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A survey on traffic violations prediction with deep learning

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Abstract

Despite growing interest in traffic violation prediction, there is a lack of comprehensive survey research on this topic. A systematic survey is essential to understand the current state-of-the-art methodologies and to identify promising directions for future work. This paper surveys research on traffic violation prediction from the past five years, with a particular focus on machine learning and deep learning approaches. It provides an in-depth analysis of model architectures, data characteristics, and the types of traffic violations addressed in existing studies. In addition, this survey highlights current challenges, underrepresented violation types, and methodological best practices. Finally, it explores possible opportunities for future research, including possible integration with other domains such as gamified intervention.

Keywords: Survey paper; Traffic violation prediction; Deep learning; Machine learning

1. Introduction

Traffic violations remain one of the leading causes of accidents. Data from 2020 shows that speed-related crashes accounted for 29% of traffic fatalities in the U.S NHTSA (2022). In Belgium, 36,855 road traffic accidents resulted in 45,243 casualties StatBel (2023). These violations not only cost lives but also lead to significant economic losses.

A promising approach to reducing traffic violations is proactive prevention through predictive modeling. Traffic violation prediction can support this idea by identifying high-risk locations or periods where violations are likely. To build such systems effectively, it is essential to understand the key factors, data characteristics, and modeling techniques involved in violation prediction. Reviewing recent studies helps clarify current methodologies and informs future research directions.

Similar works has been conducted before in adjacent fields including anomaly detection, traffic flow forecasting, and accident prediction. However, focused review on traffic violation prediction is still lacking. For example, Santhosh et al. (2020) conducted a systematic review of anomaly detection from traffic dataset. Medina-Salgado et al.

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(2022) reviewed urban traffic flow prediction, focusing on deep learning (DL) and machine learning (ML) models. Additionally, ElSahly & Abdelfatah (2022) did a comprehensive review on traffic accident prediction.

Despite growing interest in traffic violation prediction, there is limited review that focuses on traffic violation prediction, which this paper addresses. This review aims to examine state-of-the-art methodologies for traffic violation prediction, focusing on the key aspects that influence model development and performance. By reviewing recent studies, it identifies current trends, modeling approaches, and common challenges in the field. No recent review has comprehensively addressed this topic to the authors' knowledge. The contributions of this paper are as follows:

- Identify the state-of-the-art method used for the traffic violation prediction method
- Synthesize the common aspects needed in conducting traffic violation prediction studies

2. Methodology

This literature survey follows a clear and structured methodology to ensure reproducibility. First, we define our research question and then design the search strategy, including the databases we will use. Then, we will explain the search criteria used for the search and explain how we filter out the sources to get the relevant studies we used for the review. Additionally, we will also explain how we extract the sources. Lastly, we will analyze the relevant studies retrieved.

2.1. Research questions

We formulated our research questions based on these objectives: (1) understanding the state-of-the-art traffic violation prediction, including the types of data and modeling techniques used, (2) understanding the common challenges and limitation in the current methodologies, and (3) exploring how this prediction task might integrate with related domains. Based on these considerations, we developed the following research questions:

- RQ1: What types of traffic violations are underrepresented in current prediction models?
- RQ2: Which modeling approaches demonstrate better performance for specific types of traffic violations?
- RQ3: What common methodological challenges are shared across existing studies?
- RQ4: What opportunities exist to integrate traffic violation prediction with other domains?

2.2. Search strategy

Creating a well-developed search strategy is crucial to ensure the reproducibility and accountability of search results. Here, we define the four necessary steps in our search strategy to obtain relevant studies. First, we set the databases we wanted to consult to obtain the search result. Next, we constructed the search query by specifying the search criteria, including selection criteria and publication range. After that, we filtered out the paper by removing duplicates and screening the papers collected. Finally, we extracted the papers and use them for analysis and discussion.

2.3. Search database

We used Scopus, Web of Science, and Google Scholar databases. These databases are chosen for their comprehensive collections of scientific articles, particularly in transportation topic. Scopus and Web of Science are beneficial as they allow us to build advanced search query terms and export the papers we found to popular citation formats. Google Scholar is used as an addition to fill in missing articles that could be considered in our review process.

2.4. Search criteria

We build our query by defining the central theme using the terms "traffic violation*" or "driver violation*". After that, we combine it with "predict*" to get a result related to prediction. Then, we combine it with "deep learning" or " machine learning" to specify the methodologies. These queries are combined with logical operators "AND" and

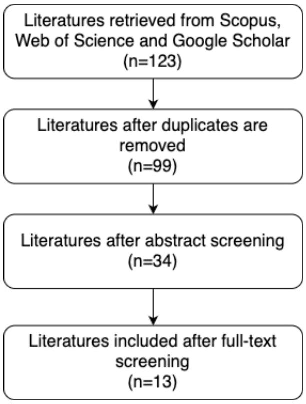

Fig. 1. Flow of literature retrieval and selection process

”OR”. Additionally, we use the ”traffic violation prediction” query in the Google Scholar database to get missing articles not captured by Scopus and the Web of Science database. Afterwards, we will apply filtering criteria to our queries.

Ahmed et al. (2025) emphasized that well-defined criteria are essential to reduce bias and make the result reproducible. The requirements are as follows: (1) The study range is from 2020 to 2025, (2) We only include primary studies, and (3) We only take from a peer-reviewed journal. Using these criteria, we ensure that we capture the current trends in our research and that the credibility of the study we reviewed is accountable.

2.5. Extracting the data

Fig. 1 illustrates the process we followed to identify relevant studies for inclusion in our review. The screening process was conducted using the tool rayyan.ai Ouzzani et al. (2016), which facilitated the efficient selection of eligible papers. To minimize bias and resolve potential disagreements, we used rayyan.ai *blind-on* feature, which allowed reviewers to make independent decisions. Final inclusion was based on a majority vote among the reviewers.

3. Result

We categorize the reviewed studies into five thematic groups based on their relevance to our research questions. This will help us find similarities between the studies and analyze the typical pattern in traffic violation prediction. These categories include the method used for the traffic violation prediction, data features used in the studies, variable or feature analysis done in the studies, a method for handling imbalanced data, and the type of traffic violation detected.

These condensed studies are shown in Table 1. We can see that the DL method dominates the methods used in these studies. Also, spatiotemporal features are standard and found in almost all of these studies, which shows their importance in traffic violation prediction. We will discuss this in more detail in the following subsections.

3.1. Methodology

Traffic violation prediction requires a nuanced understanding of driving behavior, which involves dynamic interactions among various factors Yang et al. (2025). As a result, many studies have adopted DL techniques, particularly graph-based models, due to its ability to capture spatial relationships in road networks and surrounding regions Karantaglis et al. (2024); Yang et al. (2024, 2025); Zhou et al. (2023). These methods rely on the principle that traffic violations always occur in road networks, thus influencing spatially adjacent road networks in the nodes Zhou et al. (2023)

Temporal modeling has also been key, with long short-term memory (LSTM) networks used to capture sequential patterns in traffic data Karantaglis et al. (2024); Wang and Li (2024); Zhang et al. (2024). Some studies enhance these approaches with attention mechanisms, originally from the transformer architecture Vaswani et al. (2017), to

Table 1. Summary of modeling approaches and features used in traffic violation prediction studies.

Paper	Method	Features	Var. Analysis	Imb. Handling	Traff. Violation(s)
Li et al. (2021)	ML (RF)	Spatio-Temporal	Stepwise logistic model	ProWSyn	Binary value for violation detected by AES
Zhu et al. (2022)	DL (Modified Dense Net & SE-DenseNet)	Spatio-Temporal	None	CGAN	6 types of bus driver violations
Alomari et al. (2023)	ML (KNN, SVM, RF, AdaBoost)	Spatio-Temporal	LR, Multi-nominal LR	None	RLR
Jiang et al. (2023)	ML (XG-Boost+Active Learning+Tri-training)	Spatio-Temporal	None	CSTA (tri training+active learning+crowd voting)	Violations hotspot
Zhou et al. (2023)	DL (Graph Attention Road Network)	Spatio-Temporal	GNN Explainer	None	Binary value for traffic violation
Karantaglis et al. (2024)	DL (TGCN + FCN + LSTM)	Spatio-Temporal	None	Spatio-temporal smoothing	Parking Violation
Masoud (2024)	ML (KNN, DT, AdaBoost, Bagging)	Spatial	None	None	RLR
Mostafi et al. (2024)	DL (Embedding + Dense)	Spatio-Temporal	OLS, ANOVA	None	Speed limit compliance
Wang and Li (2024)	DL (CNN+LSTM+Attention)	Temporal & Driver Behaviour	Significance analysis	None	5 groups of traffic violations
Yang et al. (2024)	DL (Behavior-Aware Hyper-graph Conv + Multi-level Attention)	Spatio-Temporal	None	Spatial-Temporal illegal parking approximation module	Parking violation
Zhang et al. (2024)	DL (LSTM+FC)	Spatio-Temporal	None	None	RLR
Owais and El Sayed (2025)	DL (Deep Residual Network)	Spatio-Temporal	VBSA	None	RLR
Yang et al. (2025)	DL (GCN + MLP)	Spatio-Temporal	Gradient analysis	Downsampling	9 categories of traffic violation

uncover complex dependencies or incorporate insights from patrol activity Yang et al. (2024). Others apply attention to prioritize key indicators, improving predictive accuracy Wang and Li (2024); Zhou et al. (2023). In contrast, traditional ML approaches such as tree-based models and ensemble methods remain relevant Alomari et al. (2023); Masoud (2024). Notably, Jiang et al. (2023) introduced a context-aware self-training approach using XGBoost with active learning, which outperformed some DL models in predicting violation hotspots.

3.2. Features

Spatiotemporal features are essential to traffic violation prediction, with nearly all studies incorporating them due to their complex characteristic, capturing spatial and temporal attributes. Spatial context influences how drivers respond to their environment, such as differences in urban and rural settings, environmental density, and pedestrian activity

Yang et al. (2025). Temporal aspects such as time of day or day of the week also impact driving behavior, particularly in conditions like rush hour or nighttime driving FHWA (2007); Li et al. (2020, 2021).

Common spatial features include road attributes Alomari et al. (2023); Jiang et al. (2023); Li et al. (2021); Yang et al. (2024, 2025); Zhou et al. (2023), Points of Interest (POIs) Jiang et al. (2023); Karantaglis et al. (2024); Yang et al. (2024, 2025); Zhou et al. (2023), and trajectory-based data such as position displacement Zhang et al. (2024). Temporal features typically include hour, day, and date. Many studies also integrate non-spatiotemporal features such as driver characteristics Masoud (2024); Wang and Li (2024), weather Jiang et al. (2023); Karantaglis et al. (2024); Li et al. (2021); Yang et al. (2024, 2025); Zhou et al. (2023); Zhu et al. (2022), and traffic flow Alomari et al. (2023); Li et al. (2021); Mostafi et al. (2024); Owais and El Sayed (2025).

3.3. Variable analysis

An essential component of traffic violation modeling is variable analysis, which helps interpret black-box outputs from ML and DL models and improves model transparency Owais and El Sayed (2025). It is also used to understand the influence of input variables on prediction outcomes.

For example, Mostafi et al. (2024) applied analysis of variance (ANOVA) to evaluate the impact of predictors on model performance. In contrast, Owais and El Sayed (2025) employed variance-based sensitivity analysis (VBSA) with Latin Hypercube Sampling (LHS) to explore input–output relationships. Other techniques include GNNExplainer for interpreting node-level feature contributions in graph-based models Zhou et al. (2023), and statistical methods such as p-values and confidence intervals to assess variable importance Alomari et al. (2023); Li et al. (2021); Wang and Li (2024).

3.4. Data imbalance handling

Another problem in traffic violation prediction is the disproportionate ratio between violation and non-violation cases. This imbalance can reduce model sensitivity and lead to poor predictive performance Alomari et al. (2023). Several studies have explored various techniques to mitigate this issue, ranging from deep learning based methods to smoothing techniques.

Karantaglis et al. (2024) and Yang et al. (2024) implemented temporal and spatial smoothing by averaging values from neighboring features to impute missing data. Zhu et al. (2022) applied a contextual generative adversarial network (CGAN) to balance violation type distributions. The proximity weighted synthetic (ProWSyn) algorithm has also generated synthetic minority samples based on proximity to majority instances Li et al. (2021). A more straightforward method involves downsampling, where different class ratios are tested to find an optimal balance Yang et al. (2025).

3.5. Traffic violations types

Red-light running (RLR) violations are among the most frequently predicted types due to their severity and prevalence Masoud (2024); Zhang et al. (2024). These violations typically occur at intersections, making them easier to observe and model Masoud (2024). In contrast, parking violations are often approached using graph-based methods that represent parking spots and urban layouts through road networks Karantaglis et al. (2024); Yang et al. (2024).

Beyond specific violation types, some studies predict whether any violation will occur in a given region or time interval Li et al. (2021); Zhou et al. (2023), while others address multiple violation types simultaneously Wang and Li (2024); Yang et al. (2025); Zhu et al. (2022). Indirect prediction approaches also exist. For example, Mostafi et al. (2024) estimated speed compliance levels before and after automated enforcement system (AES) deployment. Similarly, Jiang et al. (2023) predicted hourly traffic violation hotspots using crowdsourced trajectory data.

4. Discussion

4.1. RQ1: What types of traffic violations are underrepresented in current prediction models?

RLR and parking violations are the most commonly targeted in traffic violation prediction studies Alomari et al. (2023); Masoud (2024); Owais and El Sayed (2025); Zhang et al. (2024); Karantaglis et al. (2024); Yang et al. (2024). Traffic violations are also grouped by type or legal classification based on local transportation codes Wang and Li (2024); Yang et al. (2025); Zhu et al. (2022). A few studies also use binary classification to predict whether any violation will occur, regardless of the type of violations Jiang et al. (2023); Li et al. (2021); Zhou et al. (2023).

However, traffic violations that focus on driving style or behavior, such as tailgating, reckless driving, or driving under the influence, are rarely mentioned in the predictions. One of the main challenges is introducing driver factors, such as driver personality, which might introduce some bias due to driver preference Wang and Li (2024). Integrating this with behavioral theory, might give some understanding of underrepresented traffic violations, as showed by Castanier et al. (2013), who applied theory of planned behavior (TPB) to predict traffic violations.

4.2. RQ2: Which modeling approaches demonstrate better performance for specific types of traffic violations?

The choice of modeling approach for traffic violation prediction depends on both the characteristics of the data and the type of violation being predicted. For example, RLR is modeled using a combination of ML techniques Alomari et al. (2023); Masoud (2024) and DL architectures such as deep residual networks (DRN) and LSTM layers Owais and El Sayed (2025); Zhang et al. (2024). Both Owais and El Sayed (2025) and Zhang et al. (2024) showed that their DL networks outperform ML algorithms in RLR violation prediction such as support vector machine (SVM) and random forest (RF). Owais and El Sayed (2025) achieved root mean square error (RMSE) and mean absolute percentage error (MAPE) scores of 2.26 and 2.55%, respectively, compared to 9.43 and 6.23% for SVM, and 6.37 and 4.68% for RF, demonstrating the capability of DL for RLR violation prediction tasks.

In contrast, parking violations are addressed with graph-based models, as violations may be spatially correlated with nearby parking spots or road segments. In this case, adding a temporal graph convolutional layer decreases the mean absolute error (MAE) and mean squared error (MSE) by 11.40% and 14.11%, respectively, compared with a DRN Karantaglis et al. (2024). Yang et al. (2024) further showed that the Behavior Aware Hypergraph Convolutional Network (BHIPP) achieves an RMSE of 2.52 in rush hour parking violation prediction, compared with RMSEs of 5.10 for XGBoost and 4.60 for LSTM.

Multi-violation prediction, which aim to classify the specific type of violation that may occur, is addressed using various DL techniques, including attention layer + LSTM Wang and Li (2024), graph based networks Yang et al. (2025) or dense layer Zhu et al. (2022). Binary prediction tasks, which focus on whether any violation will occur regardless of type, are approached using ML models Jiang et al. (2023); Li et al. (2021). Furthermore, Jiang et al. (2023) showed that for traffic violation hotspot prediction the XGBoost-based CSTA model achieved an F1-Score of 0.901, outperforming the best DL model, which scored 0.858. Graph-based methods have also been used for binary prediction task Zhou et al. (2023). However, it is important to note that direct comparisons between models remain difficult because most studies rely on different datasets, prediction windows, and evaluation setups.

4.3. RQ3: What common methodological challenges are shared across existing studies?

Although studies mentioned in the review provide techniques to predict traffic violations, the real-time capabilities of the proposed methods are rarely discussed. Most of the studies incorporated hourly time windows for the predictions Karantaglis et al. (2024); Yang et al. (2025), also daily time windows Zhou et al. (2023). Li et al. (2021) mentioned that 30-minute prediction windows are optimum for predicting traffic violations. Still, studies such as Wang and Li (2024); Zhang et al. (2024) try to predict traffic violations in narrower time windows, which can be used for real-time traffic violation intervention.

Another challenge is the imbalance of traffic violation data, since violations are rare. The ProWSyn algorithm has been shown to handle high imbalance ratios (IR) more effectively than synthetic minority over-sampling technique (SMOTE), with an IR of 1 achieving statistically superior precision–recall performance Li et al. (2021). In parking-violation prediction when data is represented as a graph, spatio-temporal smoothing leverages temporal and spatial information to mitigate sparsity in the dataset Karantaglis et al. (2024); Yang et al. (2024). Another approach uses deep-learning generative models to upsample under-represented data by generating synthetic samples, which improve the accuracy of the model by 3% Zhu et al. (2022).

Furthermore, not all studies explained the variables that are important in traffic violation prediction. This is important to interpret the black-box prediction provided by machine learning or deep learning method Owais and El Sayed (2025). Statistical approaches, such as ANOVA Mostafi et al. (2024), VBSA Owais and El Sayed (2025), and logistic models Li et al. (2021), have been used to address these issues. Additionally, GNNExplainer have been employed to clarify the influence of edges and nodes in graph-based approaches Zhou et al. (2023).

4.4. RQ4: What opportunities exist to integrate traffic violation prediction with other domains?

There is no direct answer to how traffic violation prediction can be combined with other domains. However, some examples and ideas illustrate potential ways to integrate traffic violation prediction. Jiang et al. (2023) directly applied traffic violation hotspot prediction to design a patrol system routing algorithm that effectively covers all violation hotspots. On the other hand, traffic violation prediction has been combined with trajectory prediction tasks to improve road safety and help drivers avoid accidents Zhang et al. (2024).

Another related domain is gamification, which is often used to promote safe driving Wang et al. (2022). van Gent et al. (2019) proposed a system-centric model based on the persuasive systems design (PSD) framework, which uses gamification techniques to influence driver behavior and reduce travel time delays and congestion. In this case, the traffic violation prediction model can serve as a traffic system that decides the goals for the driver to change behaviour, for instance, if the system predicts there will be a traffic violation.

5. Conclusion

Deep learning has become the dominant approach in recent traffic-violation prediction studies, mainly because the spatio-temporal nature of the data is well-suited to neural network architectures. Various deep-learning techniques have been applied, with each architecture chosen to match the specific violation type and underlying data characteristics. Despite these advances, several challenges remain that point to future research directions, particularly in handling data imbalance and missing values, real-time traffic violation prediction, and integrating prediction into another domain.

In data imbalance handling, ProWSyn has been extensively studied and proven effective at managing high imbalance ratios Li et al. (2021), which is particularly advantageous when traffic-violation instances are severely under-represented. However, this approach has longer training times compared to SMOTE. Deep learning based methods, especially generative adversarial networks (GAN), have also been applied to upsample under-represented traffic violations Zhu et al. (2022). Yet, the benefits of GAN are not as comprehensively documented, and their implementation can be more complex than ProWSyn.

Real-time prediction has also been a challenge, since studies use different time windows for prediction. In one previous study, the optimal window was found to be approximately 30 minutes Li et al. (2021), which can help mitigate and reduce violation counts in the mid-term range. However, a real-time prediction is still necessary to prevent and intervene in traffic violations as they arise.

Near real-time prediction could also enable integration of traffic-violation prediction into other domains. van Gent et al. (2019) explained that interventions need to occurs within two minutes to allow driver follow any advices and change their behaviour. Future work should therefore target models capable of near real-time prediction and narrowing prediction time window, opening the door to cross-domain applications.

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