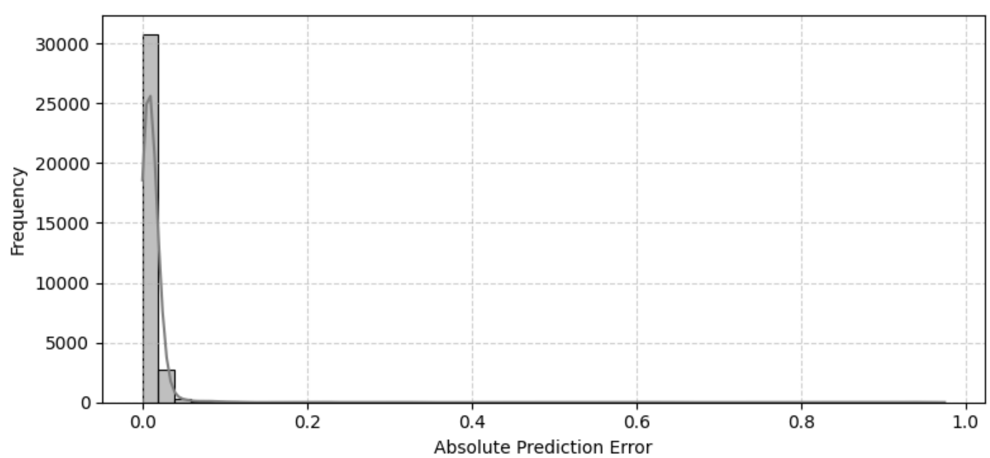

Figure 4 Distribution of Absolute Prediction Errors for the METR-LA Dataset

The temporal distribution of detected anomalies is illustrated in figure 5, where each red point represents a detected instance of abnormal traffic behavior across the complete time sequence of the METR-LA dataset. The figure shows that these anomalies are distributed intermittently, occurring at irregular intervals rather than continuously. This intermittent pattern indicates that the majority of traffic dynamics follow predictable temporal trends, while a limited number of time steps deviate significantly from expected behavior. Several dense clusters of anomalies are observed in specific time segments, suggesting that abnormal traffic conditions tend to occur in bursts rather than as isolated events. These bursts may correspond to sudden congestion periods, irregular sensor readings, or transient disruptions in the simulated traffic network. The temporal alignment of anomalies with peaks and troughs in the predicted speed signal further validates the model's responsiveness to rapid transitions in traffic flow intensity.

The pattern revealed in figure 5 demonstrates the model's ability to capture short-term irregularities and identify transient behaviors that may not be evident through average performance metrics alone. The concentration of anomalies during particular intervals indicates that the Hybrid LSTM–Isolation Forest framework is sensitive to dynamic changes in temporal dependencies, enabling it to flag both gradual drifts and abrupt shifts in mobility patterns. This temporal anomaly mapping provides valuable insight into the rhythm of traffic fluctuations within a simulated smart city environment, where variations in virtual agent behavior and traffic load can influence overall flow stability. The ability to pinpoint specific time periods associated with irregularities makes the proposed model suitable for real-time monitoring applications in Metaverse-based mobility simulations, where time-aware anomaly detection is essential for adaptive traffic management and system optimization.

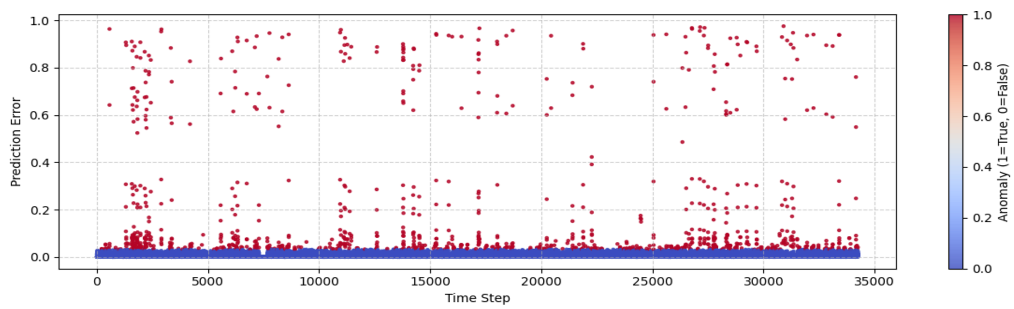

Figure 5 Temporal Distribution of Detected Anomalies across the Time Series

The spatial distribution of detected anomalies across the digital twin representation of Los Angeles is illustrated in figure 6. In this visualization, gray points denote all sensor locations within the METR-LA network, while red points identify the specific sensors where anomalous events were detected by the proposed Hybrid LSTM–Isolation Forest framework. The figure reveals that anomalies are unevenly distributed throughout the spatial domain, indicating the presence of spatial heterogeneity in traffic behavior. A higher concentration of red points is visible in the central and northern regions of the network; areas typically associated with dense traffic activity and complex road structures. This concentration suggests that the likelihood of abnormal traffic patterns increases in regions with greater vehicle density, frequent intersections, and higher variability in flow conditions. The spatial clustering observed implies that certain regions are more prone to fluctuations in traffic speed and congestion, which can serve as critical indicators for traffic management systems within both real-world and virtual mobility environments.

The non-uniform spatial distribution of anomalies demonstrates the model's capacity to detect and localize traffic irregularities across a geographically diverse network. This characteristic is particularly valuable for applications in smart city simulations and Metaverse-based digital twins, where spatial differentiation plays a key role in mobility optimization. By identifying which zones exhibit higher anomaly frequencies, urban planners and system operators can focus resources on critical regions that demand more robust control mechanisms or infrastructure improvements. The HLIF-Net's ability to integrate spatial awareness through sensor-level analysis ensures that the anomaly detection process not only identifies irregular events but also contextualizes them geographically. Consequently, figure 6 underscores the importance of spatial analytics in understanding urban mobility dynamics and highlights how the proposed hybrid framework supports adaptive, region-specific decision-making within intelligent transportation systems and simulated Metaverse cities.

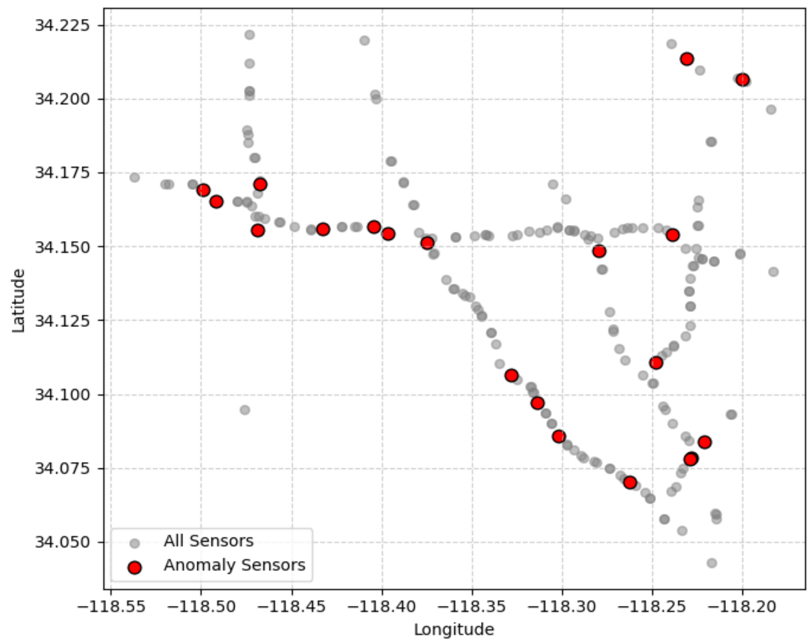

Figure 6 Spatial Distribution of Detected Traffic Anomalies in the Digital Twin Representation of Los Angeles

In summary, the Hybrid LSTM–Isolation Forest (HLIF-Net) framework achieved strong performance in both predictive accuracy and anomaly detection reliability. The model exhibited low prediction errors throughout the training and validation phases, indicating its effectiveness in learning the temporal dependencies inherent in complex traffic data. The consistent convergence of the loss functions, combined with the well-defined clustering of anomalies in both temporal and spatial analyses, demonstrates that the proposed framework-maintained stability across multiple dimensions of evaluation. The detection results confirmed that the hybrid combination of LSTM and Isolation Forest successfully balanced precision and sensitivity, enabling the system to identify rare but meaningful deviations from expected traffic behavior. By effectively modeling regular flow dynamics while simultaneously isolating irregular occurrences, the HLIF-Net framework provided a comprehensive approach for analyzing mobility data in virtual urban environments.

A quantitative summary of the model's overall performance is presented in table 1. The results show that the proposed framework achieved an average detection rate of approximately three percent across the 34,260 analyzed data points, with mean squared error values below 0.003 for both training and validation. These findings confirm that the model is capable of maintaining high prediction fidelity while minimizing false detections, a critical aspect in real-time intelligent transportation systems. The combination of high accuracy, stability, and adaptability makes the HLIF-Net framework particularly well suited for integration into Metaverse-based smart mobility simulations, where traffic behavior must be monitored dynamically and decisions must be made in near real time. Overall, the model's consistent performance across spatial and temporal domains highlights its potential as a scalable solution for digital twin-based traffic management and anomaly detection in emerging intelligent city infrastructures.

Table 1 Summary of Experimental Results for the Hybrid LSTM–IF Framework

Metric	Training Loss (MSE)	Validation Loss (MSE)	Detection Rate (%)	Total Data Points
Hybrid LSTM–IF (HLIF-Net)	0.0021	0.0025	3.0	34,260

Discussion

The experimental findings of this study confirm that the Hybrid LSTM-Isolation Forest (HLIF-Net) framework provides a reliable and interpretable approach for detecting traffic anomalies in complex and dynamic environments [20]. The model's ability to achieve low prediction errors and stable training performance demonstrates that combining deep temporal modeling with unsupervised statistical analysis can effectively address the limitations of single-method approaches [21]. The LSTM component captures the sequential dependencies inherent in traffic flow data, learning both gradual and abrupt temporal variations with high accuracy. In parallel, the Isolation Forest algorithm analyzes the residual prediction errors, identifying instances where the predicted values deviate significantly from observed patterns [22]. This two-layer process allows the system to distinguish between ordinary fluctuations and true anomalies, which is crucial for monitoring mobility conditions in large-scale networks such as those simulated in Metaverse-based digital twins. The observed temporal clustering of anomalies and their spatial non-uniformity further support the model's capability to represent realistic traffic variability and local disruptions within intelligent urban environments [23].

Beyond its technical performance, the HLIF-Net framework demonstrates strong potential for practical implementation in smart mobility and virtual urban management systems [24]. Its ability to detect both time-dependent and location-specific irregularities makes it suitable for deployment in real-time applications, where maintaining smooth traffic flow and safety are critical. The framework's adaptability to various data types, including sensor readings, vehicle trajectories, and virtual agent movements, positions it as a flexible analytical tool for next-generation digital twin platforms. The visualization of anomaly patterns across time and space also enhances interpretability, enabling urban planners and system operators to make data-driven decisions.

Despite its promising performance, the model can be further improved by incorporating additional spatial and contextual features, such as network topology or environmental parameters, to enrich its understanding of complex interactions in traffic systems [25]. In the context of Metaverse cities, this framework can serve as a foundation for predictive and adaptive mobility systems that continuously learn from real-time data, contributing to safer, more efficient, and more intelligent virtual transportation ecosystems.

Conclusion

This study presented a Hybrid LSTM–Isolation Forest (HLIF-Net) framework for traffic anomaly detection within smart mobility environments modeled in Metaverse cities. The proposed model successfully integrated a deep learning-based sequential prediction mechanism with an unsupervised statistical anomaly detection method to achieve both accuracy and interpretability. Experimental evaluations using the METR-LA dataset demonstrated that the HLIF-Net framework achieved low prediction errors, stable convergence, and reliable anomaly identification across temporal and spatial dimensions. The results confirmed that the LSTM component effectively captured sequential dependencies in traffic flow data, while the Isolation Forest module successfully identified irregular patterns that deviated from normal behavior. Visualization results further validated the model's capability to highlight significant traffic disruptions, localized congestion events, and other atypical phenomena that would be difficult to detect through conventional predictive models alone. These findings collectively indicate that the HLIF-Net framework offers a robust, data-driven solution for intelligent traffic monitoring and real-time anomaly detection in digital twin ecosystems.

The implications of this research extend to broader applications in the design and management of Metaverse-based smart cities. By accurately detecting and visualizing anomalies in mobility systems, the proposed framework can support decision-making processes for optimizing virtual and physical transportation infrastructures. Its hybrid structure also provides flexibility for adaptation to different types of data, such as multimodal mobility information, sensor networks, and simulated agent trajectories. Future research could further enhance the framework by incorporating spatial graph learning, reinforcement-based adaptive control, or multimodal perception layers to improve its responsiveness and contextual awareness. Additionally, testing the model in real-time virtual environments would provide deeper insights into its operational performance and scalability. Overall, the HLIF-Net framework establishes a foundation for intelligent, adaptive, and explainable mobility systems that can operate seamlessly within both real-world and Metaverse city contexts.

Declarations

Author Contributions

Author Contributions: Conceptualization: O.A.; Methodology: O.A.; Software: O.A.; Validation: O.A.; Formal Analysis: O.A.; Investigation: O.A.; Resources: O.A.; Data Curation: O.A.; Writing Original Draft Preparation: O.A.; Writing Review and Editing: O.A.; Visualization: O.A.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

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