Data-Driven Approaches for Road Safety: A Comprehensive Systematic Literature Review

Ammar Sohail*[1], Muhammad Aamir Cheema[1], Mohammed Eunus Ali[2], Adel N. Toosi[1], Hesham A. Rakha[3]

[1]Monash University, Australia

[2]Bangladesh University of Engineering and Technology, Bangladesh

[3]Virginia Tech, USA

Abstract

Road accidents cost over a million lives each year. Consequently, researchers and transport engineers continue the effort to improve road safety and minimize road accidents. With the increasing availability of various sensor technologies to capture road safety-related data and the recent breakthrough in modern data-driven techniques, in particular Machine Learning and Deep Learning techniques, data-driven road safety research has gained significant attention in the past few years. As road safety involves a number of different aspects, including road infrastructure (e.g., surface conditions), road user behaviors (e.g., driver/pedestrian behavior), and traffic congestion; critically reviewing all these major aspects and their relationships with road accidents is a challenging task. In this paper, we present a systematic approach to review recent data-driven road safety approaches involving all these major aspects of road safety. To better analyze existing data-driven road safety research, we first introduce a number of taxonomies to characterize data sources, equipment & sensors to capture data, and methodologies to analyze and make decisions based on data. We explore major techniques on improving different aspects of road safety and analyze major data-driven road safety research outcomes. Finally, we discuss major challenges and outline possible future directions for data-driven road safety research.

Keywords— Road Safety, Accident Prevention, Accident Prediction & Detection, Road Surface Condition, Driver & Pedestrian Behavior, Traffic & Congestion

1 Introduction

With the rapid urbanization and increased mobility around the world, road safety has become one of the key components of a modern city, touching the lives of almost everyone in the community. Despite efforts from all the stakeholders, road accident-related casualties are continuously increasing [LM10, GOP20, LZLH20]. According to a World Health Organization (WHO) 2018 report [WHOa], road accidents are one of the leading causes of death and severe injuries, where over 1.35 million people are killed, and up to 50 million people are injured by road accidents every year. The estimated economic cost of these accidents is 518 billion dollars per year, and many families suffer lifelong physical disabilities and mental trauma due to these tragic road accidents. Hence, a wide range of strategies and actions have been taken both locally and globally to ensure road safety and to reduce the damage and/or loss of life. WHO recently announced "Decade of Action for Road Safety 2021-2030", setting an ambitious target of preventing at least 50% of road traffic deaths and injuries

*Corresponding author: ammar.sohail@monash.edu

by 2030 [WHOb]. Due to its importance, road safety has been a major focus for transport engineers, policy makers, and researchers.

Road safety involves a multi-facet of factors that include road infrastructure (e.g., roadway surface conditions), road user behaviors (e.g., driver/pedestrian behavior), traffic (e.g., congestion), and other environmental issues (e.g., inclement weather), etc. Developing road safety strategies and action plans involving all these factors is challenging. Traditional approaches to road safety [YDL+17, SKZM20] focus on changing the behavior of road users by enforcing strict traffic rules, running awareness campaigns, conducting workshops and seminars on safe driving. Thus a large body of research considers the historical accident data and analyzes accidents and other related data to propose different traffic and driving rules [BD11, AM21]. Large adaptation of IoT sensors in monitoring road safety factors in recent years fuels a plethora of big-data-driven related research in almost every road safety sector. The key areas of these big-data-driven research include road surface condition monitoring [SKZM20, SOA+19], road user behavior monitoring and prediction [OYK21, PATY19], traffic/congestion monitoring [RZW15, NS18], and accident prediction or detection [RAAS+08, KJN17, WKF19]. Different recommendation systems (as well as accident prediction systems) may use the outcome from the above one or multiple data-driven approaches along with other environmental parameters to better predict accidents [BBF+21, ASABZ13].

With the increasing attention to road safety research in recent years, we have witnessed a plethora of research and consequent survey papers reviewing different aspects of road safety. Efficient road surface monitoring plays a vital role in road safety. Salau et al. [SOA+19] summarized existing literature for road surface anomaly detection, where they identified challenges in detecting the anomaly and classifying anomalies as potholes or bumps using direct signals obtained from the accelerometers of the vehicles. Sattar et al. [SLC18] evaluated and compared different smartphone-based methodologies to monitor road surface conditions. Another major catalyst in road accidents is road user behavior. There has been significant research on different road user behaviors, including identifying risky driver and pedestrian behaviors on roads. Kaplan et al. [KGYK15] reviewed drivers' drowsiness and distraction detection through visual and non-visual approaches. A detailed assessment of smartphone-based approaches for detecting driver tiredness is reviewed in [CCCZ19]. They covered sensing systems, detection algorithms, and the accuracy and limitations of each smartphone-based system. In road safety research, pedestrian behavior is generally analyzed through various dimensions such as their physical locations, their interaction with other vehicles, data collection methods and their demographics [SA03, ZP17, RRL+18, BN20, TVCZ20]. Zsifkovits et al. [ZP17] presented a review of the methods for identifying pedestrian behavior in public places, whereas Ridel et al. [RRL+18] focused on the prediction of pedestrian behavior in urban scenarios. As traffic flow and congestion affect road safety, numerous research papers also focus on traffic flow and congestion prediction. In this category, Nagy et al. [NS18] reviewed data-driven approaches for traffic flow prediction in smart cities, Akhtar et al. [AM21] focused on artificial intelligence-based congestion prediction research, and Hossain et al. [HAAQ+19] carried out a systematic review of real-time accident prediction methods. Krichen et al. [Kri21] proposed a short survey on the use of smartphone sensors in the detection of various kinds of anomalies in several sub-fields like environment, agriculture, healthcare and road/traffic conditions. Though they considered several aspects of road safety, including road surface anomalies, accident detection and driver's behavior monitoring, this survey is not comprehensive as they only reviewed smartphone sensor-based approaches. Another short survey presented by Lian et al. [LZLH20] focused on intelligent transportation systems and connected/automated vehicles using big data. Although they considered more than one road safety aspect (including accident prediction and driver behavior analysis), this survey ignored many other important road safety aspects such as road surface condition monitoring, pedestrian behavior analysis, and traffic flow & congestion prediction.

Although the review papers discussed above contribute significantly by analyzing and summarizing the existing research on road safety, these papers are limited in at least one of the following ways: 1) most of the existing review papers focus on only one particular aspect of road safety (e.g., road user behavior) and fail to capture the holistic view of the road safety research covering all major aspects; 2) many of the above-mentioned review papers focus on data obtained only from a specific device (e.g., smartphones) and ignore the existing research that utilizes data from other popular devices/sensors (e.g., LiDAR, RADAR, OBD2 etc.); and 3) road safety research has gained huge research attention in the past couple of years and there is a need to review the most recent research that is not covered in previous review papers published a few years ago. We address the limitations mentioned above and present a comprehensive systematic literature review on road safety. In particular, to the best of our knowledge, we are the first to present a systematic literature review covering all the major aspects of road safety, including road surface condition, road users, traffic & congestion, and accident prediction & detection. We present several important taxonomies and categorize the existing research based on different dimensions such as data sources, equipment/sensors used to capture the data, and methodologies used to solve the problems. In summary, we make the following key contributions in this paper.

- We identify major aspects of road safety and provide a holistic, top-down view of these aspects including road users, road surface condition, and traffic condition. We conduct a systematic literature review of the existing research addressing these major road safety aspects and critically review the impactful papers collected from two well-known research databases.
- We provide three major taxonomies to categorize the existing road safety research: (i) data source taxonomy to categorize different types of data sources; (ii) equipment and sensors taxonomy to identify the types of sensors used to collect the data in the road safety domain; and (iii) a taxonomy to group different approaches based on the data-driven techniques employed in the existing research.
- We review relevant existing works under four major aspects of road safety: road surface condition, road users, traffic & congestion, and accidents, and critically analyze each of the works from various dimensions, including the perspective of our defined taxonomies.
- We discuss major research challenges hindering the research in data-driven approaches for road safety and outline important future research directions.

The remainder of this paper is organized as follows: Section 2 provides an overview of the paper. Specifically, in this section, we first discuss the paper's scope and structure, present the review methodology, and finally present several taxonomies of data-driven road safety research. Section 3 describes the state-of-the-art data-driven approaches for accident prevention. Section 4 presents data-driven approaches to carry out accident prediction and detection. Section 5 highlights the major research challenges and future research directions. Section 6 concludes the paper.

2 Overview

In this section, we first present the scope and structure of this review. Then, we present the methodology we used for conducting the systematic literature review. Finally, we present a number of taxonomies to categorize existing research in each of the different aspects of road safety.

2.1 Scope and Structure of the Review

For this review, we adopted scoping review and thematic analysis methodologies [SKZM20]. Through the scoping review, key definitions and concepts of the topic were determined and then, using the thematic analysis, the reviewed studies were classified into different categories and subcategories as shown in Figure 1 (which also guides the structure of this review). Specifically, the existing research works mainly at two fundamental aspects: (i) preventing accidents by taking pre-emptive measures through the monitoring or analysis of different factors of road safety; and (ii) predicting and/or detecting accidents based on previous historical accident data and the other associated road safety factors such as weather, visibility, etc. Thus, we have divided this review into two major components: (i) accident prevention (Section 3); and (ii) accident prediction and detection (Section 4).

Research in the accident prevention category focuses on different aspects of road safety that can lead to risky situations. Major aspects are listed as follows:

- Road surface condition (potholes, cracks, bumps)
- Road users (drivers, pedestrians)
- Traffic conditions (flow, congestion)

Significant research has been carried out to minimize the adverse effects of these factors on road safety. For example, numerous studies have been proposed in the literature where the aim is to automatically identify/monitor risky road surface conditions such as potholes, bumps, and cracks [EGH+08, SZT+15, BPS+21] for their timely maintenance and also to propose improvements in roadway design and geometry such as junctions, crosswalks, signals, and roundabouts [HA21, CPS21, DSG+21]. Another vital aspect of road safety is road users, and several studies have shown that the behavior of road users (drivers, pedestrians) is one of the primary causes of road accidents [CWZ+15, NBM+18, BRP20]. This may include over-speeding, drunk driving and jaywalking. Therefore, monitoring road users and their behaviors is critical for accident prevention. Beyond driver and pedestrian behavior analysis, there are some road safety implications related to the other road users such as vehicles/bicycles and autonomous vehicles (AVs) [JRD15, PQI19]. However, in this paper, our focus is on data-driven approaches for identifying/monitoring risky human (driver, pedestrian) behavior. The readers interested in work related to vehicles/bicycles are referred to [SNHM22, HCRB21, OESU21, CD13a, CD13b, RT20, DR18, VMLM11, FYKC19]. Another critical factor that can influence road safety is traffic flow and congestion [THT+18, NS18, ARI14]. Therefore, accurate and timely traffic flow and congestion prediction are imperative in road safety analysis.

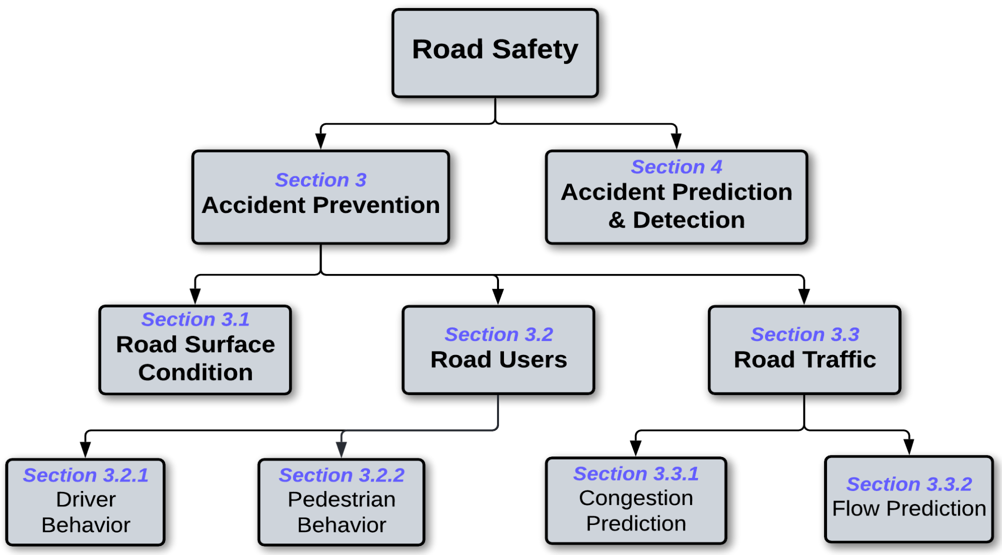

Figure 1: Scope and structure of this paper

Similarly, accident prediction and detection are essential for road safety. A vast body of knowledge has proposed various methods and systems to predict and detect accidents [XYOY19, AKFC20, WAASP15]. Reliable and timely prediction and detection are critical to assist road users in avoiding further risks and selecting safe and fast alternate routes. It also aids state police and the transportation management sector to provide timely medical assistance and restore traffic flow as early as possible. Note that accident prediction and detection have also been studied considering different factors mentioned earlier, such as road surface condition, road users, and traffic conditions [LZZ+10, CK16, GBD13]. In other words, there are some overlaps among different categories and subcategories shown in Figure 1. However, we choose these categories and subcategories to guide the organization of this review.

2.2 Review Methodology

We used the systematic literature review (SLR) approach [PSMW19] to select the relevant state-of-the-art research. Figure 2 shows the details. First, we search for the papers relevant to the different subcategories of accident prevention (see Figure 1), and accident prediction and detection. For this, we used Scopus and IEEE Digital Library databases because these two major libraries cover majority of the articles in this area. We

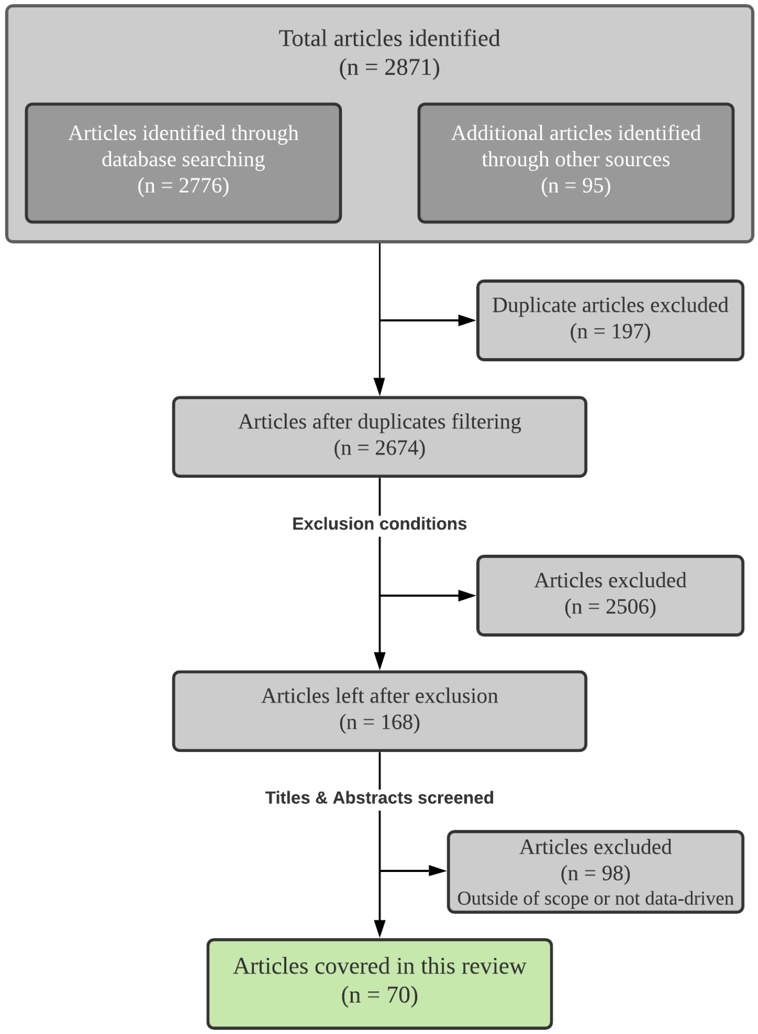

Figure 2: System Literature Review (SLR) flow diagram

use various combinations of keywords with Boolean operators "AND/OR" (search strings) for each category to identify relevant articles. Specifically, we use the following search strings where * indicates wildcard (e.g., "detect*" matches "detecting", "detection", "detected" etc.):

- **Road Surface Condition:** "road safety" AND (pothole* OR crack* OR bump*) AND (detect* OR monit*)
- **Driver behavior:** "road safety" AND "driv* behavi*" AND (reckless OR aggressiv* OR drunk* OR drows* OR distract* OR ((sudden OR unsafe) AND (brak* OR stop*)))
- **Pedestrian behavior:** "road safety" AND (crossing OR junction OR intersection) AND "pedestrian behavi*"
- **Traffic Flow & Congestion:** "road safety" AND ("traffic flow prediction" OR "traffic flow detection" OR "traffic prediction" OR "traffic detection" OR "traffic flow forecast*" OR "traffic forecast*" OR "congestion prediction" OR "congestion detection" OR "predict* traffic" OR "predict* congestion" OR "forecast* traffic" OR "forecast* congestion")
- **Accident Prediction & Detection:** "road safety" AND (crash* OR accident*) AND (predict* OR detect* OR forecast*)

The search using the above-mentioned search strings on Scopus and IEEE Digital Library returned 2,776 articles in total. In addition, we also added 95 articles manually (these included the articles that we were already familiar with or those that we found during the scoping review). In total, we had 2,871 articles, and we shortlisted the articles reviewed in this paper as follows (see Figure 2).

- We found and removed the duplicates from our list of articles. After removing the duplicates, we had a total of 2,674 articles.
- After removing the duplicates, we applied the following exclusion conditions to filter the papers. Any paper that was published in a journal not ranked Q1 or Q2 (according to Scimago Journal Rank[1]) was excluded. For conference papers, we excluded the articles published in a conference with h5-index less than 20 according to Google Scholar. If a conference was not indexed by Google Scholar, we excluded the paper if it had less than 10 citations. We also excluded the articles that were published over ten years ago (i.e., 2012 or earlier) because key big data-driven approaches on road safety mostly appeared in recent years. Finally, any article published in 2018 or earlier but had less than 10 citations was also excluded. After applying the exclusion conditions, we were left with 168 articles.
- We read the abstracts (and introductions if needed) of the remaining 168 articles and excluded the articles that were out of scope. The papers that focused on qualitative evaluations of road safety methods or pure mathematical modeling but did not present any data-driven approach were also excluded. Finally, we had a total of 70 articles which we included in this review.

2.3 Taxonomies of Data-Driven Road Safety Research

We propose three types of taxonomies to better analyze the data-driven road safety research: (i) data-driven methodologies utilized in road safety, (ii) data sources, and (iii) sensors/equipment utilized to acquire the data. We use these taxonomies to characterize and classify the articles reviewed in this paper. Next, we provide the details of each of these taxonomies.

2.3.1 Data-Driven Methodologies

We provide some of the most popular data-driven road safety techniques used in the literature as listed in Figure 3. The methodologies can be classified into three major categories: traditional statistical, machine learning (ML) and deep learning (DL) approaches. As the efficacy of a specific model is highly dependent on the data used, environmental characteristics, and the underlying problem domain, a complete analytical comparison of the existing models is difficult. As a result, different models perform better than other models in different scenarios. Thus, to opt for the most suitable method for road safety, various parameters and scenarios under consideration should be well understood beforehand [NS18].

The earlier methods for road safety typically use traditional statistical models. These approaches rely solely on fundamental statistical assumptions such as historical average and k-sampling. Therefore, these methods are unable to use external road safety-related features to minimize the uncertainty during the analysis process. However, due to their brevity and reasonably accurate outcomes, such models are commonly adopted in real-world applications.

Machine learning (ML) techniques have become very popular in solving various real-world applications [Ayo10]. The ML methods can perform well in predicting road safety-related components such as road anomalies, drowsy/aggressive behavior, accidents, traffic flows and the detection of accident-prone locations, among other things. As a result, these models outperform sophisticated mathematical models. Some popular ML techniques used for road safety research include Regression Analysis [PATY19], Decision Trees [CFRLV$^+$17, PS15] and Support Vector Machines (SVMs) [BPS$^+$21, QTM15] (see Figure 3 for details).

With the availability of large datasets and huge computing resources, deep learning (DL) techniques have become very popular in the past several years. The DL approaches have proved to be very effective in solving

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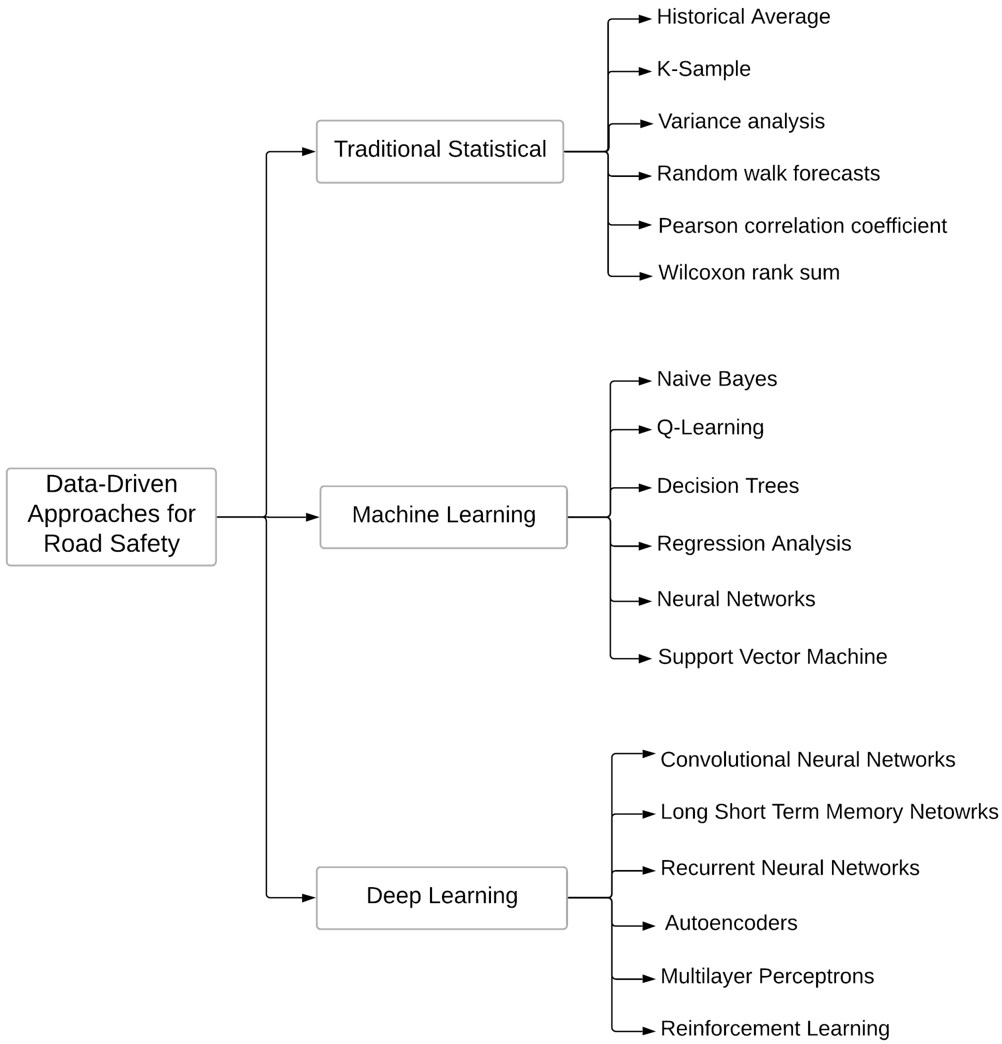

Figure 3: Data-Driven Approaches for Road Safety

challenging real-world problems. A few examples of popular DL approaches include Convolutional Neural Networks (CNNs) [FLC+20, CYL18], Autoencoders [ZYH+19] and Long Short-Term Memory Networks (LSTMs) [FWL+18]. Figure 3 shows the DL methods employed in data-driven road safety approaches.

2.3.2 Data Sources

Various data sources have been used to collect data related to road safety research. Figure 4 provides an overview of the most relevant data sources. Here, primary data is used to refer to the data collected by the researchers conducting the study. This may include observational data (such as collected through on/off-board devices or sensors, social media and simulation) and data collected using surveys (such as questionnaires). Secondary data is the data that the researchers themselves do not collect. This may be internal data collected by a government or private organization and made available to the researchers for use in their research. Alternatively, this may be external data such as open-source data or the data collected by other researchers for their research/reports.

Several existing studies used publicly available datasets. These datasets may include environmental, road conditions-related, geographical, and vehicle-specific data [DSB06, KFW11]. A lot of existing studies opted for the internal data provided by private or government organizations involved in traffic monitoring related activities, such as highway police and road security agencies [GOP20, TAT17]. Many existing studies also used primary data collected by the researchers themselves where they installed various types of equipment alongside the roads or on vehicles, such as GPS, cameras, LASER and other sensors, to collect data (acceleration, vibration, sudden lane changes, braking events, and driver's stress level and drowsiness). Social media is another common source of data that can be used to develop road safety-related models [SGP17]. Due to the widespread usage and accessibility of social media, it is now possible to acquire real-time updates from road users about traffic incidents, road infrastructure damages, parked vehicles, and incidents on the road that cannot be easily collected from other data sources. Similarly, data acquired from simulations is also used, e.g., VISSIM, which is a simulator of urban mobility [LZLH20].

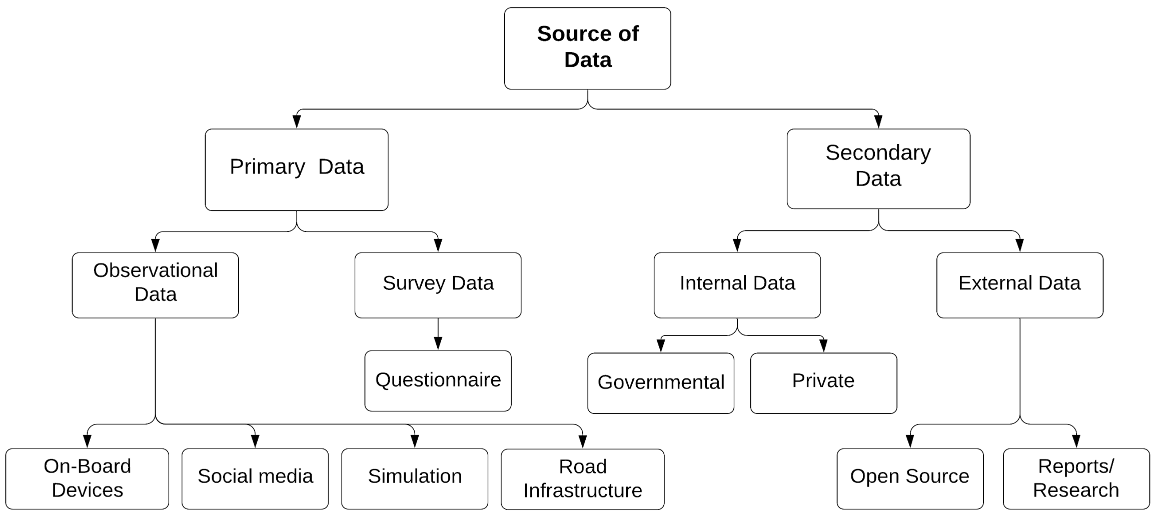

Figure 4: Different data sources used in the existing studies

2.3.3 Data Acquisition Sensors and Equipment

Various types of equipment based on different sensors have been used in the existing studies on road safety [NS18]. These sensors include but are not limited to proximity-, positional-, inertial-, optical-, auditory-, and light-based sensors. Data from these sensors have been used for road safety-related tasks such as road surface condition analysis, accident detection and prediction, and traffic and driving behavior monitoring. The types and hierarchy of sensors used for data collection in the existing studies are depicted in Figure 5.

Different types of stationary sensors at fixed positions, which can detect nearby vehicles/objects, were used to collect data in the initial generation of road safety systems. Inductive loop detectors, for example, in traffic flow monitoring, have been among the most popular. A wide range of other sensors, such as magnetic sensors, are also used [KMG06]. Video image sensors scan images from surveillance cameras on the road and offer traffic flow updates. Microwave radar sensors send out electromagnetic waves and listen for reflections from nearby objects. Infrared sensors employ low-power infrared energy transmitted by laser diodes to illuminate detection zones, then use the reflected energy to detect objects. Active sensors that broadcast scanning infrared beams in the near-infrared band over one or more lanes are known as laser radar sensors. Likewise, passive sensors such as audio sensors can be used to estimate traffic volume and density by using different audio signal processing techniques.

With the emergence of GPS-enabled vehicles and smartphones, a new type of data source has emerged that can be used to aid fixed-position sensors to acquire more precise information or obtain data on routes that are not yet covered by fixed-position sensors. The real-time and historic road safety data from GPS and other smartphone-based sensors have enabled us to produce improved and more accurate road safety-related systems. Using mobile sensing approaches, data from moving sensors are collected through GPS and other sensors (e.g., accelerometer, gyroscope), where sensors are fitted in cellphones or vehicles (such as cabs or bikes). Through this data, many road safety applications target problems connected to urban transportation systems, such as tracking public vehicles, accidents, traffic flow and congestion or detecting potholes so that authorities can respond swiftly [PSGB15].

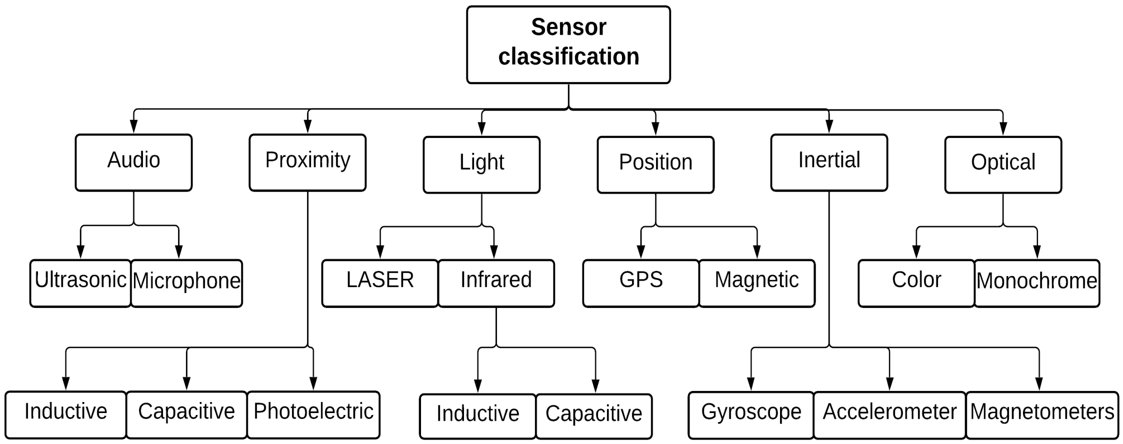

Figure 5: Data acquisition sensors

Next, we present a thorough review of existing research on accident prevention (Section 3), and accident prediction & detection (Section 4). In each section, we also present a summary of each reviewed article in a tabular format that categorizes each work based on the taxonomies mentioned above. Each table has the following columns (we provide their descriptions in parentheses): (i) Reference (a citation to the article); (ii) Real-Time (it is a checkbox indicating whether the article provides results in real-time or not, e.g., real-time pothole detection); (iii) Parameter category (it denotes the high-level category of data parameters used in the work, e.g., vehicle-related data); (iv) Parameters (this column lists the parameters used in the work, e.g., speed and acceleration of a vehicle); (v) Technique used (this lists the main technique from Figure 3 used in the article); (vi) Source of data (how the data was obtained – see Figure 4); (vii) Data type (it describes whether the data are real-world or based on simulation etc.); (viii) Smartphone (this is a checkbox indicating whether the data were collected using smartphone sensors or not); and (ix) Equipment/sensors used (this lists the type of sensors used to acquire the data – see Figure 5).

3 Accident Prevention

This section reviews the existing works that address various road safety issues to prevent accidents. Such road safety issues include risky road surface conditions, risky or reckless road users (drivers, pedestrians), and traffic conditions (flow, congestion). The rest of the section is organized as shown in Figure 1. Specifically, Section 3.1 provides a review of existing data-driven approaches to monitor and analyze road surface conditions. Section 3.2 discusses the techniques and methodologies related to the road users (drivers and pedestrians) and their behavior. Section 3.3 examines the approaches to monitor and analyze traffic conditions (flow and congestion).

3.1 Road Surface Condition

Road surface conditions (e.g., potholes, cracks, bumps, etc.) can significantly impact road safety [MSB16, HA21]. Poor road surface conditions and lousy road design can lead to accidents. Thus, road management authorities have utilized manual examination of the road infrastructure for years, prioritizing and planning road designs, maintenance and repairs [LM02]. However, such manual approaches are less efficient, time-consuming, and error-prone. In addition, there are persistent road safety challenges relating to road surface conditions, with particular concerns about rural roads (including highways), urban regions, and junction locations. These necessitate additional research in the identification of specific important road surface treatments and their impact on road safety outcome indicators, which cannot be accomplished solely by manual approaches [PMB+18, BGPL21]. Many solutions have been proposed to automate the process to overcome these limitations, such as equipping vehicles with different equipment/sensors and installing advanced equipment alongside roads to monitor road infrastructure. This section primarily focuses on road surface condition monitoring as road surface may change over time due to different factors.

Road anomalies such as potholes, cracks and bumps prevent traffic from having free and smooth flow and can cause risky situations like accidents and congestion, leading to discomfort and potential loss of lives [BPS+21, ST21, SOA+19, SVDZD+15]. Constant monitoring and regular maintenance of road surface are crucial to ensure safe travel and reduce vehicle damage. International Roughness Index (IRI) is applied worldwide for classifying longitudinal road roughness and managing road systems. IRI measures surface performance and ride quality and is highly correlated with vibration level during ride [Say98]. IRI can be calculated for each wheel track by measuring longitudinal road profiles. Different methods have been adopted to measure it, including automated inspection through vehicles equipped with special devices (such as inertial sensors) and surveying the surface manually using walking profilometers.

The rest of the section provides a comprehensive review of different data-driven approaches in road surface condition monitoring and analysis. The overall summary of road surface monitoring approaches is given in Table 1 (at the end of Section 3.1). Most of the studies reviewed in this work opted for machine learning or deep learning models [JR15, BPS+21, LCR21]. Furthermore, most approaches utilized GPS, accelerometer, and/or camera sensors/equipment (onboard) to obtain necessary data. Besides, due to the ubiquitous nature of smartphones, numerous studies utilized them for data acquisition. Similarly, the parameters mostly taken into account include speed, three-axis acceleration and road surface images.

The existing work on road surface condition monitoring can broadly be divided into three categories: 3D-reconstruction-, vibration-, and vision-based approaches [SLC18]. Next, we present a brief review of the selected studies in these categories.

3.1.1 3D-reconstruction-based monitoring

3D-reconstruction-based approaches can be classified into 3D laser scanner, stereo vision and visualization methods [KR14]. The 3D laser scanning approach uses reflective laser pulses to build precise surface models in a three-dimensional reconstruction method. To detect road surface irregularities, the output of these models is then compared to base criteria (real objects). In this approach, a 3D laser scanner is used to build accurate 3D digital representations of road surface defects such as potholes using reflected laser pulses. The anomaly characteristics are then retrieved using a collection of points representing a 3D shape of anomalies [AAU+21]. In the stereo vision approach, two digital cameras are used to construct 3D images of any object, whereas in visualization methods, a Kinect sensor and high-speed USB camera are used to detect and analyze the road surface. The authors in [AAU+21] proposed a method for 3D reconstruction of potholes for automated road surface monitoring. To generate 3D images, a laser triangularization technique and a Structure from Motion (SfM) algorithm was employed.

3.1.2 Vibration-based monitoring

In vibration-based monitoring approaches, the rates of vibration in different moving vehicles are obtained through motion sensors such as accelerometers or gyroscopes and are used to identify road surface irregularities. In theory, a vehicle will shake more when traveling over a road surface abnormality like potholes and cracks than when traveling on smooth roads. However, it does not give as much information on road surface conditions as a vision-based system. In order to compare findings, the vehicle's service condition, such as tyre pressure, should also be adjusted [KR14]. This method has been most widely used recently because of easily accessible and cheap equipment consisting of inertial sensors such as smartphones. For instance, Eriksson et al. [EGH+08], Sharma et al. [SNJ+15] and Bajic et al. [BPS+21] utilized this approach to analyze road surface anomalies.

In work presented in [EGH+08], a system to detect and report road surface conditions using mobile sensor-equipped vehicles is proposed. Using data gathered from accelerometer sensors, simple signal processing and machine learning-based methodologies were adopted to identify road anomalies such as potholes. The data is obtained through vibration and GPS sensors before it gets processed to assess the surface condition of the road. The reported results showed that their approach did not produce more than 0.2% false positive detection rate, and over 90% of accurately detected anomalies required some repair.

Another notable work to detect road anomalies is presented in [SZT+15]. The proposed method analyzes driver's behavior by utilizing inertial sensors embedded in smartphones. The extracted data is then processed to calculate the angle of swerving while considering driver's behavioral characteristics. In addition to this, they also proposed a mechanism to reduce the error in angle estimated using a gyroscope. The overall improvement in the angle was up to 2° for curves and overall, up to 5°. Using simple machine learning and clustering algorithms, their method could detect 70% of the swerves and 95% of the turns on the road. Also, their proposed method was able to detect and distinguish among various parking scenarios such as parallel parking and parking in ordinary lots. However, this algorithm has low detection accuracy in rural settings where the speed is high.

The authors in [BPS+21] introduced a machine learning pipeline to predict road conditions. In order to obtain necessary data, in-vehicle sensors such as GPS and accelerometer, were considered. They recorded the vehicle speed and vertical (z-axis) acceleration using these sensors. Various supervised machine learning models like support vector machine, random forest, linear regression were tested and compared during training and testing phases. The results demonstrated that machine learning-based methods are reasonably capable of predicting road roughness and look promising to meet future road surface monitoring demands.

A deep-learning-based approach to measuring the quality of road surface is introduced by Tiwari et al. [TBR20]. They used smartphone GPS and accelerometer sensors data. They utilized 36 hours of data collected through various types of roads and showed that the proposed method could achieve 98.5% accuracy.

3.1.3 Vision-based monitoring

The most widely used vision-based approaches are traditional image processing techniques such as extracting road texture and comparing collected pictures to detect pavement degradation signs. This method primarily relies on geotagged images of road surface collected through a video system mounted on a moving vehicle pointing downwards. For instance, using Canny edge detection algorithms [RLZS14], any potential road surface anomalies such as cracks and potholes can be automatically recognized from the pictures. Although the performance of such approaches is subject to some environmental factors like shadow effects and lightening, they are cost-effective compared to the 3D-reconstruction-based methods. Below, we briefly discuss some of the most notable vision-based approaches.

In [JR15], the authors presented a study in which they argued that road anomalies detection techniques based on vibrations and laser-scanning are insufficient and incur high costs generally associated with laser-based equipment. They developed an image processing algorithm to detect potholes based on a black-box camera. The algorithm was tested in a simulated environment while considering the limited computation capabilities of the system. The results demonstrated that the system could effectively filter pothole regions from the captured images. However, the proposed system has some limitations, such as the rate of false positives increases with the change in light intensity and poor ability to detect similar objects.

Deep learning-based techniques have recently been adopted for pothole and crack detection from images. Most of these techniques used deep convolutional network (CNN) and its variants to perform these tasks [FBZ+19, FLC+20, YZY+19, QCW+21]. Fan et al. [FBZ+19] proposed a deep convolutional neural network to determine whether an image contains cracks or not and then use an adaptive thresholding technique to determine the cracks in road surfaces. Fan et al. [FLC+20] used an ensemble of multiple CNN models and then performed several post-processing steps to identify the cracks on the pavement finally. Yang et al. [YZY+19] proposed a novel CNN based architecture, Feature Pyramid and Hierarchical Boosting Network (FPHBN), for pavement crack detection, where the network integrates context information with low-level features in a hierarchical way. Recently, Qu et al. [QCW+21] proposed attention-based encoder-decoder architecture that combines the strength of CNN based Res2Net with contextual modeling for fast detection of cracks in pavements.

Another road surface monitoring estimation system was presented in [LCR21]. They introduced a smartphone-based system capable of obtaining images of road surface anomalies and acceleration measurements of the vehicle when an irregularity in the road surface is detected. The images taken are classified based on anomaly type using a fully convolutional neural network for image recognition and gravitational acceleration measurements. The system prototype was installed on a smartphone attached to the vehicle's windscreen for automatic road-surface anomaly detection. However, their system did not account for vehicle type and speed.

Reference	Real-time	Parameter category	Parameters	Technique used	Source of data	Data type	Smart phone	Equipment/sensors used
[EGH+08]	☐	Vehicle specific	Speed and three-axis acceleration	Machine learning	Onboard devices	Real-world	☐	GPS, gyroscope and accelerometer
[SZT+15]	☐	Vehicle specific, and driving behavior	Angle of swerving, acceleration, position and speed	Machine learning, Stationary Wavelet Transformation (SWT)	Onboard devices	Real-world	☑	GPS, accelerometer and gyroscope
[JR15]	☑	Road Infrastructure	Road Images	Vision-based, Image processing	Simulation-based	Simulated images	☐	Camera
[SNJ+15]	☑	Vehicle and driving specific	Speed, three-axis acceleration, angle of swerving	Fourier and Wavelet Transform	Onboard devices	Real-world	☑	GPS, accelerometer, gyroscope and magnetometer
[LCR21]	☑	Vehicle specific and Road related	Road Images and acceleration	Fully Convolutional Neural Network (FCNN)	Onboard devices	Real-world	☑	Camera, accelerometer
[AAU+21]	☐	Road and surroundings	Road surface images and depth measurement	Structure from Motion (SfM)	Onboard devices	Real-world	☑	Cameras, LASER (pointer)
[BPS+21]	☑	Vehicle specific	Speed, vertical acceleration	Support Vector Machine, Random Forest, Linear Regression	Onboard devices	Real-world	☐	GPS and accelerometer based sensor network board
[QTM15]	☑	Road Infrastructure	Road surface images	Image processing, Support Vector Machine	Onboard devices	Real-world	☐	GPS & linear camera
[CFRLV+17]	☑	Road Infrastructure	Road surface images	Image processing, J48 Decision Trees	Onboard devices	Real-world	☐	camera

Reference	Real-time	Parameter category	Parameters	Technique used	Source of data	Data type	Smart phone	Equipment/sensors used
[FBZ+19]	☐	Road Infrastructure	Road surface images	Image processing, Deep Convolutional Neural Networks (DCNN)	Open source/ research	Real-world	☐	camera
[QCW+21]	☐	Road Infrastructure	Road surface raw images	Deep Convolutional Neural Networks (DCNN)	Open source/ research	Real-world	☑	camera
[FLC+20]	☐	Road Infrastructure	Road surface raw images	Convolutional Neural Networks (CNN)	Open source/ research	Real-world	☑	camera
[YZY+19]	☐	Road Infrastructure	Road surface raw images	Fully Convolutional Neural Networks (FCNN)	Open source/ research	Real-world	☑	camera

Table 1: Summary of the existing approaches for road surface condition analysis. Details of column names are given at the end of Section 2.

3.2 Road Users

3.2.1 Driver behavior

Driving behavior refers to how motorists behave while driving, such as taking specific actions like steering or accelerating [HA14]. Different drivers respond differently to the same situation, e.g., either applying brakes or accelerating on amber light at a traffic signal [MNO+07]. Besides, some external factors may also influence their behavior, such as human (e.g., mood, mental condition, age, demographic background and gender) and environmental (e.g., visibility, weather and traffic) parameters [MHW+17]. In a broader perspective, driving behavior could mainly be divided into two categories: 1) inattentive driving; and 2) aggressive/reckless driving [CCCZ19, Tas00, IGL21, JRD16]. Inattentive driving is when the driver is not paying attention, e.g., distracted or drowsy. Aggressive and reckless driving habits refer to actions such as speeding, unsafe overtaking, and tailgating. Several studies have highlighted driving behavior as a primary cause of traffic accidents, e.g., the U.S. Department of Transportation reported that the risk of crash/near-crash increases up to six times when someone is driving while drowsy or distracted [KDN+06]. Therefore, monitoring driving behavior is critical for improving road safety. Next, we discuss the existing studies to detect or monitor inattentive and aggressive/reckless driving.

3.2.1.1 Inattentive Driving

Among various causes accounted for risky road situations, drunkenness, distraction and fatigue are the most prevalent [CCCZ19, JXZG21, OR20a, OR20b]. Drunk drivers tend to accelerate or decelerate unexpectedly and have a slow reaction [IGL21]. A reckless driver is similar to a drunk driver in that they may be influenced by environmental or emotional stimuli that force them to abruptly change the vehicle's speed and exceed the speed limit. Similarly, symptoms of a drowsy driver include excessive yawning, quick and persistent blinking of the eyelids and irregular head movements [SSM12]. Distracted driving can be induced by various unpredictable factors, e.g., a driver has a longer response time to environmental cues and may mistakenly slow down or move the vehicle in an unpredictable manner [HXHM17, RK14]. In [FWL+18], the authors proposed a framework to predict driving behavior by monitoring eye gaze through a frontal camera. They analyzed the eye gaze patterns by employing deep learning models such as Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) networks. Another study [KHCL10] looked at how drivers' eyes moved while driving on public highways in various illumination situations. They investigated various real-life situations such as a segment of highway without street lighting, a segment of highway with street lighting, the approach to a stop-sign controlled intersection without street lighting, and the approach to a signalized intersection with street lighting. Using binary logistic regression modeling, the researchers used previously gathered eye movement data from 11 drivers traveling a pre-determined route at night to assess the likelihood of drivers gazing at specific regions on the road scene.

A smartphone-based application to monitor driving behavior is developed in [NBM+18]. In this work, a smartphone is mounted to a vehicle's windscreen, and both front and back cameras are used to observe the driver's status and driving behavior. The proposed system is a low-cost alternative to expensive sensors such as LIDAR and RADAR. The system provides real-time information about driver and driving behavior such as distraction, drowsiness, lane changing and tailgating. To avoid risky situations due to driving distractions, several other techniques have been used in the existing studies. For example, Schmitt et al. [SBM+16] used lane-keeping performance, driver attention tracking and head distance measurement to detect distracted behavior. Due to the popularity of smartphones, Papadimitriou et al. [PATY19] analyzed driving behavior during mobile phone use and collected necessary data through smartphone sensors like GPS and accelerometer. In their experiments, one hundred drivers were hired to collect real-time data. Statistical analysis was conducted using driving metrics to correlate the use of a mobile phone with other driving behavior indicators using logistic regression.

Osman et al. [OR20a] studied the feasibility of accomplishing driving behavior monitoring tasks using deep learning methods and sensory data. Three secondary activities were identified using two deep neural network models (a multi-layer perceptron neural network model and a long short-term memory networks model). These secondary activities included talking on the phone, texting, and talking to the passengers in the vehicle. The model was trained and tested using time series data from the Second Strategic Highway Research Program Naturalistic Driving Study, which was obtained using car sensor technologies. Another research [TV16] on risky road behaviors analyzed Integrated Behavioral Models (IBM) to evaluate their capability to predict three types of risky behaviors, including speeding, changing direction illegally and drunk driving. The results demonstrated that IBM could successfully predict these behaviors, particularly drunk driving. Various important parameters were considered in the model, for example, perceived severity, subjective norm and cognitive attitude. Among the parameters, perceived severity was the only one affecting all three behaviors. Similarly, the subjective norm contributed largely to predicting drunk driving and illegal direction change behaviors. The work also proposed potential measures such as campaigning public awareness to counter such risky behaviors based on the model outcome.

A research work presented in [CWZ+15] claimed that generally, distracted and drowsy driving behaviors are studied through specific devices like visual sensors and biosensors. Therefore, the objective of this work was to identify such behaviors by utilizing a set of vehicle motion parameters. They hired fifty drivers and used a vehicle equipped with all the necessary sensors and other equipment to obtain the relevant data. The vehicle motion data were recorded under four different driving scenarios: drowsiness, drinking, distraction, and talking. After collecting the data, the standard vehicle motion features were extracted and then analyzed using descriptive statistics and Wilcoxon rank-sum tests [RGTL03]. The findings showed that the yaw rate and lateral acceleration rates were significantly higher during distracted and drowsy driving when compared to safe driving behavior. In addition, it was shown that the standard deviations of both the yaw rate acceleration and acceleration rate were the applicable standard features to distinguish between safe driving and inattentive driving.

A cost-effective approach to detect road surface anomalies and driver behavior through smartphone sensors was presented in [SNJ+15]. Despite the smartphone sensors not being commercial-grade, their proposed model was able to achieve reasonably good performance and can be implemented in various settings such as commercial and private. They developed an Android application, namely "S-Road Assist", for the analysis. The model uses accelerometer, GPS, and magnetometer to use some existing algorithms and tailor these to suit their approach to detect road conditions and driver behavior such as potholes, sudden braking, and frequent lane changes. Besides, historical data was collected for anomaly detection, and real-time data was utilized for driving behavior analysis.

3.2.1.2 Aggressive/Reckless Driving

Aggressive or reckless driving is defined as a driver's willful behavior that increases crash risk and is motivated by hostility, impatience, aggravation, or a desire to save time [Tas00, IM20]. Such behavior can trigger due to stress and can result in sudden braking, tailgating, improper lane changes and driving at speeds [GQJ+14].

An essential aspect of risky driving behavior is unsafe stopping, such as sudden braking, which can compromise the safety of road users, vehicles, and fuel economy. Therefore, monitoring these actions is critical to ensure road safety while preventing accidents and injuries. To this end, various techniques have been proposed to monitor unsafe stopping. The authors in [BRP20] presented a smartphone-based system, "FullStop", to detect a specific type of risky driving behavior associated with buses, like stopping the bus some distance away or in the middle of the road. They claimed that GPS and inertial sensors could not detect, such unsafe stopping events. Therefore, they designed an algorithm to detect such events using a smartphone camera sensor and optical flow-based metrics. By mounting the smartphone on the windshield, FullStop can detect three unsafe stopping behaviors: longitudinal and lateral displacement from designated bus stops and rolling stops. Another recent study uses a fusion of visual and sensors data to decide if a driving session involves aggressive driving [KAY16]. They took pictures of road lines and vehicles, while sensors were utilized to obtain vehicle speed and engine speed. Both types of data are used to create feature vectors representing a driving session. These feature vectors are created using Gaussian distributions to model time series data. For the aggressive behavior classification, they used an SVM classifier.

In [PS15], a crowd-sensing system was proposed to capture transient traffic events along with various types of driving behaviors. To achieve this, they used GPS and accelerometer sensors integrated in smartphones. They suggested that the accelerometer data obtained from smartphone sensors alone is insufficient to detect physical activities in the traffic domain. Therefore, they paired this data with crowd-sourced traffic information to provide real-time recommendations and notifications related to road events to drivers in the vicinity. For this purpose, they employed collaborative mechanisms and participatory sensing techniques for crowd-sensing and detected important traffic-related events and situations using packet data transfer services such as cellular networks. Another work by Lattanzi et al. [LF21] distinguished between safe and unsafe driving behavior by applying machine learning techniques on the data obtained through onboard vehicle sensors. On a publicly available dataset encompassing more than 26 hours of total driving time, two different classification techniques, namely Support Vector Machines and feed-forward neural networks, were trained and assessed. They extracted the information about vehicle and engine speed, throttle position, brake pedal pressure and steering wheel angle by using an Onboard Diagnostic (OBD) device.

A study presented in [KIHM19] proposed a data mining and vision-based approach to extract features related to sudden braking behavior on the road. The candidate feature set includes vehicle features related to time and environment. Following this, a feature selection and machine learning technique was adopted to detect the most relevant features, then mapped onto the locations through the visualization process. The reported results demonstrated that some of the detected sudden braking locations were different from those obtained through frequency-based approaches. The results also concluded that the events related to sudden braking depend both on the vehicle-related factors and temporal factors such as time of the day.

Table 2 provides a summary of the data-driven techniques to monitor driver behavior.

Reference	Real-time	Parameter category	Parameters	Technique used	Source of data	Data type	Smart phone	Equipment/sensors used
[CWZ+15]	☑	Vehicle specific	Lateral acceleration, yaw rate, longitudinal acceleration and orientation angle	Descriptive statistics and Wilcoxon rank sum test	On-Board devices	Real-world	☐	GPS, accelerometer, gyroscope, camera, laser radar
[PS15]	☑	Traffic and vehicle specific	Lateral acceleration, yaw rate and longitudinal acceleration	Machine learning (J48 decision tree)	On-Board devices and road infrastructure	Real-world	☑	Accelerometer sensors
[TV16]	☐	Driver specific	Perceived severity, subjective norm and cognitive attitude	Integrated Behavioral Models (IBM)	Survey	Real-world	☐	Questionnaires
[NBM+18]	☑	Driver and driving specific	Eye aspect ratio, mouth aspect ratio, face direction, vehicle ranging and lane changing	Deep Neural Network (DNN), Image processing	On-Board devices	Real-world	☑	Front and back cameras
[KIHM19]	☐	Vehicle, temporal and environment specific	Location, X, Y and Z directions of acceleration, G-Force, date and time	Support Vector Machine (SVM)	Open source / research	Real-world	☐	GPS and accelerometer
[BRP20]	☑	Road and surroundings specific	Longitudinal and lateral displacement	Optical flow-based metrics	Onboard devices	Real-world	☑	Front and back cameras
[KAY16]	☑	Road & vehicle specific	road lane & front vehicle images, vehicle and engine speed	Hough Transform, Support Vector Machines (SVM)	Onboard devices	Real-world	☐	CCD camers & CAN bus port

Reference	Real-time	Parameter category	Parameters	Technique used	Source of data	Data type	Smart phone	Equipment/sensors used
[SBM+16]	☑	drive, road and vehicle specific	road lane monitoring, longitudinal acceleration, eye gaze	Markov decision processes	Onboard devices	Real-world	☐	mono-camera, infrared cameras, accelerometer
[PATY19]	☑	driver, and vehicle specific	location, barking, acceleration, turning	ML & Logistic regression	Onboard devices	Real-world	☑	GPS, accelerometer
[FWL+18]	☑	driver specific	Eye gaze, aspect ratio	CNN & LSTM	Onboard devices	Real-world	☑	camera
[LF21]	☐	vehicle specific	vehicle and engine speed, throttle position, brake pedal pressure, steering wheel angle	Support Vector Machines (SVM) & feed-forward neural networks (FFNN)	Open source / research	Real-world	☐	On Board Diagnostic (OBD)

Table 2: Summary of the existing approaches for driver behavior analysis. Details of column names are given at the end of Section 2.

3.2.2 Pedestrian behavior

Pedestrians also often pose a crash risk, e.g., when crossing a road while listening to music, drinking or eating, conversing/texting on the phone, or under the influence of drugs etc. Such behaviors put them and other road users at risk for injuries and deaths in the event of a collision [DDEM+10, RCR21]. Some other common factors that can increase the chances of a vehicle-pedestrian accident include their gender, age, vehicle type, and the environment around them (light conditions, weather) [AM22, DDEM+10, TS19, GBE17]. Besides, too young or old pedestrians are more likely to get injured in vehicle-pedestrian accidents due to their limited cognitive/physical abilities and higher inattention. Thus, pedestrians are classified as "vulnerable road users" because they are more susceptible to severe injuries, and existing road rules typically prioritize them to protect them better. However, this may lead to pedestrians behaving recklessly in traffic and failing to pay attention to road conditions [OAAA19]. According to recent statistics on road safety, around 6,200 pedestrians in the U.S. [A+20], and 4,668 pedestrians in the E.U. [O+21] died in road accidents in 2019, which roughly translates to one pedestrian death every two hours. Not only this, around 150,000 injured pedestrians were sent to hospitals for treatment due to minor road accidents. To this end, it is vital to monitor pedestrians' behavior on the roads to identify risky behavior and situations, which also may help road management authorities to devise safer road rules. For example, pedestrians crossing the road in a big group can significantly reduce accident risk. A study presented in [Jac15] explained this phenomenon and argued that increasing the number of pedestrians to double reduces the chance of an accident by 32% because drivers can see the pedestrians better and are aware of their presence; thus, the drivers adjust their vehicle's speed and control. Below we present a brief review of the state-of-the-art pedestrian behavior road safety research.

A study in [OTSP17] examined the critical elements of road crossing through the ground and a footbridge. It was observed that road speed limit and crossing location are critical factors in the decision-making of pedestrians whether to use the footbridges. A pedestrian may not cross the road using footbridges owing to various causes such as traffic density, distance to the footbridge, hastiness and age. Although most of the study participants mentioned that the ground crossing was dangerous compared to the footbridge crossing, one-third of the participants preferred to use the ground. The authors used logistic regression to predict the road crossing mode using features like footbridge distance, security and past frequency.

Sometimes pedestrians (especially younger ones) get distracted due to the roadside environment (such as audio or visual distractions). The effects of roadside distractions on elementary school children who have limited decision-making capabilities were explored in [TOGP18]. Various audio and visual distractions were used in a simulated environment to observe their effect on the participants. For this purpose, they utilized the Dome simulator with 180 degrees screen and an eye-tracking system. For each of the dependent measures, they applied linear mixed statistical model (LLM) [Bat07] using age, visual & audio distractions and the two-way interactions parameters to predict the effects. The findings demonstrated that when participants were exposed to surrounding distractions, they were less attentive, took longer to make a crossing decision while having slower reaction time and picked smaller crossing distances.

Other factors that can influence pedestrians crossing behavior at signalized crosswalks include red light times and the width of roads. An empirical study [BAA+21] assessed the behavior of pedestrians at signalized crosswalks. The authors performed a pilot study using 25 important pedestrian crossing factors such as gender, day of the week, temperature and cycle time. They adopted a statistical approach by applying the Chi-Square Test to analyze data and see the effects of given parameters. The results demonstrated that the gender of pedestrians affected crossing speed, with males taking higher risks than females (e.g., crossing on red or walking faster on average). When it comes to age, younger pedestrians were shown to incur more risks than older pedestrians when crossing the road on red and were more inattentive when using their phones while crossing the road.

Larue et al. [LW21] utilized the Technology Acceptance Model (TMA) [CFF07] to get insights into the acceptance of interventions aimed at attracting the attention of pedestrians who were distracted by their mobile devices. The survey consisted of demographic questions and an acceptance questionnaire based on TMA. On the approach of passive railway crossings, three alternative interventions were tested to remind pedestrians to look for trains. In-ground lights in the pathway, an audio message, and a mix of both were the interventions prompted by the pedestrian's crossing. The statistical data analysis was performed in R statistical software by calculating means, standard deviations and range for the independent and dependent variables.

Another study [ASZ18] assessed the effect of mobile phone usage on pedestrians. The impact of types of distraction (visual and aural) was studied at crosswalks to observe vehicle-pedestrian conflicts. The analysis was based on video data collected through an automated computer vision algorithm (Kanade–Lucas–Tomasi Tracker (KLT)) [Suh09] to compute pedestrians' trajectories, clustering of features (temporal and spatial) and classification of pedestrians. They utilized power spectral density (PSD) to determine the step frequency of the speed profile, and two-sample T-Tests were applied to compute and compare means and standard deviations of walking speed, walk ratio, speed-length etc. The findings demonstrated that pedestrians who are distracted while walking texting/reading (visually) or talking/listening (auditory) have significantly lower step lengths and are less stable in walking.

Diego et al. [ECHP21] explored the relationship between risky pedestrian behavior and road infrastructure while clustering the pedestrians in different age groups. The factors affecting pedestrians behavior included location, type of intersection, road geometry and their influence on various age groups. They applied descriptive & inference statistical analysis and logistic regression models to analyze the results. The study found that most behaviors do not depend on age group except at specific locations near schools due to high traffic density and relatively young pedestrians. Further, some efforts have been made to collect pedestrian behavioral data automatically and in [HSRK15], the main goal of the authors was to diagnose pedestrian safety issues and identify contributing elements at the intersection. Also, they performed experiments to show the possibility of automatic pedestrian data extraction for pedestrian behavior analysis. This research was conducted on video data employing computer vision techniques using an automated system. The Traffic Conflict Techniques (TCT) were utilized in [SZ99] to assess pedestrian safety by observing frequent traffic events involving road users' interactions. The results showed that pedestrian infractions, particularly temporal violations in which people crossed the roadway during the “Don't Walk” or flashing “Don't Walk” phase, contributed significantly to the high number of pedestrian-vehicle conflicts. Table 3 presents a summary of the existing approaches for pedestrian behavior.

Reference	Real-time	Parameter category	Parameters	Technique used	Data Source	Data type	Smart phone	Equipment/sensors
[OTSP17]	☑	pedestrian & traffic specific	walking speed, traffic density, age, distance, location	Logistic Regression	Observations/ Survey	Real-world	☐	Questionnaire
[TOGP18]	☑	pedestrian & Environmental (visual, audio) specific	walking speed, inattention level, reaction time, distance	Linear Mixed statistical Model (LLM)	Simulation	Simulation-based	☐	Dome Simulator
[BAA+21]	☑	pedestrian & road infrastructure specific	gender, speed, age, distance, waiting time, temperature, carrying load	Statistical analysis (Chi-Square Test)	Observations	Real-world	☑	unobtrusive video recording (cameras)
[LW21]	☑	pedestrian & Environmental (light, audio) specific	age, gender, walking speed, inattention level, mobile phone usage	Statistical analysis (Mean, Standard Deviation)	Observations/ Survey	Real-world	☑	eye tracker (camera), Questionnaire
[ASZ18]	☑	pedestrian & Environmental (visual, aural) specific	walking speed, inattention level (talking/listening or texting/reading), step length	power spectral density (PSD), two-sample T-Tests	Observations	Real-world	☑	video recording (cameras)
[ECHP21]	☑	pedestrian & road infrastructure specific	location, type of intersection, road geometry, age	Descriptive & inference statistic, Logistic Regression	Observations	Real-world	☐	Data collection sheets

Table 3: Summary of the existing approaches for pedestrian behavior analysis. Details of column names are given at the end of Section 2.

3.3 Road Traffic

The rapid increase in urban living has made our roads busier than ever, leading to various traffic flow related issues such as congestion, increased fuel consumption and traveling times. A significant body of research focuses on travel time prediction using traditional statistical models [RVZ04, CR12, CR14], machine learning models [CR16, ECR14], and deep learning models [ZWSZ18, HDL+21]. These works mainly focus on real-time travel time prediction, e.g., given the current traffic conditions, the estimated travel time for a vehicle to reach the destination. However, travel time prediction is beyond the scope of this work (see Section 2), and we focus on the existing studies that predict traffic flow and congestion which are imperative to safe travel and efficient road transportation. Timely and accurate predictions of congestion can lead to shorter travel times, the improved mental health of road users and a better impact on the overall economy [AM21]. It also supports traffic managers in managing road networks and utilizing resources effectively.

The rest of the section is divided into congestion prediction, short-term traffic flow prediction, and long-term traffic flow prediction.

3.3.1 Congestion Prediction

Traffic congestion is a significant problem and can lead to risky situations. In most cases, traffic congestion decreases the capacity and efficiency of road networks, and accurate and timely prediction of congestion enables taking preventative actions [THT+18]. Road users can benefit from timely congestion prediction and plan their travel accordingly. Congestion prediction can also help road transportation authorities by enabling them to make better choices (such as better alternate routes that will help reduce congestion and accident risk) and making better decisions to optimize road network to improve road safety [Coi05]. Inspired by its importance, various traffic congestion prediction algorithms have been proposed, and we review the most notable approaches below.

In [CYL18], the authors proposed a technique based on deep convolutional neural networks to predict short-term traffic congestion. The overall system was divided into two phases. Initially, a 2D matrix is constructed using historical and real-time time-series data. Then, by constructing a series of convolutions over the matrix, multi-scale congestion features were extracted, which were then fed into the network for traffic congestion prediction. Accurate congestion prediction requires large scale datasets and, in [ZYH+19], the authors proposed a system to produce traffic congestion related data on a large scale based on image analysis. They implemented a neural network (NN) model based on a deep auto-encoder with symmetrical layers to learn temporal correlations from historical traffic congestion data and to predict traffic jams and congestion of the transportation network. The results demonstrated that their method was superior to the other two state-of-the-art NN models in prediction, generalization and computation capability. However, their method is limited to only one data source based on traffic congestion snapshots. It does not consider other vital factors such as speed, volume, travel time and weather conditions which could be more meaningful to the commuters and administrative agencies. Majumdar et al. [MSR+21] implemented machine learning models, such as long short-term memory networks (LSTM), to predict traffic congestion during the next few minutes. The model incorporated vehicle-specific variables such as speed to forecast congestion propagation over a 5 minute time interval. The model was evaluated (depending on road layout) using univariate and multivariate models for prediction. The relevant data was obtained using road traffic speed sensors.

3.3.2 Traffic Flow Prediction

Accurate traffic flow prediction is essential for road safety as it helps in preventing, predicting or detecting accidents and is also valuable for incident management [MDL+17]. Therefore, traffic flow prediction has received huge research attention in the past. Machine learning and deep learning models [ARI14, CCLL18, CYL18, ER17] are among the best performing data-driven approaches for this traffic flow prediction task. Hence, we mainly focus on machine learning and deep learning models in this section. In general, the approaches for predicting traffic flow are classified into two categories: short-term prediction and long-term prediction. Short-term prediction is based on recent or even real-time data on traffic conditions. Such prediction can estimate traffic conditions 5 or 15 minutes in advance using current traffic data; but it requires a lot of historical traffic data collection. On the other hand, long-term forecasting is based on daily, weekly, monthly or yearly traffic patterns that are usually linked to the season or weather. Next, we review the approaches for both the short-term and long-term traffic flow prediction.

3.3.2.1 Short-term Traffic Flow Prediction

To predict short-term traffic flow, in [CCLL18], the authors presented a multi-model technique with the inclusion of a different time lag for each model. To achieve this, a harmony search algorithm and SVR (support vector regression) in the least-squares (LSSVR) is adopted as a base model. Initially, it builds multiple nonlinear LSSVR models before each model's output is passed to another LSSVR with the linear kernel function that produces the final forecast. The system parameters were calibrated using an improved harmony search algorithm. A unified model using Spatio-temporal metrics is introduced in [DMLZ18]. The model utilized a physically initiative approach to capture the Spatio-temporal correlation between the road traffic. This correlation is determined by incorporating time-varying lag and turning rate at intersection information. Also, the model takes into account various parameters to control diverse traffic conditions such as time-varying speed, time-varying trip distribution and road network topology. Owing to the simplicity of the variables, the computational complexity of the model was significantly reduced. Finally, the model was shown to outperform two popular models: backpropagation neural network (BNN) [HN92] and space-time autoregressive integrated moving average (STARIMA) [DWZS11]. However, it was shown that combining multiple STARIMA models outperforms this approach. In [ARI14], an approach to predict traffic flows for all the links in a transportation network was introduced owing to the scarcity of real-time traffic flow data and unforeseeable factors such as road works, public events and accidents. The model first simulated flows on all links for the training phase using on-demand, historical and limited real-time data. In the second step, by utilizing the generated traffic flow data, the model recursively predicted future flows while considering the changes in real-time data. The prediction module design was based on an autoregressive model that could adjust parameters according to uncertain events. For the model evaluation purpose, the Monte Carlo simulation methodology was adopted. For 5 and 30 minutes prediction windows, the model reported an average error of 2% and 12% in prediction, respectively. One of the limitations of this work was not being able to evaluate the model due to a lack of sufficient data related to the incident and normal traffic conditions.

3.3.2.2 Long-term Traffic Flow Prediction

In [ZFW+19], the authors present techniques for long-term traffic flow prediction such as for the next day as it is crucial for traffic management and planning. To this end, a residual deconvolution-based deep generative network (RDBDGN) was proposed. The whole model can be considered a Generative Adversarial Network (GAN) consisting of a discriminator and a generator. The discriminator was composed of a convolutional neural network to optimize the adversarial training process. In contrast, the generator consisted of multi-channel residual deconvolutional neural networks aiming to retrieve useful periodic and Spatio-temporal based features for the forecasting. In [AZW18], the authors proposed a traffic prediction model using ML techniques such as ensemble decision trees for regression, namely the gradient boosting regression trees (GBRT) and random forest (RF). In addition to sensory data, they also utilized accidents and roadworks data because these also impact the traffic flow. Another study on long-term traffic flow forecasting [QLL+19] introduced a supervised learning algorithm consisting of Deep Neural Network (DNN) to forecast daily traffic flow based on contextual factors (day of week, season, weather) and historical traffic data. The method first runs the training phase using the multi-level supervised learning algorithm to determine the correlation between key contextual factors and historical traffic flow data. Besides, a batch training approach was proposed to reduce the time taken by the training phase. To evaluate the performance of the method, a Seattle-based case study was adopted where the results demonstrated that their method outperforms the other conventional methods. However, their method does not examine special events such as construction activities and accidents which can notably affect the traffic flow. Similarly, [SAB20] tested various ML-based prediction models for traffic prediction by taking into account both the computational time cost and prediction accuracy. According to their analysis, supervised machine learning-based prediction models are better suited to delivering accurate long-term traffic flow predictions.

Table 4 presents a summary of the existing data-driven approaches on traffic flow & congestion prediction. The most common equipment for data collection for traffic flow prediction is the inductive loop detector. Other commonly used equipment/sensors include magnetic sensors, cameras, microwave & laser radars, active and passive infrared and audio based sensors. However, onboard equipment and smartphones have rarely been used for traffic flow prediction.

Reference	Real-time	Parameter category	Parameters	Technique used	Source of data	Data type	Smart phone	Equipment/sensors used
[ARI14]	☑	Vehicle and traffic specific	Speed, volume	Auto-regression, Monte Carlo	Governmental	Real-world (historical & real-time)	☐	Inductive loop detectors
[MSR+21]	☑	Vehicle specific	Speed, flow, length, headway	Long short-term memory networks (LSTM), uni-variate and multivariate models evaluation	Road Infras-tructure	Real-world	☐	Inductive loop detectors
[CCLL18]	☑	Traffic specific	Flow, time interval, time lag	Linear squares support vector regression (LSSVR), harmony search algorithm	Road Infras-tructure	Real-world	☐	Inductive loop detectors
[DMLZ18]	☐	Traffic specific	Time-varying speed, time-varying trip distribution	Unified Spatio-temporal model	Open source/ research	Real-world (historical)	☐	Dual-loop detector stations
[ZFW+19]	☐	Traffic specific	Density, speed	Residual deconvolution-based deep generative network (RDBDGN)	Governmental	Real-world (historical)	☐	Loop detectors
[QLL+19]	☐	Traffic specific and weather	Traffic flow, occupancy and point speed	Deep neural network (DNN)	Private research lab	Real-world (historical)	☐	Loop detector
[CYL18]	☑	Traffic specific	Day, time, location and vehicle ID	Deep convolutional neural networks	Road Infras-tructure	Real-world (historical & real-time)	☐	Road network equipment including cameras
[ZYH+19]	☐	Traffic specific	Road network images, traffic congestion levels	Deep auto encoder based neural network	Governmental	Real-world (historical)	☐	Road network Cameras

Table 4: Summary of the existing approaches for predicting traffic flow & congestion. Details of column names are given at the end of Section 2.

4 Accident Prediction and Detection

In recent years, significant research efforts have been spent to develop accident prediction models (APMs). These help road authorities and decision-makers in analyzing potential road safety problems. Reliable and timely prediction and detection of the accident is also critical in assisting drivers to avoid further risks and selecting safe and fast alternate routes. Academics across the globe have investigated the impact of different road safety measures by taking into account accidents frequency (number of accidents/year), severity of incidents (level of injury), and other associated factors [YDL+17, SSP16, AKFC20, WAAC+18]. This section summarizes the existing works on accidents under two sub-categories: accident prediction and accident detection.

4.1 Accident Prediction

Vehicle-, traffic-, road surface-, driver- or weather-related information can be utilized to predict accidents, and leveraging more than one of these elements can enhance the accuracy of the prediction system [LZZ+10, ZSM21]. In [WAASP15], the authors employed a Bayesian logistic regression model to predict an accident on weaving segments of an expressway. The proposed multi-level model utilized Microwave Vehicle Detection System (MVDS) along with weather-, geometric- and crash-related data. According to the study, wet pavement conditions increase the chances of an accident, and the results demonstrated that traffic volume, the speed difference between weaving and non-weaving segments and speed at the beginning of the weaving segment significantly account for a high crash risk. The study was conducted using a limited weaving segment sample size, and therefore, is not scalable in various weaving segment types and speed limits. In [WXD19], the authors proposed a bivariate extreme value theory-based (EVT) crash prediction framework involving driver's failure to percept along with failure to take evasive action. To collect visual data of ten intersections in Fengxian China, they used an unmanned aerial vehicle (UAV). They showed that bivariate EVT models are better at predicting angle and rear-end accidents when compared to univariate models. Another similar study [GAAX+19] assessed the accident risk during mandatory merging at freeway interchange merging points. They obtained video footage of individual vehicles on the freeway through an unmanned aerial vehicle to collect trajectory information. A logistic regression model based on multi-level random parameters was proposed to investigate each driver's merging behavior in the acceleration lane. The model can also identify various factors pertaining to driver's ability and traffic conditions that can impact merging behavior. In addition to this, a time-to-collision safety measure was paired with the model's output to estimate accident risk between surrounding vehicles and merging vehicles. The results suggested that the merging location, driving ability and merging speed can largely affect the accident risk at interchange merging locations.

The prediction capabilities of machine learning (ML) and deep learning (DL) models for accident prediction is explored by Athanasios et al. [TCA19], and for this purpose, the data from Attica Tollway in Greece related to real-time traffic and weather conditions were combined with historical data. It was shown that the DL models generally performed better than the ML models. However, their results also showed that the Naïve Bayes model achieved a good performance despite its simplistic architecture. They also showed that the total rainfall and standard deviation of speed were significantly correlated with high crash risks. Besides, the goal of the study in [GSF18] was to create a prediction model for urban roadways that can anticipate the number of accidents in three scenarios: a roundabout, a three- or four-way intersection, and a straight stretch of road. It was also shown that the proposed Poisson's and negative binomial algorithm based models could easily be used to predict accidents or identify black spots.

In [XYOY19], the authors focused on identifying high-risk locations by utilizing data generated from connected vehicles (CV). In order to enhance the system accuracy, along with traditional surrogate safety measures (SSMs) [AHB+21], the study proposed time-to-collision with disturbance (TTCD) for risk detection by introducing hypothetical disturbance. The results demonstrated that by using TTCD, the system achieved a better Pearson correlation coefficient with rear-end crashes when compared to traditional SSMs. Since high-risk locations detected through CVs data were similar to those detected through historical data, it significantly reduced the data collection time. However, the vehicle trajectory measurement in the data could be prone to significant errors, and crash data obtained could contain false negatives.

In another work [AKFC20], the authors used a micro-simulation model to examine the effects of varying traffic conditions at signalized intersections on the risk of left-turn crashes. An approach involving surrogate safety measures and a calibrated model was adopted to develop an analytical tool. As a surrogate measure of left-turn crash risk, the expected number of conflicts for every 100 left-turning vehicles was considered. To analyze the probability of risk, traffic, intersection geometry and signal timing information were also considered in the simulation. Based on the simulation results, various statistical models were developed to discover the risk of left-turn crash occurrences per given hour.

Wang et al. [WKF19] used a backpropagation neural network model to predict the accident risk on expressways. Based on the simulation experiment results, a two-staged model was created that classified accident risk into three categories: no risk, low risk, and high risk. Similarly, to predict highway accidents, Singh et al. [SPYS20] employed deep neural networks (DNN). According to the study's findings, the DNN strategy outperforms both Random Effect Negative Binomial (RENB) and Gene Expression Programming (GEP) techniques.

The authors in [XCL17] proposed a framework for predicting traffic collisions based on an SVM that identified driver maneuver as leaving lane (LL) or remaining in lane (RL), and a Gaussian-mixture hidden Markov model (HMM) was used to recognize the accident versus non-accident situations. Another ML-based methodology is introduced in [SSP16] in which the authors explored how the M5 model tree and the fixed/random effect negative binomial (FENB/RENB) regression model could be used to forecast non-city sector accidents on the highway. The results reveal that the two models work pretty well in terms of correlation coefficients and root mean square error values.

A visibility monitoring and traffic monitoring system consisting of a remote traffic microwave sensor (RTMS) and wavetronix smart sensor HD for fog monitoring was proposed in [PAASY17]. These sensors can provide accurate visibility and vehicle-related data such as speed, category, lane assignment, and length. Several surrogate safety measures were employed to compare and analyze the reduced visibility cases with the clear visibility cases. Also, vehicle type and different freeway lanes related information were incorporated in the system to identify the impact of reduced visibility due to fog on the crash risk. The Log-Inverse Gaussian regression model was implemented to explore the relationship between visibility, time-to-collision, and other surrogate safety measures. They studied the impact of visibility as the type of vehicle, and freeway lane under consideration varies, and the results demonstrated that reduced visibility considerably increases the probability of crashes such as rear-end crashes. For example, in some foggy conditions, a driver of the following vehicle might not see the vehicle's brake lights in front. Thus, [WAAC+18] proposed a method to warn the driver about braking of the vehicle in front via a warning message or an alert to avoid rear-end collision.

4.2 Accident Detection

Traffic flow data from roadside equipment such as loop detectors and microwave radars can be used to detect accidents. Systems utilizing such data generally detect accidents based on vibration generated by the impact. Similarly, other types of equipment/sensors are also being used for this purpose like, ultrasonic sensors and CCTV cameras [LTZL09, KJN17]. Due to the emergence of new and sophisticated technologies, other devices/equipment such as smartphones, GSM, GPS, VANETs and mobile apps are also used in different detection systems [NK16, Lee11, WDZG20]. In the past two decades, a large body of work has focused on accident detection by analyzing vehicle interactions, traffic flow patterns, and vehicle trajectories [TZFL10, HXF+06, Lee11]. The study in [HWS20] aimed at exploring the viability of using deep learning (DL) models for crash detection and crash risk prediction. Data related to sensor occupancy, speed and volume were obtained through roadside radar sensors. This real-world data was then used to extract useful features for the DL models. It was found that convolutional neural networks (CNN) with drop-out operations outperformed basic ML models in terms of classification accuracy. The results showed that DL models generally have better performance for accident detection than the ML models. For the prediction, it appeared that they had similar performance. In addition, for crash risk prediction, a sensitivity analysis was also performed using various time-slots prior to the crash occurrence, and it was revealed that it is hard to predict the risk 10 minutes before the crash.

In [WDZG20], the authors presented a methodology to detect crash events in low-visibility conditions based on visual data for mixed traffic conditions. After collecting images under low visibility (e.g., fog, darkness, heavy rain, etc.) conditions, they applied a Retinex image enhancement algorithm [RJW04] to improve the image quality. Towards crash detection, first, multiple crash-related objects such as fallen cyclists and vehicle rollover were detected from the images by implementing a Yolo v3 model [XLY+20], which was then trained on the captured images. Based on the Yolo model outputs, features were extracted for crash detection model training. The experimental results showed that the model outperformed the traditional empirical rule-based models. A recent study [AAI+21] introduced a real-time social network-based traffic accident and condition analysis. A query-based crawler was used to extract relevant data from social networks, and the data was transformed into a structured format. An ontology and latent Dirichlet allocation (OLDA) [AKK+19] based topic modeling approach was adopted for sentence labeling to extract meaningful traffic information. Following this, the sentiment analysis of the sentences was performed to identify traffic's accurate conditions. Once the data was prepared, a bidirectional long short-term memory (Bi-LSTM) [LSCC19], and FastText [WM92] models were trained to detect the traffic condition and events. The results demonstrated that their model is reasonably capable of detecting accidents.

Table 5 presents a summary of the existing approaches for accident prediction & detection.

Reference	Real-time	Parameter category	Parameters	Technique used	Source of data	Data type	Smart phone	Equipment/sensors used
[WAASP15]	☑	Weather, vehicle specifics and surroundings	Speed, weather, road geometry	Bayesian logistic regression	Open source / research	Real-world	☐	Remote Traffic Microwave Sensor (RTMS) radars
[PAASY17]	☐	Vehicle specifics, surroundings and weather	Speed, traffic density, weather, time of day, vehicle trajectory, SSMs	Log-Inverse Gaussian regression model	Research / Open source	Real-world	☐	Magnetoresistive, sonar, microwave and other sensors
[XYOY19]	☐	Vehicle specifics, surroundings	Speed, traffic density, Time of day, vehicle trajectory and SSMs	Pearson correlation coefficient	On-Board Devices	Real-world	☐	On-board connected vehicle sensors
[GAAX+19]	☐	Vehicle and driving specifics	Distance, road geometry, time of day, travel time, driver behavior, SSMs, traffic density, speed, congestion	Logistic regression analysis	Observational	Real-world	☐	UAV cameras
[WXD19]	☐	Driving and vehicle specific	Driver behavior, SSMs, vehicle trajectory	Bivariate extreme value theory	Observational	Real-world	☐	UAV Cameras
[TCA19]	☑	Traffic and vehicle specifics	Speed, traffic density, congestion level, time of day, travel time	Machine learning	Private / Open Source / Research	Real-world	☐	Loop detectors
[WDZG20]	☐	Weather and surroundings	Weather, environment	Machine learning	Road infrastructure	Real-world	☐	Cameras
[AKFC20]	☐	Traffic and vehicle specifics	Speed, vehicle trajectory, SSMs	Generalized linear mixed regression	Simulation-based	Simulation	☐	Simulation-based
[HWS20]	☐	Traffic and surroundings	Traffic density, speed and congestion level	Machine learning	Governmental	Real-world	☐	Remote Traffic Microwave Sensor (RTMS) radars
[AAI+21]	☑	Social networks	Tweets, messages, comments	Natural language processing	Social media	Real-world	☐	Social networks-based

Reference	Real-time	Parameter category	Parameters	Technique used	Source of data	Data type	Smart phone	Equipment/sensors used
[XCL17]	☐	Traffic & vehicle specifics	Time to collision, initial speed, distance	SVM & Hidden Markov Models (HMM)	Simulated onboard equipment	Simulation	☐	simulation-based
[WKF19]	☐	Traffic & road specifics	speed, headway distance, traffic volume	Back Propagation Neural Networks	Simulation-based	Simulation	☐	simulation-based
[SSP16]	☐	Traffic & road specifics	speed, traffic volume	M5 Model Tree (Decision Trees)	Governmental	Real-world	☐	Remote Traffic Microwave Sensor (RTMS) radar
[WAAC+18]	☑	Traffic, weather & road specifics	date, time, visibility, speed, length, lane	Statistical analysis (Chi-square test, Logistic model)	Road Infras-tructure	Real-world	☐	Fog monitoring system (FMS) & Remote Traffic Microwave Sensor (RTMS)

Table 5: Summary of the existing approaches for accident prediction & detection. Details of column names are given at the end of Section 2.

5 Challenges and Future Research Directions

In this section, we discuss some of the major challenges and possible future research directions in data-driven road safety research. Perhaps not surprisingly, most of the research challenges are data related such as challenges in data collection, poor data quality, and lack of ground truth data. Next, we discuss these and other challenges, and also highlight potential future research directions to address these.

5.1 Data Collection

Data collection is typically the first and most important step for data-driven road safety research [QCW+21, YZY+19, FLC+20, EGH+08, LCR21]. The techniques employed for data collection by the existing research on road safety face at least one of the following major challenges: (i) Data collection is typically labor-intensive and time consuming. For example, the techniques that rely on capturing road images for monitoring road surface conditions require operating dedicated vehicles to collect new surface images on a regular basis [JR15, JR15, QCW+21]. (ii) Many data collection techniques rely on expensive and specialized equipment. For example, techniques that adopt 3D-reconstruction methodologies for road surface condition monitoring typically need high-cost laser scanners and thus can be prohibitively expensive for large-scale road networks [AAU+21, AAU+21]. (iii) Another major data collection challenge is the lack of real-time and/or large data sets. In several road safety problems, static, outdated and/or small datasets are not sufficient and lead to poor quality results. For example, in the existing research works where the primary focus is to assess the effect of various interventions on road users (e.g., pedestrians), a small number of participants were generally recruited. However, due to the small sample size, it is difficult to infer and generalize any outcomes to the larger population. (iv) Inherent limitations of certain equipment/sensor used for data collection also pose major issues. For instance, many data-driven road safety methods rely on smartphone sensors to capture necessary data. However, smartphone sensors alone cannot capture many vital parameters that include but are not limited to headway/rear-end distances, visual parameters like eye gaze behavior and driver reaction time (such as acceleration or brake response etc.).

Addressing the key challenges related to data collection is a key future research direction. For example, there is a need to investigate whether cost effective sensors can be used instead of more sophisticated and expensive sensors. E.g., instead of relying on expensive laser scanners one may use cheap laser scanners that produce dense point clouds or a variety of data from OBD-II devices/smartphones to monitor road surface conditions. One of the possible solutions to solve data scarcity issue is to study the effectiveness of crowd-sourced based approaches to collect and integrate massive data from edge devices. This will also make the data collection less labor-intensive. More advanced devices and setups (such as technologically advanced smartphones, multiple cameras, 5G networks, etc.) can be used to overcome the equipment data collection capability issues. For instance, pedestrian data may be collected from CCTV cameras and labeled manually or using advanced machine learning approaches. Also, new machine learning and deep learning techniques are needed that are specifically designed for the cases when the datasets used for training are small or not up-to-date. For example, it may be possible to exploit the data collected for one region to do similar tasks for another region or one may explore using the datasets collected to solve one particular problem to address another similar problem. Finally, a coordinated effort is needed by the research community and other organizations to make their datasets publicly available.

5.2 Data Quality

High-quality data is crucial for any data-driven approach as the quality of the data directly affects its accuracy and utility. The existing data-driven approaches for road safety face several challenges regarding poor data quality due to the type of equipment/sensors used, observation strategies, undersampling etc. Next, we provide details of some major challenges related to data quality. (i) Different equipment/sensors have different signal reading accuracy and integrating data from different types of equipment/sensors without taking into consideration their peculiarities leads to poor data quality. For example, fluctuating signals coming from different vibration-based sensors may introduce noise in the data which can affect the classification results. Similarly, if a technique utilizes smartphone sensors to capture necessary data for training, due to the varying quality of sensors used in different smartphones, the prediction accuracy suffers if a different smartphone is being used during prediction. Hence, inconsistency in the distribution and quality of data require tailored analysis and prediction methods [SZT+15, YZY+19, FLC+20, AAU+21]. For example, an inherited issue with GPS is error-prone speed estimation of up to 1.4m/s, which can result in noisy data [YZH+15]. Many approaches utilize an accelerometer sensor to get information about vehicle jerkiness [PS15, LF21, SBM+16]. However, this phenomenon greatly depends on the actual state of the vehicle (i.e., stopped, moving slowly or very fast) and can affect the quality of classification results. (ii) In some scenarios, direct observation at a specific time and day is a common data retrieval mechanism in road safety, such as pedestrian behavior analysis. However, it may introduce biases for pedestrian behavior interpretations. Another drawback is that the study participants are often asked to complete certain activities which may not accurately reflect their actual behavior in everyday life. (iii) Missing or incomplete data is another major challenge. Different sensors may have different data generating frequencies and some sensors may have been unable to generate data for some duration leading to missing values. Similarly, data integrated from different sources may be incomplete due to different data collection techniques and strategies adopted by different sources. This leads to major issues. For example, as traffic flow prediction is a nonlinear dynamic problem due to accidents and road works, in most cases, the data used in the research does not contain information about these events [ZFW+19, QLL+19, SAB20]. However, the data related to such events is critical in predicting long-term traffic predictions.

To address the challenges mentioned above, some future directions are presented next. Firstly, considerable efforts are needed to clean noisy data before it can be used and, for this purpose, data acquisition, cleaning and analysis methods must be designed accordingly to optimize (and ideally automate) the whole process. Also, robust learning algorithms must be designed that can deal with missing or incomplete data, at least to some extent. In addition, different comparison studies may be performed to evaluate the effectiveness of various models (e.g., Bayesian deep learning models) and can be an interesting future research direction. Secondly, to address the issues associated with different equipment/sensors, one possible solution is to design algorithms that take into account small fluctuations and uncertainties in data during the training phase. To address data quality related issues associated with observations/surveys, one possible direction is to use some extra means to record/obtain the necessary data. For example, video recordings may better capture behaviors and potentially dangerous circumstances and allow for more in-depth investigations in some scenarios, such as road users behavior analysis. Also, intelligent data filling techniques tailored for road safety applications must be designed to handle the missing data problem. To handle false classification issues, non-deterministic clustering and classification algorithms such as Fuzzy C-Means (FCM) can be utilized, which in most cases will generate globally optimum results. Moreover, more effort can be made for multi-level classification, for example, classifying congestion by considering non-traffic related parameters (e.g., fog, rain, day, time etc.).

5.3 Ground Truth Data

Obtaining ground truth data (e.g., labeling risky and safe conditions) is one of the fundamental challenges for data-driven road safety approaches, particularly in supervised learning. For example, while it is possible to collect a large set of images (or readings from smartphone sensors) for the task of monitoring road surface condition, obtaining the ground truth data (e.g., the actual locations of potholes on the road network) is much harder as it requires manually labeling the data. Novel techniques are required to handle this major challenge. For example, crowd sourcing the ground truth data is one possible option. However, the crowd sourced data may contain inconsistencies and techniques must be designed to handle such inconsistencies. Another promising solution is to first manually collect a small set of ground truth values and then evaluate the existing algorithms on this small data to confirm their effectiveness. Based on the effectiveness of these algorithms for the small ground truth dataset, one can create a large set of *loose ground truth* values which are the values recorded if these algorithms report the same value at a certain location many times. A similar solution was successfully employed in [EGH+08] for pothole detection. However, the techniques need to be generalised for other important road safety problems. Another possible solution to overcome the lack of ground truth data is redefining the relationships among various parameters (e.g., speed, yaw rate, longitudinal and lateral accelerations, etc.) of the vehicle and then using some classification tools to label the data. Finally, unsupervised learning approaches [PS15, FWL+18, PATY19] must also be explored that do not rely on ground truth data.

5.4 Miscellaneous

Modeling human behavior is an inherently challenging problem. Researchers have recently started to look into different psychological aspects of human behavior by exploiting social media [AAI+21, SGP17]. However, these works are still preliminary and more research is needed to better predict human behavior especially in the context of accident prevention, prediction and detection. Considerable research has been conducted to understand and predict pedestrian behavior mostly using statistical methods (due to limited dataset size). However, there are some limitations in the context of experimental setup and many of the existing studies use simulated environments in controlled laboratory settings. Validity of such techniques is still in question for pedestrian behavior analysis as the participants are not in a real environment. Also, as many studies focus on environmental effects, it would be useful to conduct similar studies in real surroundings, either through a field study or by showing panoramic recordings from real-world environments in a laboratory setting. Moreover, future work on the impact of distraction on pedestrian behavior may take into account the content, context, and sentiment of the distractors. For example, advertising billboards with more appealing material for youngsters may cause greater disruption for them than for the other age groups.

There are also some challenges faced by the road safety research community due to different model parameter settings, traffic scenarios, and prediction intervals particularly in ML- and DL-based methods. For example, it is not easy to evaluate the proposed methods for short-term traffic prediction and only up to 15 minutes of prediction intervals are generally considered for the single-step prediction phase, which is insufficient because most vehicles remain on roads for extended periods (more than 15 minutes) and require traffic information during that time. Multi-step prediction can be one of the possible solutions to address this shortcoming. In addition, when the traffic volume is massive and conditions are mixed (road infrastructure, weather etc.) [MOL+21], the short-term traffic prediction algorithms lack in meeting the forecasting demands and cannot achieve high accuracy. To this end, new methodologies for short-term traffic are sought to deal with big-data environments.

Many of the current accident prediction models aim to predict or detect incidents on expressways and freeways because traffic flows on these are uninterrupted and mainly consist of controlled access points [WKF19, RZW15, WAASP15], which help reducing the complexity and variability of the model development process. However, such road types constitute a relatively small percentage of the existing road network. It is important that future research studies also focus on urban road networks including intersections, roundabouts etc. Furthermore, certain machine learning algorithms may be unable to gather critical information from data sources such as social networks, adversely affecting the accuracy of predictions. Among the future possibilities, the scope of the proposed models can be enhanced by taking into account heterogeneous data sources that may include traffic statistics (such as volume), social & personal data (such as videos, audios, texts etc.) and spatial information. Similarly, there is only limited research on accident detection in mixed traffic flow environments with low visibility. Thus, in future, these limitations need to be addressed by considering mixed traffic environments while leveraging big data for the detection purposes.

6 Conclusions

In this paper, we present a systematic and comprehensive literature review on data-driven approaches for road safety. We present several different taxonomies and categorize the modern data-driven road safety techniques using these taxonomies. The review covers all major aspects of data-driven based road safety research including monitoring, predicting and detecting risky road surface conditions, road user behavior and traffic conditions. We analyze all these aspects under two broad categories: accident prevention; and accident prediction & detection. We have systematically selected and reviewed more than 70 influential papers from different subdomains of data-driven-based road safety. We critically examine the existing techniques and present their summaries in a tabular format using the taxonomies presented in the paper. Finally, we highlight several major research challenges and outline possible future directions for data-driven road safety research. This multi-disciplinary work can be hugely beneficial in bridging the gaps among researchers and practitioners in the fields of computer science, data science and transport engineering.

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