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Abnormality Detection in Urban Traffic Data: A Review

Iman Taheri Sarteshnizi, Majid Sarvi, Saeed Asadi Bagloee, Neema Nassir[1]

[1] Department of Infrastructure Engineering, University of Melbourne

Email for correspondence: itaherisarte@student.unimelb.edu.au

Abstract

Anomalous data is called to a data sample or a sequence of data that significantly differs from the others. Accurately and on-time detection of anomalies (abnormalities) is crucial for system managers since it may convey important information to them. Anomaly detection is widely investigated in different research areas as well as transportation and traffic field. In this paper, we review the literature of anomaly detection in urban traffic networks to find the most recent state-of-the-art methodologies in this field. A search method is used in this paper to find the most relevant research papers, and they are studied and analyzed regarding anomaly type, data type, and methodology. Different types of anomalies, data collectors, spatiotemporal scopes, and detection methods in the literature are categorized and investigated in this work. Finally, a summary and conclusion section is provided in this work to show the possible future research directions. Based on the findings, accidents and city-wide events like festivals or concerts are mostly detected in previous works as anomalies using loop detector (LD), and trajectory data (GPS data). Moreover, supervised methods are mostly employed for accident detection aims, but papers using unsupervised approaches detect city-wide events with GPS data.

Keywords: Abnormality Detection, Urban Traffic Data, Spatiotemporal Data, Traffic Network

1. Introduction

Detecting urban traffic anomalies (abnormalities) is crucial for system managers to provide appropriate actions in different situations. Anomalies are considered beneficial information from two key aspects. First, they may convey valuable information about some unintended rare events that may happen in urban traffic networks (Abduljabbar et al., 2019). Hence, on-time detection of these events helps to avoid significant economical damages or human death (Zhang et al., 2020). Second, finding anomalies is a primary step for data cleaning and using the data for different aims. Outliers or sudden noises are some kinds of abnormalities that are mostly observed in the data. Sometimes, data scientists are not interested in using anomalies (or abnormalities) in their analysis since anomalies may mislead scientists in inferring the results of any conducted experiment. Therefore, before removing or replacing the anomalies, we need to detect and recognize them as well.

Nowadays, with the massive usage of different data collection platforms, anomaly detection has attracted more attention. Traffic data is mostly collected within the city exploiting connected vehicles, loop detectors, microwave detectors, and radar sensors (Emami et al., 2019). Since the traffic data include spatiotemporal scopes, it is a controversial task to find abnormalities among the vast multi-dimensional available information. Multiple solutions are presented in the literature tackling specific kinds of anomalies. New Machine Learning (ML) classifiers and Deep Neural Networks (DNN) along with Density-Based models and different dimensionality reduction methods are utilized to find anomalous data or patterns in traffic data (Djenouri et al., 2019).

In this paper, we review the literature to answer these three questions: 1) what types of anomalies are defined previously in the area of traffic engineering. 2) what types of data are mostly exploited in the literature to find anomalies. And 3) what are the most recent state-of-the-art methods for anomaly detection. We investigated the literature by a search method regarding these three questions. A summary of the findings is reported in this research.

In the next following sections, we first introduce our search method for selecting research papers. Then, in section 3, anomaly types considered in the literature are categorized and presented. Section 4 and 5 discuss different data collection approaches and detection methods, respectively. Finally, in the last section, a summary of the findings and some future research directions are presented.

2. Search Method

According to the high number of publications related to urban traffic, a search method is adopted in this paper to find the most relevant research papers to our topic which is “Anomaly Detection”. Figure 1 shows our scheme to dig into the literature and select the desired articles. Primarily, we searched for research papers containing some keywords, indicated in Figure 1, in their titles, abstracts, or index terms. At this stage, we decided to exclude research papers related to surveillance cameras or trajectory anomaly detection as these areas are very different from the rest in terms of methodology and problem definition. Moreover, it should be noted that recently published papers, specifically after 2017, were our target for investigation. After choosing many relative research papers and analysing them, some new keywords were again obtained (second phase of Figure 1). We also explored the literature according to these new keywords to not miss any research paper linked to our topic. In the last step, we analysed the connections between the articles. All the references of the selected papers were considered, and a few new papers were found and studied.

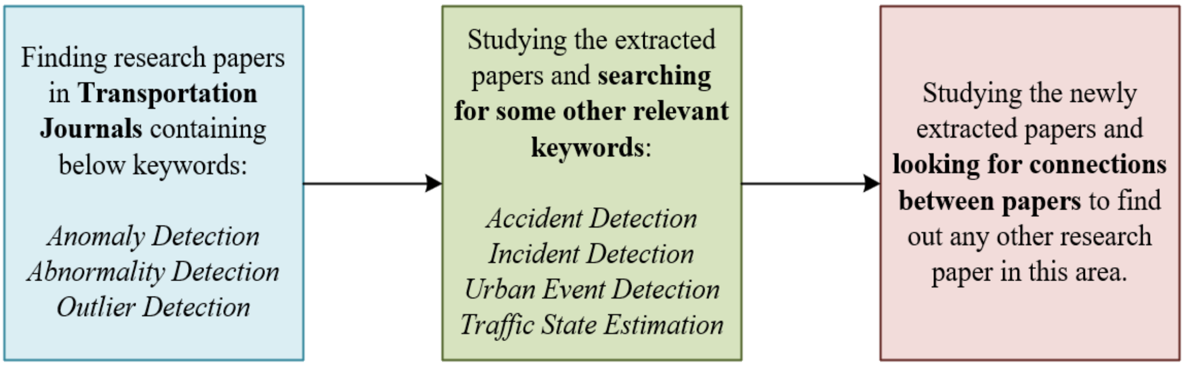

Figure 1: Search method scheme

Totally, 33 research papers are extracted from the literature using our search method. A summary of these research papers regarding our three remarked questions is provided in Table 1. More discussion about these three aspects is provided in the following sections.

3. Anomaly Type

Based on Table 1, anomalies are studied in the literature from different points of view, and practically, it is crucial to highlight the differences and similarities between them with a general overview. Online detection of any abnormal situation, not just one specific type, can help both traffic engineers to apply proper traffic policies, and commuters to make informed decisions. However, since there are different traffic data sources and different attitudes toward abnormality detection, this area is mostly investigated in specific branches regarding different types of abnormality. Therefore, a conclusive and comprehensive review is needed to cover all aspects of abnormality detection and related solutions. Two major targeted anomalies, observed in the most of research papers, are accidents and city-wide events. In addition to these perspectives, few other authors investigated this area by new unique attitudes. These different categories of anomalies will be more discussed in the following paragraphs.

Table 1: Summary of the research papers

Ref	Targeted Anomaly	Data	Spatiotemporal Scope	Critical Variables	Method
(Mercader & Haddad, 2020)	Accident	Bluetooth	3 months Ayalon Highway, Tel Aviv	Velocity of up and down stream	Isolation forest (clustering algorithm)
(Y. Lin et al., 2020)	Accident	LD	2 weeks I-80 in California	Speed, flow, and occupancy (up and down stream) and extracted features	Generative Adversarial Networks and SVM
(F. Jiang et al., 2020)	Accident	LD	Sample selection from 2 years of data I880-N and I805-N in California	Speed, flow, and occupancy on each lane (up and down stream)	LSTM
(Parsa et al., 2020)	Accident	LD	Sample selection from 1 year of data Chicago metropolitan	Speed and occupancy of up and down stream	XGBoost for classification, SMOTE, SHAP
(Huang et al., 2020)	Crash prediction	Radar sensor	Not mentioned Interstate 235 in Des Moines, IA	Spatiotemporal interpolated speed matrices	CNN
(H. Jiang & Deng, 2020)	Accident	LD	4 days of data from an urban expressway	Speed, flow, and occupancy (up and down stream)	Factor Analysis, Weighted RF
(Fang et al., 2020)	Accident	Microwave detector	5 months of data from Hangzhou viaduct's section	flow, speed, and occupancy of downstream	Random forest for feature selection, Deep cyclic limited learning, SMOTE
(Parsa et al., 2019)	Accident	LD	7 months Eisenhower expressway in Chicago	Speed, flow, and occupancy on each lane (up and down stream)	SMOTE, SVM and Probabilistic NN
(Chakraborty et al., 2019)	Accident	GPS	7 months I-80/35 and I-235 of the Des Moines region, in Iowa	Filtered lane-based speed matrices	Laplace distribution, bilateral and total variation filters
(Asakura et al., 2017)	Accident	GPS	2 months data of 25000 probe vehicles in Shibuya Line, Tokyo	Simulated speed of probe vehicles	Threshold based model
(Yang et al., 2018)	Crash prediction	LD	1 month An expressway of Shanghai	Volume, speed, and occupancy of up, down, and crash stream	Bayesian dynamic logistic regression

Ref	Targeted Anomaly	Data	Spatiotemporal Scope	Critical Variables	Method
(Cai et al., 2020)	Crash prediction	LD	1 year SR 408 in Orlando	Speed and volume data of up and down stream	Generative Adversarial Networks with CNN
(Kwak & Kho, 2016)	Crash prediction	LD	Sample selection from 3 years of data Gyeongbu expressway in Korea	Features extracted from Volume, speed, and occupancy	Conditional logistic regression analysis
(Basso et al., 2020)	Crash prediction	AVI gates	1 year and 6 months Autopista Central in Chile	Flow, speed, and density	RF for feature selection, SVM and Logistic Regression
(Xiao, 2019)	Accident	LD	Not mentioned I-880 freeway in San Francisco	Speed, volume, and occupancy of detectors	SVM and KNN ensemble learning
(Agarwal et al., 2016)	Accident	LD	1 month US-95 and I-15 in the Las Vegas	Volume, speed, and occupancy of crash station	Wavelet transformation and logistic regression
(El Hatri & Boumhidi, 2018)	Accident	Simulatio n	-	Volume, speed, and occupancy of simulated detectors	Fuzzy deep learning with stacked autoencoder
(Theofilato s et al., 2019)	Crash prediction	LD	Sample selection from 6 years of data Attica Tollway, Greece	Flow, speed, and occupancy before crashes	Comparison study (DT, RF, SVM, SNN, KNN, NB, DL)
(Shang et al., 2021)	Accident	LD	Not mentioned I-880 highway, United States	Volume, speed, and occupancy of up and down stream	RF for feature selection and LSTM
(Liu et al., 2019)	Accident	GPS	1 month I-80 westbound across Iowa	Speed for different road segments	D Markov model and xD Markov model, Restricted Boltzmann Machine
(Gao et al., 2021)	City-wide event	GPS	2 weeks of taxi trajectories in Shanghai	Number of vehicles in each region	Information entropy, Boltzmann entropy and Fractal dimension
(Xu et al., 2019)	City-wide event	GPS	8 months 30000 cabs Beijing	Number of vehicles in each region (tensor)	Tensor factorization and statistical thresholds
(Kuang et al., 2015)	City-wide event	GPS	6 months 15000 taxi drivers Harbin	Traffic flow of any path between different regions	PCA, Wavelet filter, threshold
(Kong et al., 2020)	City-wide event	GPS	1 month of 13695 taxies' trajectories in China	Boarding and alighting matrices of a network	LSTM for flow prediction, OC-SVM for anomaly detection
(C. Lin et al., 2018)	City-wide event	GPS	1 year of 3 million taxi trajectories from New York city	OD matrices of a network during each time	Tensor factorization, Local Outlier factor
(H. Wang et al., 2017)	City-wide event	GPS	1 month of taxi trajectories in Beijing, China	Vehicle presence in each road (binary tensor)	Tensor factorization, likelihood ratio test
(Gao et al., 2020)	City-wide event	GPS	2 weeks of taxi trajectories in Shanghai City	number of vehicles in a given period and a specific region	Spars representation for flow prediction

Ref	Targeted Anomaly	Data	Spatiotemporal Scope	Critical Variables	Method
(Tišljarić et al., 2020)	Road congestion	GNSS	5 years (summer months and weekends are excluded) of 4200 tracked vehicles from Croatia's road network	Change of speed between two consecutive road segments	Agglomerative clustering
(Zeroual et al., 2017)	Road congestion	Detector stations	98 days I-210 and SR60 in California	Traffic density	EWMA statistic for testing anomalies
(Bouyahia et al., 2021)	Road congestion	GPS + LD	1 year A1 highway in England	Speed and volume data for different location	Conditionally Gaussian Markov Fuzzy Switching Model (CGMFSM)
(Kalair & Connaughton, 2021)	Atypical flow-density data	LD	1 year and 7 months M25 London orbital	Flow and density of independent stations	Bi-variate kernel density function
(Djenouri et al., 2019)	Daily anomalous flow pattern	-	1 year of flow data from different locations	Daily flow profiles	K nearest neighbors
(X. Wang & Sun, 2021)	General anomaly	LD	1 month 4 freeways in Seattle	Spatiotemporal speed and flow tensors	Autoregressive model using factorized tensors

The first category of the studies includes accident detection problems. Different types of accidents may happen in a traffic network, but those with a significant effect on traffic flow are mainly considered in the literature. These types of accidents usually reduce the road capacity and interrupt the regular flow of the road. The main objective in these studies is to detect and localise accidents as soon as they happen in a road segment. Accident detection is also referred to as "crash detection" or "incident detection" in the literature. Although "incident" is a general word that also contains accidents, there is no difference between the aim of the research papers using "incident" instead of "accident" in their titles. In this category, usually, data from one road segment is monitored to detect abrupt changes of flow, speed, or occupancy. It should be also noted that some research papers in this area have similar methodologies to accident detection papers, but their main aim is to predict the crash risk. These studies use different data sources like loop detectors and weather reports to predict how dangerous is one situation to trigger a car accident. Papers related to this area are shown in Table 1 with "Crash prediction" label.

Other studies in this area focus on detecting city-wide events. By city-wide events, we mean occasions when the normal pattern of traffic movement in a network change. So, the difference here compared to the previous group, is that the viewpoint here is more network wide. Festivals, concerts, and football matches are some examples of city-wide events mentioned in the literature. When these types of anomalies happen in the network, inflow, or outflow of some regions in the study area significantly shift. Therefore, by monitoring the city-wide flow data and looking for anomalies, unusual events happening around the city are detectable. In these studies, network partitioning is a common approach for analysing and detecting anomalies.

The last group of research papers proposes other problem frameworks of anomaly detection. In some cases, detecting road congestion is the target regardless of the causality. For instance, Tišljarić et al. (2020) created three clusters related to very congested, moderately congested, and non-congested situations for every two connected links. Bouyahia et al. (2021) predicted flow based on speed data and generated a congestion level between 0 and 1. Moreover, Zeroual et al. (2017) set a threshold for congestion situations and raised an alarm when the exponentially weighted moving average (EWMA) statistic passes the threshold. In addition to these congestion detection methods, Kalair & Connaughton (2021), Djenouri et al. (2019), and Xu et al. (2019) adopted model-based anomaly detection, anomalous daily traffic pattern detection, and spatiotemporal anomaly detection, respectively. In the first research (Kalair & Connaughton, 2021), a bivariate probability density function is fitted to flow-density data of a road section, and every new data point with a low occurrence probability is regarded as an anomaly. Djenouri et al. (2019) divided traffic flow data into normal and abnormal with a daily resolution. In other words, every day in this method is labelled as normal or abnormal by creating two clusters exploiting historical data. Spatiotemporal anomalies are detected by Xu et al. (2019) using a predictive autoregressive model. In this study, every new data with a high prediction error is considered as an anomaly.

4. Data

Data collection devices and spatiotemporal scopes of the collected data in the literature are two main areas worth exploring. The following subsections further review the literature from these perspectives.

4.1 Data collectors

Various data collection devices are used in the literature to capture spatial and temporal traffic characteristics; like loop detectors (LDs), Global Positioning System (GPS) sensors, Bluetooth devices, radar sensors, AVI gates, and microwave detectors. In a general view, these devices either store flow, speed, and occupancy of a road segment or captures individual latitude and longitude of the vehicles traversing in urban networks. LD, radar sensor, AVI gate, Bluetooth device, and microwave detector provide analysts with the traffic flow, speed, and occupancy of a road segment. On the other hand, GPS systems collect trajectory data of every single vehicle.

As we can see from Table 1, most of the accident-related papers deal with LD data, however, papers that detect city-wide events mainly benefit from GPS data. The reason is that LDs are installed on a limited number of major urban arterials, and consequently, their data does not capture city dynamics. But on the other side, vehicles equipped with GPS sensors are free to traverse around the city, and this leads to achieving rich spatiotemporal data. A high penetration rate (number of equipped vehicles/total number of vehicles) is crucial for high-resolution event (anomaly) detection. Accident detection using GPS data is not investigated in the literature since it needs high-resolution data and installing GPS sensors on most of the vehicles in the network is almost impossible.

4.2 Data Scope

Details regarding spatiotemporal scopes of the collected and used data in the literature are demonstrated in Table 1. As it is discussed before, focusing on a single roadway is the spatial scope of the research papers in the accident detection field, however, network-wide consideration is the case for city-wide event detection purposes. Collected data in the literature mostly comes from the United States or China. Some other databases from England, Greece, Korea, Chile, and Japan are also recorded in Table 1.

The temporal scope of the previous datasets varies from 4 days to 5 years. A detailed representation of previous papers' temporal scopes is depicted in Figure 2. Based on this figure, we can see that 56% of the datasets are collected for less than three months. 40% of them are recorded between 3 months and one year. The remaining (which includes 4% of the research papers) have a temporal scope of one year and more. It should be mentioned that although some studies possessed a broad temporal dataset, their analysis was just based on some limited extracted samples (F. Jiang et al., 2020; Kwak & Kho, 2016; Parsa et al., 2019; Theofilatos et al., 2019).

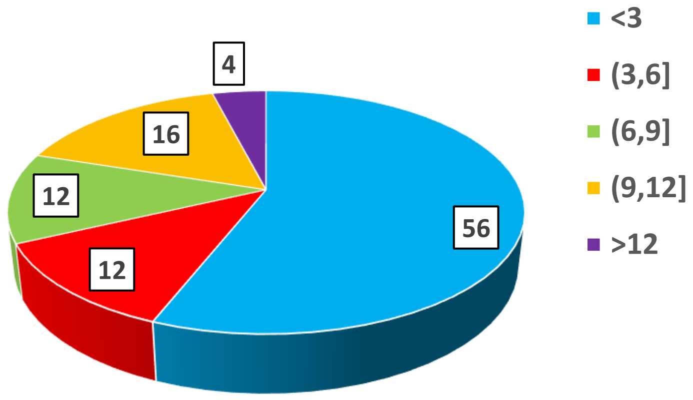

Figure 2: Temporal scope of datasets in the literature: relative frequency % of duration (month)

5. Methodologies

Based on Table 1, we can divide the proposed methodologies in the literature into two distinct groups namely 1) Supervised, and 2) Unsupervised approaches. Each of these categories is further explained below. Our aim in this section is to provide information about the general structure of the previous works rather than going deep with the mathematical background of the exploited methods.

5.1 Supervised Approaches

Accident (incident) detection in the literature is investigated by supervised approaches. Crash reports collected by different agencies are used for training and testing the proposed classifiers in the literature. Figure 3 shows an overview of the different steps included in previous papers. In the first phase, multiple features are extracted from the upstream and downstream of the accidents. In other words, different accident samples are derived from the dataset using features describing the spatiotemporal changes of flow, speed, or occupancy. Then, normal samples are also obtained from the same location and time but extracted from the data of the other days. Dimensionality reduction is conducted in some previous works (Basso et al., 2020; Fang et al., 2020; H. Jiang & Deng, 2020; Shang et al., 2021) since the number of extracted features were high and most of the features were correlated to each other. Factor Analysis and Random Forest are mainly used for this aim in the literature. In phase 3, which is considered just by some researchers, the problem of using unbalanced dataset is addressed. Since traffic accidents are some rare events observed in daily traffic, the portion of accident samples to the non-accident samples in the constructed datasets is low. Therefore, some methods like SMOTE (Fang et al., 2020; Parsa et al., 2019, 2020) or Generative Adversarial Networks (GANs) (Cai et al., 2020; Y. Lin et al., 2020) are used in the literature to compensate for this problem.

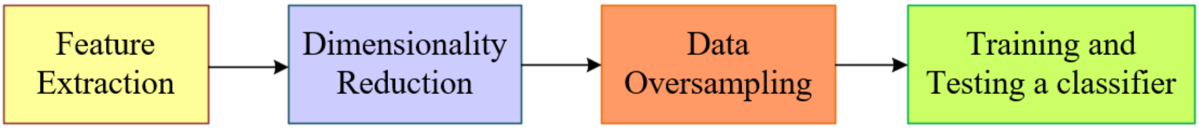

Figure 3: An overview of the supervised accident detection approaches

In the last phase, a classifier is trained to distinguish between normal and abnormal (accident) samples. Different types of classifiers are trained in the literature such as Logistic Regression (and its variants) (Agarwal et al., 2016; Basso et al., 2020; Kwak & Kho, 2016; Yang et al., 2018), SVM (Basso et al., 2020; Parsa et al., 2019; Xiao, 2019), XGBoost (Parsa et al., 2020), Random Forest (H. Jiang & Deng, 2020), and Probabilistic Neural Network (Parsa et al., 2019). Each of these classifiers showed great ability to predict the abnormality of the derived samples. Furthermore, some other studies exploited deep structures to address this classification problem, (Cai et al., 2020; el Hatri & Boumhidi, 2018; Fang et al., 2020; Huang et al., 2020; F. Jiang et al., 2020; Shang et al., 2021) and these structures demonstrated superiority over previous ML methods.

5.2 Unsupervised Approaches

In studies with an unsupervised approach, the target labels of anomalies are not provided, and the problem is to detect anomalous samples among a bunch of unlabelled data. This approach is mostly used for city-wide event detection, but there are also some works applying these approaches for the detection of other types of anomalies like accidents. Figure 4, demonstrates the general overview of the structures observed in the literature. As we can see, sometimes the raw data in previous works are directly used as an input for discriminative approaches, or in other cases developing a predictive model or reshaping the data is implemented before deciding about the abnormality of the data.

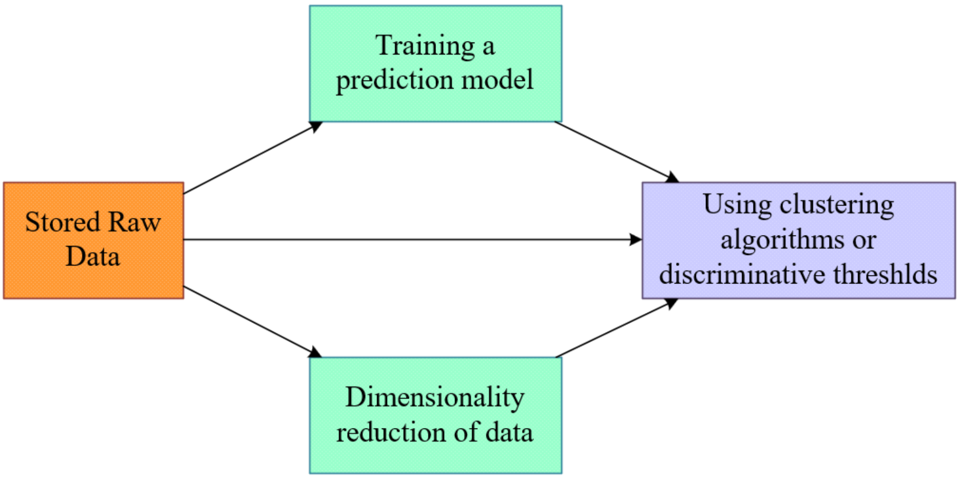

Figure 4: An overview of the unsupervised anomaly detection approaches

Before using discriminative approaches, some data pre-processing methods are suggested by different works. In some previous papers (Bouyahia et al., 2021; Gao et al., 2020; Kong et al., 2020; X. Wang & Sun, 2021) a prediction model (Autoregressive model, CGMFS model, Sparse Representation, and LSTM model, respectively) are trained to forecast the data for the next short-time interval and then the residuals (difference between reality and prediction) are used as an input for clustering methods or discriminative thresholds. In some other cases (C. Lin et al., 2018; H. Wang et al., 2017; X. Wang & Sun, 2021; Xu et al., 2019), a dimensionality reduction is suggested to change the representation of data into a smaller matrix or tensor. Tensor Factorization and Principal Component Analysis (PCA) are widely used when confronting GPS data. By these methods, the latent components of the data, which is an approximation of the whole data, is derived and used for different analysis.

Clustering approaches and density-based statistical thresholds are commonly employed in the literature to recognize anomalies. On-Class Support Vector Machine (OC-SVM) (Kong et al., 2020), Local Outlier Factor (LOF) (C. Lin et al., 2018), and Agglomerative clustering (Tišljarić et al., 2020) are the clustering methods trained for anomaly detection in this area. Beside these approaches, some other authors took advantage of density-based thresholds. Kalair & Connaughton (2021) fitted a bivariate kernel density function to the flow-density data of different road segments, and by determining a level of confidence, they defined the boundary line of the normal area. Moreover, Chakraborty et al. (2019), used spatiotemporal thresholds for a road segment exploiting Laplace distribution and filtered these thresholds according to their spatiotemporal neighbours. Other statistical approaches like the likelihood ratio test (X. Wang & Sun, 2021) and Q-statistic (Xu et al., 2019) are also employed in the literature for this aim.

6. Summary and Future Directions

In this work, a literature review is conducted to study anomaly detection in urban traffic networks. Recent research papers, specifically published after 2017, are studied in this work from three aspects 1) anomaly type, 2) data type and scope, and 3) detection methodology. A comprehensive summary table of the 33 studied papers is provided in this research regarding these proposed aspects. Results found by this paper indicate that accidents and city-wide events are the most investigated anomalies in the previous studies. Loop detectors and GPS sensors are the main platforms for data collection in this field. Recently, GPS data is mostly used to capture city dynamics for detecting city-wide events, however, loop detector data is exploited to monitor a single road segment for detecting short-time anomalies like accidents. Furthermore, the accident detection problem is mostly formulated as a classification problem in the literature, but other types of anomalies are entirely detected by unsupervised approaches like clustering algorithms and density-based thresholds.

Based on our findings from this literature review, some beneficial research directions are listed and explained here:

- *Developing unsupervised methods for accident detection*:
  Recently published papers in the area of accident detection recommend supervised classifiers that need the ground truth of data (accident data) for training. However, this information is not easily accessible. There are a few research papers using thresholds for this aim, but these methods suffer from a lack of using ML models.
- *Using GPS and loop detector data simultaneously to detect anomalies*:
  Available works in this field use just one source of information to detect anomalies, however, looking simultaneously into different data sources may strengthen the detection power.
- *Taking advantage of deep structures:*
  Deep learning is widely used for anomaly detection in other areas, but it is not completely investigated for traffic data. Unsupervised deep neural networks are a powerful tool for learning the hidden structure of data. It is highly recommended to use them as a discriminative tool rather than clustering or thresholds.
- *Adopting a framework for online detection of anomalies:*
  In previous papers, the online implementation of their proposed methods is not discussed. Some anomalies like accidents need a real-time response, and early detection of them is of paramount importance. Therefore, the lack of online anomaly detection should be addressed in future works.

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