



Application of convolutional neural networks in spatio-temporal prediction of vehicular traffic

Aplicación de redes neuronales convolucionales en la predicción espacio-temporal del tráfico vehicular

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ABSTRACT

This paper systematically reviews how convolutional neural networks (CNNs) have been used to predict vehicular traffic in space and time. To this end, research published between 2021 and 2026 in different academic databases was analyzed, with the aim of identifying the most used architectures, methodological approaches, evaluation metrics, as well as their main limitations and recent trends. From this review, it is observed that CNNs stand out especially in the identification of spatial traffic patterns. Their performance improves when combined with other approaches, such as recurrent models, attention mechanisms, and hybrid architectures, allowing traffic dynamics to be captured more completely. In particular, hybrid models have managed to increase accuracy by integrating both spatial and temporal information, in addition to incorporating external variables such as weather, accidents, events, and road conditions. However, the literature also points to several challenges: adequately representing complex road networks, avoiding the loss of topological information, modeling long-term dependencies, and reducing high computational costs, especially in real-time applications. Together, these findings offer a clear view of the current state of the field and serve as a starting point for the development of future solutions oriented to smart mobility systems.

Keywords: Convolutional neural networks; vehicular traffic prediction ; spatio-temporal analysis; hybrid models.

RESUMEN

Este trabajo revisa de forma sistemática cómo se han utilizado las redes neuronales convolucionales (CNN) para predecir el tráfico vehicular en el espacio y el tiempo. Para ello, se analizaron investigaciones publicadas entre 2021 y 2026 en distintas bases de datos académicas, con el objetivo de identificar las arquitecturas más utilizadas, los enfoques metodológicos, las métricas de evaluación, así como sus principales limitaciones y tendencias recientes. A partir de esta revisión, se observa que las CNN destacan especialmente en la identificación de patrones espaciales del tráfico. Su rendimiento mejora cuando se combinan con otros enfoques, como modelos recurrentes, mecanismos de atención y arquitecturas híbridas, lo que permite capturar de manera más completa la dinámica del tráfico. En particular, los modelos híbridos han logrado aumentar la precisión al integrar tanto la información espacial como la temporal, además de incorporar variables externas como el clima, los accidentes, los eventos y las condiciones de las vías. No obstante, la literatura también señala varios desafíos: representar adecuadamente redes viales complejas, evitar la pérdida de información topológica, modelar dependencias a largo plazo y reducir los altos costos computacionales, especialmente en aplicaciones en tiempo real. En conjunto, estos hallazgos ofrecen una visión clara del estado actual del campo y sirven como punto de partida para el desarrollo de futuras soluciones orientadas a sistemas de movilidad inteligente.

Palabras clave: Redes neuronales convolucionales; predicción del tráfico vehicular; análisis espacio-temporal; modelos híbridos.

INTRODUCTION

Vehicular traffic prediction has become a topic of significant interest in intelligent transportation systems due to its impact on mobility management, congestion reduction, and the improvement of operational decision-making. In this context, authors such as Tang et al.[51]highlight that deep learning-based models enable the integration of multiple factors associated with traffic behavior and provide more accurate predictions than traditional approaches.

This work broadly addresses the use of convolutional neural networks in the spatiotemporal prediction of vehicular traffic, analyzing how these architectures have been employed to capture mobility patterns, represent spatial relationships between road segments, and improve both short- and long-term forecasting. Based on this, the strengths and weaknesses of these techniques are also examined in light of the complexity of urban environments and the need to incorporate external variables that influence vehicular flow behavior.

To conduct this study, a systematic literature review was conducted using the Kitchenham method, which enabled the identification, selection, and analysis of relevant research on CNN architectures, hybrid models, evaluation metrics, technical limitations, and temporal and exogenous integration strategies. This methodological approach facilitates an orderly and rigorous synthesis of the state of the art, with the aim of answering the research questions posed in the project.

The project structure is organized into five main sections: abstract, keywords, introduction, methods, and results. In the methods section, the research questions and the systematic review process are presented; subsequently, the results section presents the findings on architectures, limitations, metrics, spatial modeling, temporal integration, and the use of exogenous variables in vehicular traffic prediction.

METHODS

For this work, a systematic literature review was conducted with the aim of identifying, analyzing, and synthesizing the scientific evidence related to the application of convolutional neural networks in the spatiotemporal prediction of vehicular traffic. This approach enables the rigorous organization of the findings of previous studies, the establishment of research trends, and the identification of the main contributions, limitations, and opportunities for improvement in the area.[39,38,37,36,48]

Research questions

To guide the review process, the following research questions were formulated:

- RQ1: Which convolutional neural network architectures have demonstrated greater effectiveness in the spatiotemporal prediction of vehicular traffic?
- RQ2: What are the main methodological limitations and technical challenges identified in the use of CNNs for traffic prediction?
- RQ3: What evaluation metrics and experimental protocols are commonly used to validate CNN models in traffic prediction?
- RQ4: How are convolutional neural networks used to model spatial dependencies in traffic flow prediction?
- RQ5: How do CNN-based models integrate temporal information to improve accuracy in short- and long-term traffic prediction?
- RQ6: What strategies do CNN models employ to incorporate exogenous variables such as weather, events, and accidents into traffic prediction?

These questions were formulated with the aim of delimiting the scope of the study and structuring the review according to the key components of the research problem.

Search strategy

The literature search was conducted in five specialized databases: Redalyc, Scopus, IEEE Xplore, Research Rabbit, and DOAJ. To ensure broad coverage of the scientific literature, search terms related to convolutional neural networks, vehicular traffic prediction, spatiotemporal analysis, deep learning, and hybrid models were used.

The search strategy included combinations of keywords, synonyms, and Boolean operators to retrieve relevant studies published between 2021 and 2026. The search was conducted in fields such as title, abstract, and keywords, prioritizing scientific publications directly related to the study's topic.

Table 1. Definition of general concepts with PIPOH.

Criterion	Description
Population	Applications of convolutional neural networks in the spatiotemporal prediction of vehicular traffic.
Intervention	CNN models, hybrid architectures, temporal integration, exogenous variables, evaluation metrics, and methodological strategies.
Results	Scientific studies reporting the application of CNN to vehicular traffic prediction or related phenomena.
Professionals	Computer science, engineering, intelligent transportation systems, and related areas.
Context	Academic and scientific field.

Table 2. Terms, synonyms, and filters to compose the search string

Term	Synonyms	Additional filters
Convolutional neural networks Traffic prediction; spatio-temporal prediction Hybrid models Exogenous variables	CNN, convolutional deep learning, convolutional networks traffic forecasting, vehicular traffic prediction, traffic flow prediction, spatio-temporal analysis, spatial-temporal modeling hybrid architectures, combined models weather, accidents, events, external factors	Year of publication $\geq$ 2021 Science, engineering, transportation; full text available English or Spanish language Articles, conferences, and reviews

Table 3. Main terms and databases.

Main term	Database / tool
Application of convolutional neural networks to the spatiotemporal prediction of vehicular traffic	Redalyc Scopus, IEEE Xplore Research Rabbit DOAJ

Selection criteria

The documents retrieved from the databases underwent a 2-stage selection process. First, duplicate records were removed. Subsequently, full-text availability was reviewed, and finally, the previously defined inclusion and exclusion criteria were applied.

Table 4. Search string.

Main term	Search string
Application of convolutional neural networks to the spatiotemporal prediction of vehicular traffic	(convolutional neural networks OR CNN OR deep learning OR convolutional models) AND (traffic prediction OR traffic forecasting OR vehicular traffic prediction) AND (spatio-temporal OR spatial-temporal) AND (hybrid models OR exogenous variables OR weather OR accidents OR events) AND (year $\geq$ 2021)

Table 5. Dates of consultation and file downloads.

Database	Search date
Redalyc	23/02/26
Scopus	24/02/2026
IEEE Xplore	3/03/2026
Research Rabbit	24/02/2026
DOAJ	3/03/2026

Inclusion criteria:

- Studies related to the application of convolutional neural networks in vehicular traffic prediction.
- Research focused on spatiotemporal prediction or vehicular flow analysis.
- Scientific articles, reviews, conference papers, or book chapters published between 2021 and 2026.
- Documents available in full text in Spanish or English.

Exclusion criteria:

- Works that did not directly address the use of CNN in vehicular traffic.
- Studies focused exclusively on other techniques unrelated to the project's main focus.
- Duplicate publications.
- Documents without full-text access or with insufficient information for analysis.
- Works that fall outside the established time range.

Quality assessment

Once the studies were selected, a quality evaluation was applied with the aim of assessing the relevance and methodological soundness of each document. At this stage, criteria such as the clarity of the research objective, the relevance of the problem addressed, the adequacy of the method used, the robustness of the analysis of results, and the consistency between the findings and conclusions were considered. This procedure made it possible to prioritize the most robust studies and reduce the impact of works with low methodological relevance, thus strengthening the confidence of the patient.

bility of the final synthesis.

Data extraction and synthesis

Data extraction was performed using an analysis matrix that recorded aspects such as author, year, database, objective, type of CNN model, variables used, evaluation metrics, main results, and reported limitations. This organization enabled systematic comparison of the studies and identification of common patterns in the literature.

The information was synthesized qualitatively by grouping the findings into thematic categories related to CNN architectures, temporal integration, exogenous variables, performance metrics, and methodological challenges. This approach provided an overview of the state of the art and helped answer the research questions posed at the beginning of the study.

- RQ1: Which CNN-based architectures (pure or hybrid) have demonstrated greater effectiveness in the spatiotemporal prediction of vehicular traffic?
- RQ2: What are the main methodological limitations and technical challenges identified in the use of CNN for traffic prediction?
- RQ3: What evaluation metrics and experimental protocols are commonly used to validate CNN models in traffic prediction?
- RQ4: How are Convolutional Neural Networks (CNN) used to model spatial dependencies in traffic flow prediction?
- RQ5: How do CNN-based models integrate temporal information to improve accuracy in short- and long-term traffic prediction?
- RQ6: What strategies do CNN models use to incorporate exogenous variables (weather, events, and accidents) into traffic prediction?

Table 6. Quality assessment in the search and selection processes.

Main term	Search result	Duplicate files	Excluded files	Relevant files	Database
Application of networks convolutional neural networks in prediction spatiotemporal prediction of the vehicular traffic	48	11	19	18	Redalyc
	27	3	13	11	Scopus
	8	0	1	7	IEEE Xplore
	23	1	8	14	Research Rabbit
	5	0	1	4	DOAJ
	111	15	42	54	

Table 7. Studies included in the systematic review.

Year	Quantity	Referencias
2021	2	[46], [3]
2022	3	[56], [34], [58]
2023	6	[32], [28], [10], [5], [43], [52]
2024	13	[52], [51], [18], [21], [14], [11], [17], [47], [45], [24], [50], [55], [23]
2025	12	[27], [33], [44], [31], [2], [4], [26], [1], [13], [9], [29], [41]
2026	3	[35], [12], [6]
Total	39	

Results

CNN-based architectures, both pure and hybrid, have demonstrated effectiveness in the spatiotemporal prediction of vehicular traffic.

Various architectures based on convolutional neural networks (CNN) have achieved high performance in the spatiotemporal prediction of vehicular traffic, ranging from purely convolutional models to sophisticated hybrid architectures that integrate CNN with recurrent networks, advanced attention mechanisms, and traditional machine learning techniques.

Hybrid architectures are notable in spatiotemporal traffic prediction: PPMCC-RF-CNN-BiGRU employs CNN for complex spatial features and BiGRU for bidirectional temporal dependencies, reducing RMSE by up to 39%[51]; DATC-STP (CNN Transformer-style) achieves lower MAE and higher SSIM while reducing parameters by 85% on TaxiBJ[33]; and CNN-LightGBM outperforms CNN-LSTM/Transformer with 57.58% lower RMSE in highway congestion[27].

Hybrid CNN-BiLSTM architectures with attention mechanisms are notable for predicting the risk and severity of road accidents, achieving accuracies close to 95%. The CNN captures relevant spatial traffic patterns, BiLSTM models bidirectional temporal dependencies, and the attention module identifies the most influential predictive variables in complex scenarios[26,45].

The CNN-PSO (Particle Swarm Optimization) combination increases predictive accuracy from 76.5% to 92.0% in smart city environments. Similarly, IA-CSTM uses CNN to model spatial interactions between nearby vehicles and LSTM for temporal evolution, incorporating spatiotemporal attention for dynamic scenarios[44,5].

Hierarchical CNN-LSTM networks analyze traffic violations by processing spatial sequences using CNN and capturing temporal dependencies between driving events using LSTM, consistently outperforming non-hierarchical methods in predictive accuracy[53].

Comparative studies confirm the superiority of CNNs over traditional RNNs not only in accuracy but also in energy and computational efficiency, particularly in edge computing, where resource optimization is a critical factor[47].

Methodological limitations and technical challenges exist in the use of CNN for traffic prediction.

CNNs face fundamental structural limitations when processing inherently non-Euclidean transportation networks. The required transformation into matrix structures distorts actual spatial relationships and the complex connectivity that characterizes urban road networks[35,52].

The local nature of convolutional kernels severely limits the capture of long-range spatial dependencies, which are essential for modeling congestion propagation between distant urban regions and for understanding the global dynamics of the road system[5,51].

The conversion of traffic data into matrices/images causes irreversible loss of critical topological information, including the direction of vehicular flow, the hierarchy among road types, and fundamental structural relationships. At the same time, pure CNNs exhibit significant weaknesses in modeling complex long-term temporal dependencies[35,24,31].

Static convolutional kernels, once trained, remain fixed during inference, limiting adaptation to dynamic traffic with rapid changes due to incidents, special events, or seasonal variations in mobility. Unbalanced datasets systematically skew towards free-flowing conditions over real congestion[52,5].

Deep CNN architectures demand prohibitive computational and memory resources for real-time implementation, making them particularly infeasible on edge devices with energy constraints and critical latency for road monitoring systems[35,6].

Training exhibits slow convergence, high susceptibility to overfitting when datasets are limited, and critical dependence on architectural design, filter size, and hyperparameter selection, requiring exhaustive and costly exploration of the parameter space[27,2].

The fundamental mismatch between Euclidean CNN grids and the irregular topology of road networks generates systematic distortions. The traditional hybrid CNN-RNN architecture separates spatial and temporal modules, hindering the deep fusion of spatiotemporal information[24,34,56].

Various evaluation metrics and experimental protocols are employed to validate CNN models in traffic prediction.

Mean absolute error (MAE) quantifies direct discrepancies in the native units of the phenomenon, facilitating practical interpretation. Root mean squared error (RMSE) disproportionately penalizes large deviations, which is crucial in scenarios where extreme errors severely impact operational decisions. Mean absolute percentage error (MAPE) allows relative comparisons between heterogeneous datasets[56,24,50].

The mean squared error (MSE) constitutes the primary loss function during training. The coefficient of determination (R^2) evaluates the proportion of variability explained by the model. The Huber loss offers a robust balance between the sensitivity of MSE and the stability of MAE in the presence of outliers[4,46].

Classification tasks (congestion and incidents) use precision, recall, accuracy, and F1-score to evaluate the correct identification of events. Computer vision employs intersection over union (IoU) to assess the spatial quality of vehicle/object detection[26,12].

The evaluation of computational efficiency includes latency, inference time, FLOPs, and model parameters, which are critical indicators for real-time deployment viability and for edge devices with hardware constraints[47,10,28].

Experimental protocols employ chronological splitting (70/10/20, 60/20/20, and 80/20) to avoid future contamination. Min-Max/Z-score normalization stabilizes training. Sliding windows convert time series into multi-step supervised formats[35,44,5].

Multi-horizon evaluation (15/30/60 minutes) analyzes degradation in predictive performance across horizons. Filters eliminate low-activity regions, thereby reducing noise. The Adam optimizer with early stopping prevents overfitting. Ablation studies validate the contribution of components against traditional baselines[31,51,33,50,34].

Convolutional neural networks (CNNs) are used to model spatial dependencies in traffic flow prediction.

Convolutional Neural Networks (CNNs) have been widely used in traffic prediction due to their ability to model spatial dependencies by automatically extracting local features. In this context, one of the most common strategies is to transform traffic data, such as flow, speed or occupancy, into matrix representations that can be interpreted as images. In these representations, each cell corresponds to a specific geographical location or sensor within the road network, which allows the capture of spatial proximity relationships between different segments[51,27,47,35]. This approach

facilitates the application of convolutional operations on structures that reflect the traffic topology, although simplified in a regular grid.

The spatial learning process relies on convolutional filters or kernels that slide over these matrices to identify local patterns and correlations between adjacent regions. These filters enable the modeling of phenomena such as congestion propagation or influence between neighboring segments, for example, by considering the relationship between upstream and downstream sections on a road[27,24]. Unlike traditional methods, the parameters of these filters are learned automatically through backpropagation, enabling the capture of complex nonlinear relationships in traffic data[4,22]. Moreover, stacking multiple convolutional layers enables the construction of hierarchical representations, where initial layers capture local patterns and deeper layers model longer-range spatial dependencies[52,47,24].

In more complex scenarios, such as vehicle trajectory prediction or interaction among multiple agents, CNNs are used to process structured spatial representations such as grids or social tensors. These structures enable explicit modeling of relationships between vehicles, considering relative distances and interaction patterns within the traffic environment[5,18]. Complementarily, some architectures incorporate additional mechanisms such as pooling to reduce dimensionality and improve robustness to noise, although in certain cases these operations are omitted to preserve the topological integrity of the road network[35].

Since traffic is an inherently dynamic phenomenon, CNNs are often integrated into hybrid architectures where they act as spatial encoders. In these models, features extracted by convolutional layers are subsequently processed by recurrent networks, such as LSTM or GRU, or by attention mechanisms to capture temporal dependencies[51,24,26]. Likewise, recent research has proposed more advanced variants, such as Transformer-inspired CNNs, which use larger kernels to expand the receptive field and capture long-range spatial dependencies without incurring the high computational cost of models based entirely on attention[33].

The forced Euclidean representation on irregular road topology requires zero-padding of sensor-free regions, introducing systematic artifacts and computational inefficiencies. This fundamental limitation motivates the development of GNNs while preserving the natural graph connectivity of road infrastructures[50].

CNN-based models integrate temporal information to improve accuracy in short- and long-term traffic prediction.

The integration of temporal information into convolutional neural network-based models for traffic prediction is usually carried out through hybrid architectures in which the CNN is responsible for extracting local spatial patterns and a recurrent network, such as LSTM or GRU, models the temporal evolution of the sequence. This scheme allows capturing short- and long-term dependencies in traffic behavior, and has shown good performance in multi-horizon forecasting scenarios[43,22,24].

Another frequent strategy consists of using tridimensional convolutions or spatiotemporal blocks that simultaneously process the spatial and temporal dimensions. Instead of treating time as a separate variable, these architectures learn joint correlations between consecutive observations, which facilitates detecting complex dynamics of the road network and improving the model's sensitivity to abrupt flow changes[33,31,43].

Complementarily, some approaches organize the time series into proximity, periodicity, and trend components, enabling the model to leverage both recent patterns and longer-range recurring cycles[34,15,25].

It has also become common to combine CNNs with attention mechanisms and Transformers to enhance temporal representation. In such cases, the CNN learns local features, while the attention module assigns greater weight to the most relevant historical intervals, reducing the impact of noise and improving the capture of long-range dependencies[42,49,1].

In more specialized architectures, temporal integration can be addressed through ConvLSTM, in which the convolution operation is incorporated directly within the recurrent unit. This preserves the spatial structure while updating temporal memory, making it especially useful for data organized as grids or traffic maps[15,31,54].

When the goal is to avoid classical recurrence, some approaches rely on dilated temporal convolutions or dual-attention designs that broaden the receptive field without substantially increasing computational cost[50,29,35].

CNN models employ strategies to incorporate exogenous variables, such as weather, events, and accidents, into traffic prediction.

External variables are converted into numerical vectors or matrices and incorporated into the CNN input tensor. For example, additional channels in the traffic image represent rain or accidents using Boolean logic[22]. Exogenous variables such as temperature or day type are organized into matrices or tensors and treated as additional channels by the CNN to extract hidden connections[51, 58, 55].

Exogenous data are processed using FC-NN and fused with feature maps from the traffic sensor CNN[23,35]. For accidents, third-order tensors integrate duration and severity with flow and speed, enabling joint learning of road degradation[40]. CNNs extract context from external factors, while LSTM or BiGRU processes temporal sequences, capturing future impacts such as congestion caused by accidents[51,52,45,29].

Specific schemes encode temporal anomalies, such as distinct representations for weekdays or holidays[42]. Weight factors in hybrid architectures balance structural information from CNN and external dynamics to enable rapid responses to closures[41]. Random Forest or PPMCC select relevant factors to avoid noise and optimize precision[51,26,45]. In the absence of real climate data, meta-parameters such as date implicitly capture seasonal patterns[58].

Spatiotemporal attention layers assign dynamic weights to exogenous variables, prioritizing them during disruptive events[45,26,52,5]. External data are integrated into 2D/3D inputs, as in ER-GAN-CNN, to correlate traffic and weather[4]. Models such as MF-CNN or TFFNet use separate branches for real, historical, and external data, fusing them in dense layers; embeddings are concatenated in graphs[34,50]. MDN with convolutional layers predicts probability distributions under high uncertainty[30].

Fuzzy logic in CNN robustly handles accident uncertainty[3]. Attention modules or Transformers in CNN-SKIPGRU-Transformer dynamically weight exogenous variables[24,1]. ST-ResNet uses a branch for exogenous variables such as weather, with 1-hot encoding fused residually[57]. In DMVST-Net and STDN, exogenous variables are concatenated with spatial representations before the temporal LSTM[7,8]. ST-MetaNet employs POIs as meta-knowledge for dynamic weights[20]; DGCNN decomposes tensors for anomalies by adjusting graphs[19]. Attention prioritizes exogenous variables at critical moments[16,8].

Conclusions

This work has systematically addressed the application of Convolutional Neural Networks (CNN) to the spatiotemporal prediction of vehicular traffic, covering a research period between 2021 and 2026. Using the Kitchenham method, a rigorous synthesis of the prevalent architectures, methodologies, and experimental protocols was achieved, providing an updated view of the state of the art. The study achieved its objective of identifying the technical strengths and limitations that define the use of these tools in intelligent mobility systems.

The review process was structured to answer critical questions about the effectiveness of pure and hybrid CNNs, the management of non-Euclidean road topology, and the integration of exogenous variables. Research from specialized databases such as Scopus, IEEE Xplore, and Redalyc was analyzed, enabling the establishment of a solid basis for understanding how the spatial and temporal dependencies of vehicular flow are currently modeled.

Finally, this project establishes a necessary starting point for future research, underscoring the importance of moving beyond static models. An examination of the current landscape reveals that, although CNNs have laid important foundations, the evolution toward more dynamic architectures capable of being integrated into devices with hardware constraints represents the trend that will define the next generation of transportation systems.

With respect to the results, it was determined that hybrid architectures, especially those combining CNN with recurrent networks (LSTM/GRU) and attention mechanisms, significantly outperform traditional models. These approaches enable the capture of both local spatial characteristics and complex temporal dependencies, achieving a notable improvement in the accuracy of short- and long-term predictions.

A fundamental limitation was identified: the distortion of spatial relationships when the structure of road networks is forced onto Euclidean grids. Static convolutional kernels struggle to capture long-range dependencies, which motivates exploring alternatives such as Graph Neural Networks (GNN) that can better preserve the natural topology of roads.

The integration of exogenous variables (weather, accidents, events) was a determining factor for forecast quality. Models that incorporate these variables through additional tensors or dynamic attention layers are more robust to disruptive situations, adapting more effectively to the inherent variability of the real urban environment.

With respect to validation metrics, the study highlights that there is no single metric, but rather a combination of indicators depending on the objective. Although MAE and RMSE are essential for quantifying error in continuous flow, classification metrics such as F1-score are indispensable for incident detection, demonstrating the multidisciplinary nature of evaluation protocols.

A critical finding was the computational demand of deep CNNs, which limits their real-time implementation on edge devices. Current studies are beginning to prioritize more efficient and lightweight architectures focused on reducing FLOPs and parameters, which is vital for enabling the deployment of intelligent road monitoring systems with latency and energy constraints. Finally, it is concluded that the current trend leans toward highly specialized and adaptive architectures. The use of Transformers and spatiotemporal attention mechanisms marks a new stage in traffic prediction, achieving a superior balance between methodological complexity, the ability to model complex dependencies, and the computational efficiency necessary for its operational application.

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