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Intelligent Transportation and Control Systems Using Data Mining and Machine Learning Techniques: A Comprehensive Study

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ABSTRACT Traffic congestion is becoming the issues of the entire globe. This study aims to explore and review the data mining and machine learning technologies adopted in research and industry to attempt to overcome the direct and indirect traffic issues on humanity and societies. The study's methodology is to comprehensively review around 165 studies, criticize, and categorize all these studies into a chronological and understandable category. The study is focusing on the traffic management approaches that were depended on data mining and machine learning technologies to detect and predict the traffic only. This study has found that there is no standard traffic management approach that the community of traffic management has agreed on. This study is important to the traffic research communities, traffic software companies, and traffic government officials. It has a direct impact on drawing a clear path for new traffic management propositions. This study is one of the largest studies with respect to the size of its reviewed articles that were focused on data mining and machine learning. Additionally, this study will draw general attention to a new traffic management proposition approach.

INDEX TERMS Artificial intelligent, data mining, intelligent transportation, machine learning.

I. INTRODUCTION

Nowadays, the capabilities of roads and transportation systems have not evolved in a way that is efficiently copes with the increasing number of vehicles and growth of population. Due to this, traffic jams and road congestion have increased. TomTom® reported that the commuters in 2014 spent on average 66 more hours stuck in traffic than they did in 2013 and a trip that might take 60 minutes in non-congested traffic will take 57 minutes longer during rush hour [1]. Since current expansion of the existing roads network is limited, it is essential to develop technologies to make road infrastructure well-organized, which allows smooth running of traffic. The traffic congestion issues have some other indirect overseen issues such as noise, pollution and increase travelling time. INRIX reported that the economic loss in the U.S. is estimated as \$121 billion in 2011 and is expecting to increase up to \$199 billion in 2020 because of traffic congestion [2]. Having all these concerns in mind, it was essential to think of a solution to overcome these concerns and manage traffic.

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Predicting traffic and dealing with it has taken a great attention and became a vital issue in big and smart cities.

Cities municipalities, governments, companies, and researchers have proposed many solutions to solve the traffic jam problem. Some of these solutions are using adaptive traffic signals, vehicle-to-infrastructure smart corridors, autonomous vehicle technology, real-time traffic feedback, tracking pedestrian traffic, car sharing, and multi-modal solutions. Most of these solutions are based on the concepts of Internet of Things (IoT), Wireless Sensor Networks (WSN), and Data Analytics (DA) approaches. Other partial solutions were offered including: 1) construction of new roads, bridges, tunnels, flyover, and bypass roads, 2) creating rings and performing road rehabilitation.

Traffic congestion refers to an excess of vehicles on a portion of roadway at specific time resulting in slower speeds and longer trip times and it is a major challenge in the area of traffic management and transportation planning [3]. It cannot be solved completely, but it can be solved to some extent. Informing road users in advance about the road status will help in minimizing the opportunity of occurring traffic congestion and allowing road users to make better decisions during their journey. This information includes quantifiable measures of traffic congestions, which can be represented by estimating some traffic parameters such as travel time and traffic density. Measuring these parameters from the field is very difficult [3]. Traffic congestion to the traveller means lost of time, missing opportunities and frustration. While to the employer it means lost worker productivity, trade opportunity, delivery delay, and increased cost. Reducing traffic congestion will provide safe transits to people, reduce number of accidents, reduce fuel consumption, help in controlling the air pollution, reduce waiting time and realize smooth motion of cars in the transportation routes, and help in providing the required data for future road planning and analysis. There are different causes of traffic congestion, such as insufficient capacity, unrestrained demands, large red light delay, and obstacles in the road such as accidents, random vehicle stops, double parking, road work, and road narrowing down.

Traffic generates huge amounts of data that are collected from different types of devices, such as intelligent cameras and sensors. So, there is no issue in collecting these data; the challenging issue is how to store, handle, process, analyze and manage the increased amounts of traffic data to be make useful use of it. The above-mentioned approaches mainly focus on analyzing huge amount of traffic data to extract certain aspects of traffic data -including but not limited to-traffic speed, traffic volume, vehicle arrival rate, and average waiting time.

Data mining is the process of analyzing, predicting and discovering interesting knowledge and hidden patterns from large amounts of data stored in repositories, such as databases and data warehouses [4]. This process includes statistical models, mathematical algorithms, and machine learning methods [4]. Using data mining technology in traffic management provides a powerful analysis and processing function of mass traffic data and directs drivers and systems to make better decisions. Knowledge mining and discovery is an emerging area in traffic management systems focuses on using and analyzing large amount of traffic data to be used for traffic control, route guidance, or route programming.

Despite the advancement progress in various aspects of intelligent transportation and traffic management areas, only a limited number of surveys can be found that review the growing body of literature focusing on data mining, artificial intelligent algorithms and techniques adopted in these areas. Among those, data mining methods and clustering techniques have been reviewed in [5], while Zhang et.al in [6] reviewed the data-driven approaches used in Intelligent Transportation Systems (ITS). In this paper, we investigate the usage of data mining and artificial intelligent techniques in managing traffic systems and puts forward a hierarchical architecture that summarizes and classifies these mining techniques. In this survey paper, we do not follow the typical one-by-one review; instead we provide an issue-based structure that reviews the state-of-the-art research for improving intelligent transportation, traffic management and control systems. More than 150 research articles published between 2010 and 2018 (32 from 2018 only), shown in Figure 1, were collected and reviewed from the leading journals and conferences in these areas. Some of these journals are: IEEE Transactions on Intelligent Transportation Systems, IEEE Intelligent Transportation Systems Magazine, International Journal of Intelligent Transportation Systems Research, International Journal of Transportation, Journal of Transportation Engineering, Part A: Systems, Journal of Transportation Systems Engineering and Information Technology, Transportation Engineering – Periodica Polytechnica, and Journal of Traffic and Transportation Engineering. Some of leading conferences are: IEEE Intelligent Transportation Systems Conference, IEEE Vehicular Networking Conference (VNC), International Conference on Connected Vehicles & Expo (ICCVE), and IEEE Intelligent Conference on Intelligence and Security Informatics (ISI).

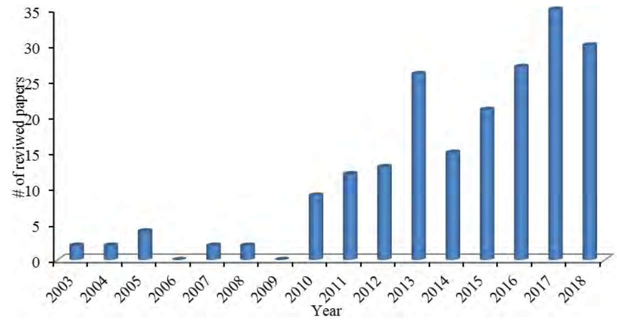

FIGURE 1. Distribution of the collected and reviewed papers from the leading journals and conferences based on the publication year.

The reminder of the paper is organized as follows. Section II discusses the general steps for developing smart traffic management systems and specifically in this study we focus on the following issues: estimating and predicting of traffic parameters, which were reviewed in section III, Section IV reviews methods in detecting, recognizing, and tracking of traffic related objects. While section V focuses on methods that identify trip routing and planning. Section VI focuses on reviewing the state of the art methods that identify traffic patterns, traffic and driver behaviors, and vehicle/pedestrian's behaviors. Methods for controlling signal and traffic lights were reviewed on section VII. After that, in section VIII, we provide a chronological review of recent surveys papers in the area of intelligent transportation and traffic management systems. Moreover, we have embedded a discussion part after each section; where we present our viewpoint, as well as our own experience, and point out current weaknesses and possible future directions.

II. GENERAL STEPS FOR DEVELOPING INTELLIGENT TRANSPORTATION AND CONTROL SYSTEMS

Figure 2 shows the general phases for developing intelligent transportation and control systems, these phases are [7], [8]:

1. *Collection*: Traffic data are collected using different methods, such as:
   A. Image- or video-based methods. Surveillance cameras are used to visually observe road traffic

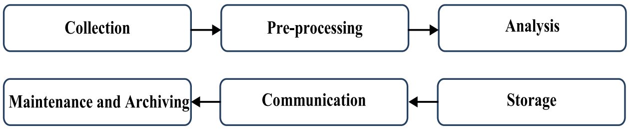

FIGURE 2. General steps for the development of intelligent transportation and control systems.

in a specific area and record or stream the captured images/videos to control rooms. It is widely used in the area of managing road traffic due to efficiency and ease of maintenance. However, video and image contents require lot of storage, network bandwidth, and computation complexity.
   - B. Sensor-based methods, such as ultrasonic sensors, RFIDs, photoelectric sensors, lasers, radar, and vehicle probe data.
   - C. Vehicle to Vehicle (V2V) and Vehicle to infrastructure (V2I) Communications using WiFi, GPRS, WiMax and Bluetooth.
   - D. Hybrid-based methods that combine two or more of the above methods together.

2. *Preprocessing*: Collected raw data from any of the above methods are subjected to noise, missing values, and inconsistent data due to sensor failures, measurement errors, and data link errors or huge size [7]. Therefore data manipulation is required, some of these approaches are:
   - A. Data cleaning, which includes noise removal, malfunction detection, recover missing data.
   - B. Dimensionality reduction in which the dimensionality of the data is reduced using manifold learning, non-negative matrix factorization, or kernel dimension reduction. This improves the performance of learning driven tasks under the reduced dimensional space.
   - C. Sparsity Analysis, which includes remove some redundant features from the original feature space using compressive sensing or heterogeneous learning.
   - D. Data fusion, which requires processing many sources of data. More details about data collection and preprocessing can be found in [7].
3. *Analysis*: Data analysis includes using different analysis tools to provide useful information such as estimation of the total number of vehicles using a specific segment of roadway at any given day of the year. Meaningful information may lead to a resolution of a problem or improvement of an existing situation. Identifying erroneous data elements and measuring the impact of various data-driven processes might also be done to ensure the quality of the analyzed data. Cloud computing and advanced data processing techniques and tools could be used to analyze big traffic data to create more effective real-time traffic decisions. In addition, it uses some learning tools to learn systems how to control the traffic lights, lane signals, visual message system (VMS), and traffic information. These approaches are generally based on machine learning, data mining, and artificial intelligence algorithms.
4. *Storage*: The rapid growth in the volume of traffic data leads to great demands of cost-effective storage technologies. Cloud storage could be used to store and secure big traffic data to create more effective real-time traffic decisions. When data is secure and appropriately structured, there is greater trust and confidence in its use [8].
5. *Communication*: Data communication includes using and sharing traffic data. Traffic data is used to study, plan, design, construct, operate, and monitor traffic systems. Traffic data communication helps researchers, policy makers, government, planner, and departments of transportation and many others to understand traveler behavior and pattern and identify ways to make their systems more efficient and cost-effective. The usage of this data depends on the goal to be achieved and how it is originally collected, processed, analyzed, and stored. Sharing traffic data obtained from a wide variety of resources, both internally and externally, can help agencies/researchers to obtain a more comprehensive picture that improves their decisions to be clear with high quality. However, sharing and communicating public traffic data has several concerns, such as transparency, privacy, security, liability, coordination with different agencies and partners, maintenance cost of shared data, . . . , etc.
6. *Maintenance and Archiving*: Data maintenance is the process of continual improvement and systematic checks that includes ongoing correction and verification. Higher levels of maintenance insure the good functioning of all the requirement systems. Data archiving includes moving and storing less common use data out of active systems and databases in specialized archival systems to optimize the performance, achieve the cost-effective strategy, and allow for future retrieval.

III. APPROACHES FOR PREDICTION OF TRAFFIC PARAMETERS

There are few good amount of approaches were proposed that work on the prediction of the traffic parameters, we categorize them into four main categories. Firstly, approaches that estimate and predict real-time traffic flow. Secondly, approaches that predict short-term traffic flow in heterogeneous conditions. Thirdly, approaches that estimate and predict travel time at real-time. And finally, approaches that estimate and predict the real-time traffic density.

A. ESTIMATION AND PREDICTION OF REAL-TIME TRAFFIC FLOW

Developing a mechanism to predict the real-time traffic flow in urban regions that reduce trip time using data mining algorithms will increases the accuracy, scalability, and adaptability of smart traffic applications. This mechanism combines several scalable data mining techniques such as decision tree, association rules, and neural networks. These approaches use some traffic parameters and historical data as input. Past traffic data were used to predict the short-term traffic flow using the Artificial Neural Network (ANN) [10]. The model uses traffic volume, speed, density, time and day of week along with the speed of each category as input parameters. Experimental results were done in [10] showed that the proposed approach produced good results and consistent performance even if time interval for traffic flow prediction has been increased.

Another attempt was done by Diao *et al.* [9] were the authors developed a model to predict the short-term traffic volume in massive transportation systems. The authors presented a novel hybrid model to accurately forecast the volume of passenger flows multi-step ahead. Comprehensive factors were considered such as temporal, origin-destination spatial, frequency and self-similarity, and historical probabilistic distribution perspectives. Simulation results with real-time passenger flow data in Chongqing city in China were used to evaluate the forecasting performance. The results showed the hybrid model can achieve on average 20%–50% accuracy improvement compared to other models, especially during rush hours.

Meenakshi et. al in [4] developed a hierarchical clustering technique for traffic signal decision support to automatically identify the time of day intervals in which traffic congestion might occur. Applying this cluster analysis approach to utilize high-resolution system takes full advantage of sensor-based traffic signal data to cluster and validate presented hypothesis, which represents benefits to the system engineering field.

An unmanned aerial vehicle (UAV) is an aircraft that carries no human pilot or passengers and guided autonomously using remote control. UAV used first in military applications and recently used to enhance the transportation systems and many prospective applications. In such trend, fast and accurate detection of vehicles and extracting traffic parameters from UAV video becomes crucial. Ruimin Keet. al in [11] proposed a new and complete analysis framework, which contains four stages that classify and estimate the traffic flow parameters (i.e., speed, density, and volume) from UAV video. The proposed framework addresses issues such as irregular ego-motion, low estimation accuracy in dense traffic situation, and high computational complexity. In addition, the authors publicly provided a dataset that contains 20,000 training and testing image samples as benchmark for researcher working on UAV. Experimental results showed that their proposed framework is able to achieve very good accuracy results with high real-time processing speed in both free flow and congested traffic scenarios.

Another attempt to estimate the average speed of traffic stream and count of vehicles from UAV-based traffic videos was done by Ruimin Ke et. al in [12]. The authors proposed a four-step framework to identify the directions of traffic streams and for each traffic stream; it extracts the traffic flow parameters. The framework uses the Kanade–Lucas–Tomasi (KLT) tracker, k-means clustering, connected graphs, and traffic flow theory to analyze motion based on interest-points, determine the connectivity of interest points belonging to one traffic stream cluster, and then estimate the traffic parameters. The experimental results showed that the proposed method achieves 96% accuracy in estimating average traffic stream speed and 87% accuracy in estimating vehicle count. In addition, it achieves high accuracy and processing speed in both daytime and nighttime settings and not sensitive to effects associated with some aerial videos such as object movements, vibration, drifting, changes in speed, and hovering.

Real-time prediction of the number of on-board passengers of a bus (i.e., passenger flow) for the running buses helps in improving the quality of bus service. Zhang *et al.* [13] used smart card fare collection systems and GPS tracing systems in public transportation to analyze and predict the passenger flow in real-time. The evaluation results showed that the proposed model outperforms existing prediction models in predicting accuracy in most time and stations. This is because it uses both historical data and recent value to predict the future passenger flow. Enhancing public transportation, route guidance systems, traffic light improvements, and incident management can minimize the traffic congestion greatly. Limitation of their proposed system is that it did not consider 24 hours traffic system, it focused on the peak hours only. In addition, night time traffic flow characteristics were not considered.

Generally, there are two main approaches to predict road traffic parameters: model-driven and data-driven [14]. Model-driven approaches use simulation to reproduce the road network behavior. Accurate predictions require a detailed knowledge about the network topology. The limitations of the Model-driven approaches are that the number of parameters and the model structure are fixed, which cannot reflect the continuity changing of the road network infrastructures to keep accurate results. On the other hand, the data-driven approach aims to examine and organize the road traffic data to analyze and interpret road traffic situation neglecting the underlying data generation process and disregarding the network topology. Table 1 summarizes the state-of-the-art research were done in predicting traffic parameters, in which we describe the set of features, input and testing environment, evaluation metrics, and intelligent algorithms were used. Figure 3 shows a general structure of the methods were used to estimate and predict traffic parameters, which are classified into pridective mining and pattern mining. The pridective mining is a process that uses data mining and statistical models to forecast outcomes. Each model is made up of a number of parameters, which are variables that are likely to influence future results. Pattern mining is a process that uses statistical models to find relevant patterns between data examples.

Future studies should focus on: 1) using other parameters like weather condition, seasonal variation in traffic

TABLE 1. Features, evaluation metrics, and intelligent algorithm were used to predict traffic parameters.

Ref.	Features	Input and Testing Environment	Evaluation Metrics	Data Mining/Artificial Intelligence Algorithm
[9]	Discrete wavelet transform used to extract flow features from both the temporal and frequency domains,	Simulations based on real passenger flow data (numerical data)	DAY-MAE: the mean absolute error during the whole day. MR-MAE: the mean absolute error during morning rush hours. MPT-MAE: the mean absolute error of peak traffic forecasting during morning rush hours. DAYPT-MAE, the mean absolute error of peak traffic forecasting during the whole day.	Gaussian process regression based on statistical learning theory and Bayesian theory.
[10]	19 features include day of week, time of day, category of vehicles divided in 8 parts, corresponding average speed of vehicles divided in 8 parts, and traffic density	Simulations based on realistic conditions of heterogeneous traffic (numerical data).	MSE: Mean Square Error, NMSE: Normalized Mean Square Error, MAE: Mean Absolute Error.	Artificial Neural Network (data-driven and self-adaptive model)
[12]	Haar cascade classifier trained using randomly generated Haar-like features	Video-based data	Recall and Precision False Positive and False Negative	Supervised learning (AdaBoost learning algorithm), Convolutional Neural Network
[13]	Shi-Tomasi features (the eigenvalue of the second-moment matrix), image registration used to match features in two consecutive frames,	UAV videos taken in different traffic scenarios.	Error Rate, Accuracy,	A connected graph-based method was used to determine the membership of interest points in each traffic flow cluster.
[14]	Temporal and spatial features of the smart card tapping events.	Data collected using Automatic Fare Collection (AFC) devices that record payments using smart card, and a GPS embedded On Board Unit (OBU) that can track the bus. Both historical and recent data were used for the prediction.	Extended Kalman Filter (EKF), ARIMA, Linear Regression, RMSE, and Accuracy.	Coarse prediction and Calibration, state transit function of an Extended Kalman Filter (EKF)
[15]	structure learning using features related to road, vehicle, weather, and time. it can starts learning the structure and parameters automatically from data.	Count of vehicle, road occupancy, vehicle speed, weather, and time. These input might be expanded using online learning tool.	Mean Absolute Percentage Error (MAPE)	Adarules framework used different machine learning and data analysis tools that strengthen the predictive system and make it robust to outliers, irrelevant features and missing data, able to grow its complexity with new data and adaptive to changes, it is also able to scale along with the network size.

flow, extreme conditions, and variability in the traffic flow. 2) Collecting real-time traffic information for longer period of time to cover all possible realistic conditions associated with traffic flow. 3) developing a more general model that considers all the above traffic parameters and use real-time traffic data to estimate traffic flow.

B. PREDICTING SHORT-TERM TRAFFIC FLOW IN HETEROGENEOUS CONDITIONS

Homogeneous traffic is composed of identical vehicles that follow a lane path. While heterogeneous traffic composed of motorized and non-motorized vehicles, such as two- and three-wheelers, along with several other vehicles and trucks with no-lane path. This heterogeneous traffic with the absence of lane discipline results into a complex traffic behavior and make the prediction of traffic flow more challenge than in the homogeneous traffic [16]. Capturing the effect of different vehicles size and the lack in lane discipline are the main challenges in modeling heterogeneity in traffic [17]. Short-term traffic prediction is the process of predicting traffic conditions at a future time, given continuous short-term feedback of traffic information and the response is returned immediately.

Despite the extensive studies were published to handle the predicting of short term traffic conditions, several proposals have been exist to handle the seasonal heterogeneity in traffic condition series. Huang *et al.* [15] proposed a real-time model that uses the seasonal adjustment factor plus adaptive Kalman filter to online predict the seasonal heterogeneity in traffic flow series. Experimental results showed acceptable results and achieved comparable performance when compared with offline models. Also, when the traffic is highly volatile, the online model improves the performance over the offline model. Longer time interval can be explored, and more data sets can be applied to evaluate the algorithm. In addition, there is an urgent need for uniform performance measurements that evaluate the overall performance of long-term prediction.

Deep learning model was used by Polson and Sokolov in [18] to predict traffic flows. The authors developed an innovative architecture that combines a linear model and a sequence of tanh layers, which are used to identify spatio-temporal relations among predictors and to model nonlinear relations. For evaluation purposes, the authors used sensor data from Interstate I-55 and predict traffic flows during two special events; a Chicago Bears football game and an extreme snowstorm event. The experimental results showed that their proposed deep learning model provides precise results for short term traffic flow predictions. In addition, the authors empirically observed that prediction based on recent traffic

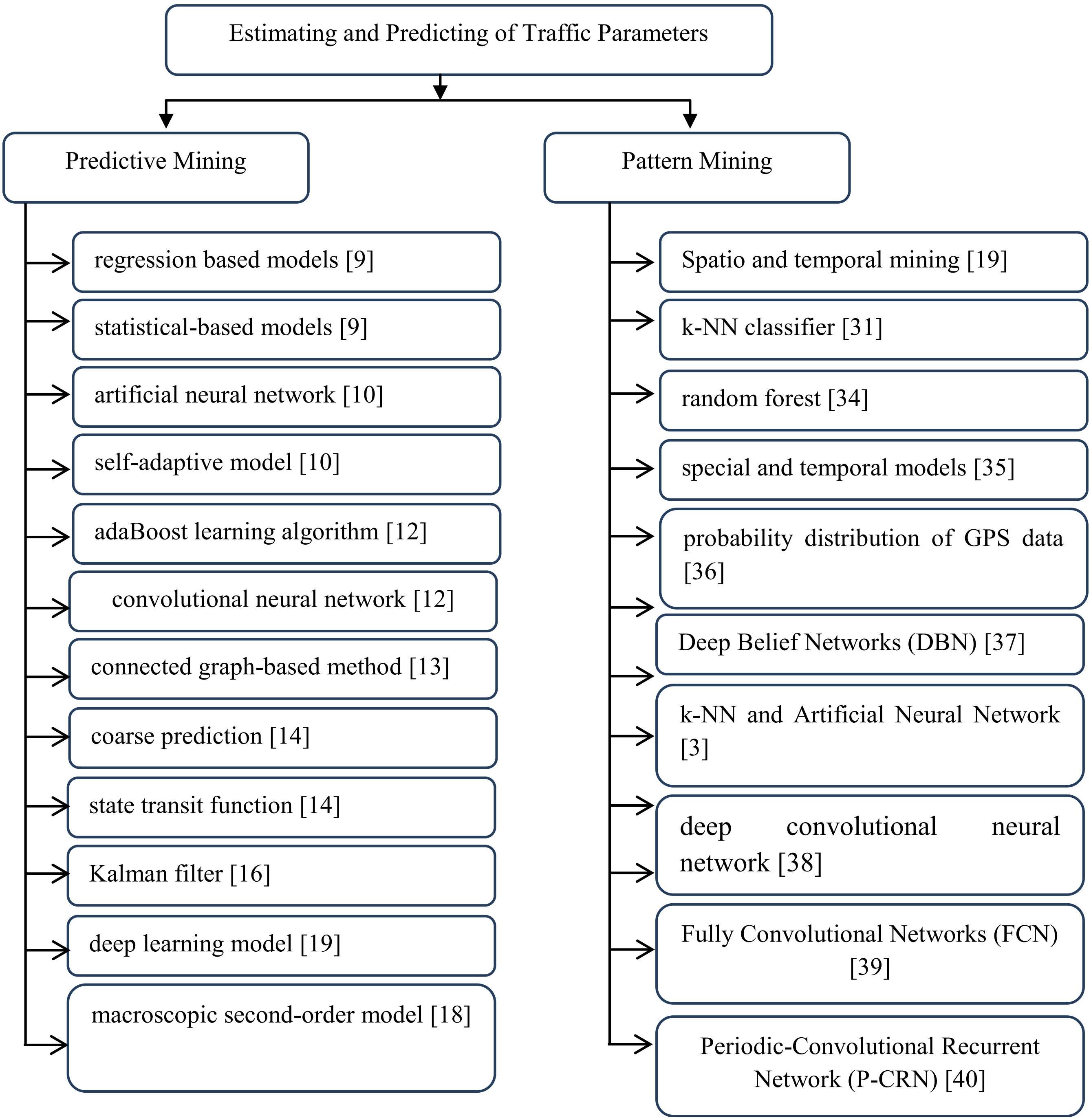

FIGURE 3. **A general structure of the methods used to estimate and predict traffic parameters.**

data within last 40 minutes generate stronger results rather than historical values within the last 24 hours. This indicates that a powerful model could be based on features generated from recent observations (i.e., within the last few minutes) rather than previous days.

Another approach was done by Qian et. al in [19], in which the authors developed a macroscopic model that approximates heterogeneous traffic flow using interplay of multiple vehicle classes; each class represents a homogeneous traffic and represented by a deterministic fundamental diagram. All these classes encounter identical traffic state, but each class realizes the impact of other classes differently. Extensive numerical experiments with the NGSIM I-80 data set showed that the proposed multi-class model can produce realistic congestion propagation for multiple classes in various scenarios. It also computes realistic time-varying travel time for each class, which cannot be obtained from conventional single class models.

Mohan and Ramadurai in [17] proposed a parsimonious model of heterogeneous traffic that can capture the gap filling. Gap filling is an event that occurs when the driver tries to position his vehicle into the available gaps in the road section ahead. The proposed model uses area occupancy, relaxation time, and the relative speed of vehicles. Field data from an arterial road in Chennai city in India were used to validate and evaluate their proposed model. The evaluation results showed that their proposed model generates results that are comparable with those from few existing generalized multi-class models.

Estimating the traffic flow based on traffic video analysis is another methods that was proposed by Hung et. al. in [20]. The authors used the captured videos from a surveillance camera mounted in a cross road to detect moving vehicles and control the traffic flow. In addition, they used the traffic flow as input for automatic timing for the traffic light accordingly. The authors used background subtraction and Gaussians model to detect and trace vehicles and then synchronized in a given time period to eliminate the shadow from the sunlight or streetlight. The authors used Vietnam as a context, which include a mixed flow of motorbikes with other transport means, to evaluate the proposed system.

C. ESTIMATION AND PREDICTING OF REAL-TIME TRAVEL TIME

Travel time is the time required for road users to travel from a source location to a destination point. Predicting travel time in a timely manner avoids congestion and increases the utilization of the entire highway network [21]. Available technologies and sensors in the transportation systems generate huge volume of traffic data in real time. Also, various prediction methods have been proposed to rapidly process these data. Factors that influence predicting of real-time travel time are: 1) the time of the predication, whether it is during the day, weekdays, weekends, summer, winter or holidays which affect the disparity of cars flow with time and thereby the accuracy of the prediction, 2) the hard coded delays where the transition time slots are fixed and do not depend on real time traffic flow, 3) the adjacency of traffic lights in which the traffic light at intersection does influence the traffic at adjacent intersections, 4) emergency cases such as accidents, roadwork, breakdown cars, ambulances, rescue vehicles, police, fire brigade, and 5) pedestrians that cross the roads.

Some of these methods are time series methods [22]–[24], regression models [25], [26], and machine learning methods [27], [28], more details can be found in [21]. Random forests and Apache Hadoop as machine learning methods were used by Shu-Kai et. al. in [21] to construct a big data analytics platform that predicts highway travel time. The authors developed two models, namely OTTP and ATTP and proposed a platform that uses data collected from highway electronic toll collection in Taiwan. Experimental results showed that the OTTP model helps highway drivers to avoid traffic congestion and minimize travel time by selecting optimal departure times. In addition, the ATTP module analyzes the current traffic conditions to provide accurate predictions of arrival time, which allows drivers to select alternate routes to further reduce travel times. Another experiments showed that combining the two models provides highly accurate travel time prediction for freeway drivers.

Classifying algorithm such as k-NN along with historic data were used by Kumar et. al. in [29] for predicting the next bus travel time. This real-time prediction uses a model-based recursive estimation scheme based on Kalman filtering. The predicted travel time can be represented in terms of the remaining time to reach the destination and displayed at bus stops, within buses, or through web portals. The evaluation results showed that the proposed method improved the prediction accuracy compared with other methods based on static inputs. Other methods and algorithms were reviewed in [30] and [31].

The accuracy of predicting the travel time information given to passengers is important in developing any Advanced Public Transportation Systems (APTS) applications and will help passengers to determine their departure/arrival times. To improve the accuracy of such applications, Bin Yu et. al. in [28] proposed a random forests based on the nearest-neighbor (RFNN) method to predict the bus travel time. Experiments were conducted using real GPS data collected from two bus routes in Shenyang city. These experiments showed that the RFNN method achieved high accuracy compared with other four methods. However, RFNN method has a longer computation time that might be optimized using parallel computing.

Another attempt was done by B. Anil Kumar et. al. in [32]. The authors used both temporal and spatial variations based on the basic traffic conservation equation to predict the travel time. Experimental results showed that the proposed method was able to perform better prediction than historical average, regression, and ANN methods and the methods that uses either temporal or spatial variations only. In addition, these results showed that using vehicle tracking data without location-based data is good enough to generate accurate prediction results.

Dawn Woodard et. al in [33] proposed a method, called TRIP, which uses GPS data from mobile phones to predict the probability distribution of travel time for a random route in a road network at any given time. TRIP also provides information about the reliability of the travel time prediction. Evaluation results using data from mobile phones collected from the Seattle metropolitan region showed that the TRIP provides predictions that are as accurate as Bing Maps predictions. In addition, it is computationally feasible even for very large-scale road networks.

Chaiyaphum et. al. in [34] proposed an effective travel time prediction technique based on a concept of Deep Belief Networks (DBN). The proposed technique uses the Restricted Boltzmann Machines (RBM) to automatically learn generic traffic features following an unsupervised learning architecture. And then following a supervised learning architecture then the sigmoid regression is used to predict the travel time. The prediction model was tested using both the PeMS data set and real traffic data. Evaluation results achieved high prediction accuracy.

D. ESTIMATION AND PREDICTION OF REAL-TIME TRAFFIC DENSITY

Throughput, travel time, safety, fuel consumption, emission, reliability, and traffic density are considered as the primary measures of quantifying traffic congestion on roadways other than signalized intersection [3]. The prediction of real-time traffic density could be done based on: 1) Aerial Photography using loop detector, 2) Data driven approach using linear model, linear regression, ANN, k-NN, pattern matching, PCA, nearest neighbor approach, Kalman filtering, clustered neural network, wavelet neural network, k-NN and Linearly Sewing Principle Components, and 3) Image processing techniques. Jithin *et al.* in [3] used the k-Nearest Neighbor (kNN) and Artificial Neural Network (ANN) as machine learning techniques to estimate the travel time and traffic density. The authors used the available data collected every five minutes from automatic sensors as input to estimate the target travel time and density. The evaluation results showed promising results in terms of Mean Absolute Percentage Error (MAPE) in Indian traffic conditions for each technique individually. However, combing these two techniques did not show any significant improvements in performance. In addition, the authors suggested that to achieve a better performance for the ANN, the number of training data is highly recommended to be huge.

Deep Convolutional Neural Network (D-CNN) method based on video images was developed by Chung and Keemin Sohn in [35] to count the number of vehicles on a road segment. The experimental results showed that their method outperforms existing approaches. Limitations of their method are: (1) it counts the number of vehicles regardless the vehicle's size, make, and model. (2) the count is based on extracting images from video without considering consecutive images or vehicle status (i.e., moving or stopped).

Zhang *et al.* in [36] analyzed and compared Fully Convolutional Networks (FCN) method with the regression-based method and concluded that the FCN generates more accurate results using the TRANCOS public dataset.

A novel Periodic-Convolutional Recurrent Network (P-CRN) method was proposed by Ali Zonoozi et. al. in [37] to predict crowd density. P-CRN adapts CRN to accurately capture spatial and temporal correlations, it learns and incorporates explicit periodic representations, and it can be optimized with multi-step ahead prediction.

IV. DETECTION, RECOGNITION, AND TRACKING OF TRAFFIC RELATED OBJECTS

There are decent amount of approaches were proposed to track objects at the traffic management space. We are able to categorize them into three general categories. Firstly, approaches that detect and count real-time pedestrians. Secondly, approaches that predict the occurrence of vehicle accident, and thirdly, approaches that recognize license pallet.

A. DETECTING AND COUNTING OF REAL-TIME PEDESTRIANS

Effectively detecting of traffic related objects often improves the accuracy of the recognition and tracking steps, which plays a crucial role in ITS. Traffic signs, cars, pedestrians, and cyclists are important classes of traffic related objects. Jifeng Shen et. al. in [38] proposed a pedestrian extraction and refinement framework for pedestrian detection. The proposed system is based on Pixel Differential Feature (PDF) and Aggregated Region Feature (ARF). PDF is a light weighted feature with a high recall rate and the authors used the multi-scale ARF to extract the co-existing dominant pixel differential patterns in a local region for fusing information from different resolutions and scales to improve the performance and to reject hard false positives. Experiments based on the INRIA, Caltech, ETH, TUD-Brussel and KITTI datasets demonstrate the effectiveness of this method at real-time speed with low computational complexity, which makes it more encouraging in the embedded or mobile platforms. David et. al. in [39] reviewed the state of the art research for pedestrian detection for advanced driver assistance systems. Table 2 summarizes the typical machine learning algorithms used to detect, recognize, and track of traffic related objects, especially the real-time pedestrians.

There has been an enormous research effort in automatic detection and classification of pedestrians. However, the feeling is that there is a need to develop more efficient algorithms and ideal systems. Going forward with this comprehensive is fully justified. We would like to provide few more suggestions:

1) Explore more features and machine learning algorithms to generate more discriminative feature representations and learning strategy.
2) Increase the robustness of existing algorithms by increasing their discrimination power and lowering their computation time, which could be done by integrated the parallel processing option. This might result in lowering the detection latency in some critical cases. These algorithms might be extended to be able to detect other important objects in the scene, such as bikes, cars, traffic signs and lights.
3) Focus on different poses, 3D views, and partially occluded pedestrians would be of interest
4) Use pedestrian tracks to predict and be aware of pedestrian intentions in advance for collision avoidance.
5) Add more dynamic situations to complement the current data sets.
6) Use 3D LIDAR technology that provides more accurate data than using machine vision and cameras. 3D LIDAR technology can be successfully used to detect pedestrians in different lighting conditions.

TABLE 2. Machine learning algorithms used to detect, recognize, and track of traffic related objects.

Machine Learning Algorithm	Definition	Role and Applications in ITS	Properties	Features
Regression	It is a statistical measure that determines the strength of the relationship between one dependent variable and other changing variables.	Deep-CNN method was used to simultaneously detect pedestrian and estimat occlusion in practical applications. This method use bounding boxes to localize the full body as well as the visible part of a pedestrian. Advantages of D-CNN method in detecting pedestrians is that it uses the visible part of a pedestrian to provide occlusion estimation and it exploits both the visible part regions and full body of pedestrians to improve the performance of pedestrian detection [40]. In addition, it was used to detect the position of pedestrians and to estimate the distance between a pedestrian and the vehicl [42]. Logistic regression analysis method was used to select optimal features for pedestrian detection [41].	• In the class of linear estimators, parameter estimates will be unbiased, consistent, and efficient. • The independent variables (predictors) are linearly independent.	Deep CNNs [40], Haar-like and Histograms of Oriented Gradients (HOG) [41], Feature map convolution layer [42]
Naïve Bayes	It is a probabilistic classifier that assigns class labels to problem instances, which are represented as vectors of feature values.	k-Nearest Neighbours (kNN), Naïve Bayes classifier (NBC), and Support Vector Machine (SVM) were used in detecting pedestrian for autonomous vehicles using high-definition 3D range data. kNN with Euclidean and Mahalanobis distances, NBC with Gauss and KSF functions were used and the SVM with linear function was selected since it offers the best results [44].	• Class decoupling: each class can be independently represented as a one-dimensional distribution. • Robust classifier: it can ignore serious deficiencies in its underlying naive probability model [43].	Shape Features, Invariant Moments, and Statistical Features [44], HOG. Visual HOG, Deep learning, CNN, visual CNN [48].
Support Vector Machine [49]	It is a supervised learning algorithm that provides linear and non-linear classification and finds a decision boundary [39].	SVM was adapted using basic statistical operators to improve pedestrian detection. The adopted SVM was used with HOG and Haar descriptors achieves better accuracy in comparison to the well-known SVM and KNN classifier [46].	• Handle different types of data, e.g. features or images. • Maximize the margin between different classes and minimize the classification error.	Haar wavelet decomposition and Histograms of Oriented Gradients (HOG) [46] [47]. HOG [48].
Random Forest	It is a supervised learning algorithm that develops large numbers of random decision trees to analyze sets of variables. It uses different learning strategies to solve complex classification and regression problems.	Cascade random forest with low-dimensional Haar-like features and oriented center-symmetric local binary patterns were used to detect Sudden pedestrian crossing [49]. Also, random forest was used to detect pedestrian using local templates with different sizes and different locations as positive exemplars [50]. Random forest with HOG and LBP was used to to detect pedestrian [51]. Discriminative Generalized Hough Transform (DGHT) that operates on edge images using deep CNN were used for pedestrian detection [52].	• Robustness to outliers, scalable and work with large learning set with tuned parameters. • Achieves high prediction accuracy with multiclass classification.	Spatiotemporal features. [49], Cascade random forest (CaRF) with low dimensional Haar-like features and oriented center-symmetric LBPs (OCS-LBPs) [54], Dominant Orientation Template (DOT) feature [55], HOG and LBP [56] [57]
Boosting/AdaBoost	It is an ensemble method that creates a strong classifier from a number of weak classifiers. It starts by building a model from the training data, and then creates a second model that tries to correct the errors from the first model. Models are added until errors are minimal or no further improvement can be made on the training dataset [53].	Adaboost with SVM and HOG using LBP encoding were used to detect pedestrian in all-weather thermal-images [54]. Additionally, a combination of Haar-LBP features was integrated with Adaboost for training the detector to detect pedestrian [55]. HAAR-LBP and HOG cascade classifier were used to improve the performance of the pedestrians detectors [56].	• Strong classifier and has varieties of applications with less parameters tuning. • It is sensitive to noisy data and outliers.	Feature map, LPB, HOG [54], Haar-LBP [60], HAAR-LBP and HOG cascade classifier [56],
Neural Network	Inspired from human biological nervous systems. It is composed of a large number of highly interconnected elements, called neurons, working together to solve specific problems.	A fusion architecture with parrallel processing using deep neural network was developed for fast and robust pedestrian detection [62]. Fully CNN YOLO-based nueral network was used to detect pedestrians, the method evaluated using low quality images which often include dense small groups of people to detect pedestrians [63]. Another method was used to detect pedestians useing multi-label convolutional neural network (MLCNN) to predict multiple attributes together in a unified framework [59].	• Has the ability to learn and model complex and non-linear relationships • No restrictions about the input variables • Provide solutions to non-algorithmic problems. • Used to deal with new and unexpected situations based on historical data	Single shot multi-box detector (SSD) [57], multiple feature maps [57] [58], low-level features [59] [60].

B. PREDICATION OF THE OCCURRENCE OF VEHICLE ACCIDENT

Accident prediction is an estimation of the occurrence of accident based on the nature of the relationships between different roadway entities, such as diver behavior, road structure and type, and surrounding environment. It is important to understand the mechanisms involved in accidents on one hand and to better predict their occurrence on the other hand [61].

Gianfranco *et al.* in [62] developed a model that aims to predict and estimate the number of accidents for three situations in an urban road network, a roundabout, a three- or four-way junction and a straight stretch of road. The model divided the accident data into homogeneous clusters, constructed are based on Poisson's and Negative Binomial (NB) algorithm. The analysis is based on analogous, be they contrasting, concepts of similarity and distance: the shorter the distance, the greater the similarity. Therefore, they used the squared Euclidean distance as the most common method for measuring the distance between cases. Prior to the analysis, the variables are standardized (divided by the standard deviation) such that the unit of measure does not affect their distance. Essentially, this involves working with standard deviations. Once the cases have been classified into groups, the absolute value of the correlation coefficient is widely used to measure the degree of similarity. They adopted the agglomerative hierarchical clustering based on the inertia criterion and on Ward's method [63] that combines clusters in such a way that at each agglomeration the two clusters merged are those with the smallest increment in the sum of squared distances (within cluster standard deviation). By analyzing and simplifying the available road traffic accident data in Italy which have been collected using the report forms created by Italian Institute of Statistics (ISTAT), they proceeded to develop three different models for predicting accident frequency at roundabouts, junctions and straight stretch of road. Each model shows that accident rates vary with risk factors. Thus, it is possible to identify appropriate countermeasures to be implemented for reducing the risk of road accidents.

Meng *et al.* in [64] proposed a connected vehicle (CV)-based dynamic all-red extension (DARE) framework for adaptive signalized intersections to avoid potential crashes caused by red-light running (RLR) behavior. The conceptual framework consists of three components: CVs, roadside equipment (RSE) and traffic control devices. The RLR prediction of signalized intersections is a crucial component of DARE that avoids potential collisions caused by RLR behavior. They formulated the RLR prediction as a binary classification problem based on continuous trajectories measured by radar sensors. In the CV environment,

TABLE 3. Features, factors, and strength of the methods were used for prediction of the occurrence of vehicle accident.

Machine Learning Algorithms	Features/ Factors/ Strength
Regression	Logistic regression [71] (independent variables used are: road, environment, vehicle and driver), Poisson regression, negative binomial (NB) regression and Zero Inflated Negative Binomial (NINB) regression [72], Rare-events logit models [73]. The predicition accurecy of the logistic regression has 86.67%, poisson regression model has a poor fitting degree, followed by a RF regression model, and AIC difference between the negative binomial (NB) regression and ZINB regression model is not huge. ZINB regression model has the best goodness of fit [72].
Naïve Bayes	Probabilistic and statistical model [74], Compare Naïve Bayes with Decision Tree, Rule Induction, and Multilayer Perception [75].
Support Vector Machine	Using particle swarm optimization to optimal parameters and improve the prediction accuracy of the SVM [76], support vector machines (SVM) with Gaussian kernel [77], The prediction model of traffic accident based on particle swarm with mutation optimization-support vector machine achieves higher prediction precision and smaller errors. It is feasible and effective to use particle swarm with mutation optimization to optimize the parameters of support vector machine [76].
Random Forest (RF)	Using RF with adaptive synthetic sampling technique to efficiently select variables [78], improved missing data and feature selection [79]. SVM using Random forest technique was applied to select the contributing factors and avoid the over-fitting issue, this combinatiion is able to successfully classify 87.52% of the car crashes on the overall dataset [78].
Boosting/AdaBoost	----
Neural Network	Artificial Neural Network [80] [70], Maximum Sensitivity Neural Network [81], Factors include driver's behavior, vehicle features, highway characteristics, environmental effects and traffic characteristics [82]. Using ANN for Road Accident Predictio has advanteges over other algorithms such as there is no need for prior knowledge about the relationships amongst the parameters being used. In addition, ANN has a novel structure of the information processing systemthe that allows to model complex, nonlinear relationships without previous assumptions of the nature of the relationship
Other models	Different road segments (intersection, roundabout and straight line) were considered to develop different models using different important parameters such as average daily traffic, internal diameter, and number of roundabout arm, [67], agglomerative hierarchical clustering [67]. These models were used to predict the occurrence of vehicle accident.

vehicle trajectories and real-time signal timing could be obtained via vehicle-to-infrastructure and vehicle-to-vehicle communications. Using continuous trajectories, individual speed, acceleration and distance to the stop line at the red-light onset time are selected as classification attributes. Non-weighted and weighted least square support vector machines (LS-SVM) are adopted to solve the RLR prediction problem. Parameter tuning is conducted by the cross-validation in the discrete parameter space and the Bayesian inference in the continuous parameter space, respectively. As a comparison, the existing DARE approach at adaptive signalized intersections based on inductive loop detectors is discussed.

Alkheder *et al.* in [65] used artificial neural network (ANN) to predict the injury severity of traffic accidents based on 5973 traffic accident records occurred in Abu Dhabi over a 6-year period (from 2008 to 2013). For each accident record, 48 different attributes had been collected at the time of the accident. After data preprocessing, the data were reduced to 16 attributes and four injury severity classes. The WEKA (Waikato Environment for Knowledge Analysis) data-mining software was used to build the ANN classifier. The traffic accident data were used to build two classifiers in two different ways. The whole data set were used for training and validating the first classifier (training set), while 90% of the data were used for training the second classifier and the remaining 10% were used for testing it (testing set).

The experimental results revealed that the developed ANN classifiers can predict accident severity with reasonable accuracy. The overall model prediction performance for the training and testing data were 81.6% and 74.6%, respectively.

To improve the prediction accuracy of the ANN classifier, traffic accident data were split into three clusters using a k-means algorithm. The results after clustering revealed significant improvement in the prediction accuracy of the ANN classifier, especially for the training dataset. Furthermore, in order to validate the performance of the ANN model, an ordered probit model was also used as a comparative benchmark. The dependent variable (i.e. degree of injury) was transformed from ordinal to numerical (1, 2, 3, 4) for (minor, moderate, sever, death) respectively. The R tool was used to perform an ordered probit. For each accident, the ordered probit model showed how likely this accident would result in each class (minor, moderate, severe, death). The accuracy of 59.5% obtained from the ordered probit model was clearly less than the ANN accuracy value of 74.6%. Table 3 summarizes the typical machine learning algorithms used to for predication of the occurrence of vehicle accident.

We would like to provide few more suggestions as future directions:

1) Using more data points makes the prediction stronger, better quality rules, ensure the reduction of accidents.
2) Adding more factors, such as weather, time, speed limit, road curvature, average traffic flows and volumes, proximity to intersections, road direction and alignment (north, south, east and west), road width, road surface type and Human factors. These factors

TABLE 4. Features, factors, and strength of the methods were used for identifying of trip routing and planning.

Machine Learning Algorithms	Features/ Factors/ Strength
Regression	Quantile Regression (QR) approach was used to analyse the impact of supply and demand data collected from automatic vehicle location and fare card systems on the reliability of transit travel times distribution rather than its central tendency. QR model provides more indicative information compared with the conditional mean regression method [84], linear regression was used to generate a transportation trip based on mixed-use and transport infrastructure near the site [85].
Naïve Bayes	Find optimal travel route between two geographical locations based on the behaviour of user trvel generated from historical GPS trajectories. The naïve Bayes mode was used to generat a route that has the maximum probability of a user's travel behaviour [86].
Support Vector Machine	Authors in [87] explored the possibility of using SVM in modelling driver's route choice behavior . In aaddition, the performance of SVM was compared with NN using three parameters for making route choice decisions, these parameters include travel time, travel time fluctuations, and fuel cost. SVM has similar prediction accuracy with NN but has much more computing efficiency in terms of the time required to calibrate the model.
Random Forest (RF)	A combination of data-driven techniques with random forests were used to select variables to be used in walking route choice. RF dramatically improves the route choice models [88]. In addition, using random forest to identify attributes generate better model fit and requires minimal assumptions. Comparing the important variables identified by the random forest with other data mining algorithms represent a future research need to compare the variations in variable importance due to algorithm selection methods.
Boosting/AdaBoost	---
Neural Network	Individual vehicle speed, destination, and traffic light status were used as feature to provide the fastest path between a source and a target point using deep convolutional neural networks [89].
Other models	A lane-level vehicle routing and navigation based on shortest path algorithms [90], decomposed Mixed Integer Linear Programming (MILP) to develop a school transportation routing and scheduling system [91]. All these methods were used to identify trip routing and planning.

allow the prediction model to produce more accurate and unbiased results.

C. RECOGNITION OF LICENSE PALLET

Automatic license plate recognition systems have been widely used in different applications such as traffic control, traffic surveillance, automated car parking, vehicle tracking, electronic toll collection, vehicle localization and long-distance vehicle localization or tracking. The detection of small and vague license plates and characters in real applications is difficult and still an open problem. Chunsheng and Faliang Chang in [78] proposed a novel hybrid cascade framework for fast detecting small and vague license plates in large and complex visual surveillance scenes. The experiments showed that the proposed framework is able to rapidly detect license plates with different resolutions and different sizes in large and complex visual surveillance scenes. The proposed framework outperforms different evaluation data sets with many small and vague plates.

V. IDENTIFYING TRIP ROUTING AND PLANNING

Development of real-time trip routing and planning systems will help users to route and plan their trip according to their preferences. These users can access these services from their mobile devices or by visiting websites over internet. Cui *et al.* [81] planned an optimal travel route between two geographical locations, based on the road networks and users' travel preferences. They defined users' travel behaviors from their historical Global Positioning System (GPS) trajectories and propose two personalized travel route recommendation methods – collaborative travel route recommendation (CTRR) and an extended version of CTRR (CTRR+). First, they estimated users' travel behavior frequencies by using collaborative filtering technique. A route with the maximum probability of a user's travel behavior is then generated based on the Naïve Bayes model. The CTRR+ method improves the performances of CTRR by taking into account cold start users and integrating distance with the user travel behavior probability. Table 4 summarizes the features, factors and strength of the typical machine learning algorithms were used for identifying of trip planning and routing algorithms.

The authors in [81] conducted some case studies based on a real GPS trajectory data set from Beijing, China. The experimental results show that the proposed CTRR and CTRR+ methods achieve better results for travel route recommendations compared with the shortest distance path method. They recommended in future to continue studying the segmentation method for the GPS trajectories with context-adaptive sampling rates and they suggested that both algorithms can be improved from the following perspectives: First, CTRR and CTRR+ consider the travel behavior by integrating spatial information (i.e. the road segment) and temporal information (i.e. time interval), but they do not consider the sequence of travel behaviors, which may lead to unreasonable routes for some cases. One possible solution is to study user's transition behavior which describes the transition between two travel behaviors on adjacent road segments in one time interval. The frequencies and probabilities of user's transition behavior can be estimated with MF and smoothing algorithm, similar to the study of user's travel behaviors. Hence, a personalized travel route could be recommended by searching the route with the maximum probability of the travel behavior and the transition behaviors, which will modify the limitation of ignoring the sequence of travel behaviors. Besides, the transition behavior probability also indicates some restrictions in road network. For instance, the transition behavior probability must be smaller at the turns with restrictions than at those without restrictions, which could modify the route with unreasonable turnings. Second, CTRR and CTRR+ assume that traveling happens in the same time interval in the route recommendation. However, in the real world, a travel may cross multiple time intervals. There are two key problems to be considered. The first one is that the travelling time on each road segment should be estimated so that the elapsed time of travelling can be tracked.

The second issue is that the transition between travel behaviors on one road segment across the adjacent time interval should be considered. As travel behavior is assumed to be composed of a set of latent factors, one possible solution is to consider the latent factors as time-dependent, and study the transition between the latent factors over the adjacent time interval. With the time-dependent latent factors involving transition relationship over time, the frequencies and probabilities estimation of travel behaviors can be better estimated. In CTRR+, the parameter α is to balance the weights between the travel behavior probability and distance. The setting of the optimal α depends on the dataset, and should be learned from the data set. A potential method for learning α is gradient ascent method which is an iterative process. The precision of CTRR+ varies with the value of α, and the gradient of the precision at α is the direction in which the precision is increased fast. Based on gradient ascent method, α can take steps proportional to the gradient of the precision at α until the process converges. The deficient of the method is that the precision may approach to a local maximum.

Slavin *et al.* in [85] introduced improvements to traffic using micro simulation methods by taking account of more realistic lane level trajectory selections made by drivers. These data can be used to analyze the likely travel times and other characteristics of potential vehicle trajectories at the lane-level from an origin to a destination. Within the context of a single simulation run, a look ahead mechanism is used to identify better lane-level guidance and ensure that the guidance is feasible considering other traffic in later time. These improved processes are based on the ability to store, manage and utilize time dependent, lane-level information on traffic and geometric conditions on highways and between and within intersections on streets. Similarly, these data items can be gathered for the components of trajectories that take place inside the intersections where delays are often experienced due to conflicting movements of vehicles and even pedestrians. A lane-level vehicle routing and navigation apparatus according to embodiments of the invention includes a simulation module that performs microsimulation of individual vehicles in a traffic stream, and a lane-level route optimizer that evaluates predicted conditions along candidate paths from an origin to a destination as determined by the simulation module, and determines recommended lanes to use and the associated lane-level maneuvers along the candidate paths. A link-level optimizer may be used to determine the candidate paths based on link travel times determined by the simulation module which then may further refined with the lane-level optimizer. They recommended using the simulation by multi-threaded and/or distributed for faster computation in order to provide more timely navigation guidance or to evaluate multiple alternatives simultaneously.

Wang *et al.* in [86] proposed a model to serve the school transportation routing and scheduling problem, which aims to reduce the cost and time using the minimum number of buses. They developed a Mixed Integer Linear Programming (MILP) model for the integrated school bus routing and scheduling problem. The model is solved to optimality on small size problems to test its correctness. An advanced decomposition algorithm, namely the School Compatibility Decomposition Algorithm (SCDA), is proposed to solve the model for larger problems. SCDA is superior to the traditional decomposition methods because it considers the valuable scheduling information (the compatibility) when solving the routing problem. They claimed that the biggest contribution of the proposed model and algorithm is that the interrelation between the routing and scheduling is kept even in the decomposed problems. The validity of the model and the efficiency of the SCDA algorithm are tested on the randomly generated problems and a set of test problems. The first experiments show that SCDA can find solutions as good as the integrated model (in terms of the number of buses) in much shorter time (as little as 0.6%) and that it also outperforms the traditional decomposition algorithms. The second experiments show that the SCDA can find better with a fewer number of buses (up to 26%), and shorter mean and maximum travel time per trip (up to 7%). A few directions for future direction can be identified. One of them is a more efficient algorithm to solve each single school routing problem such that it can handle more complicated problems with more stops to every single school. Another one is that a more flexible way to handle bus service start time can be devised, especially for morning trips. An appropriate time window might be more financially beneficial than a fixed service start time.

Liu *et al.* in [87] focused on the identification and optimization of flawed region pairs with problematic bus routing to improve utilization efficiency of public transportation services, according to people's real demand for public transportation. First, they provided an integrated mobility pattern analysis between the location traces of taxicabs and the mobility records in bus transactions. Based on the mobility patterns, they proposed a localized transportation mode choice model, where they can dynamically predict the bus travel demand for different bus routing by taking into account both bus and taxi travel demands. This model then used for bus routing optimization which aims to convert as many people from private transportation to public transportation as possible given budget constraints on the bus route modification. They also leveraged the model to identify region pairs with flawed bus routes, which are effectively optimized using their approach. To validate the effectiveness of the proposed methods, extensive studies are performed on real-world data collected in Beijing which contains 19 million taxi trips and 10 million bus trips.

The work reported by [87] showed how to optimize bus routing to attract more bus riders from taxi. As a future direction, improvements can be made through several different directions: such as taking bus stop location selection into account. In [87], it can optimize bus routing and bus stop location simultaneously to meet people's travel demands. Second, more transportation modes can be considered, for example, bus network optimization can be conducted together with subway system and city bike system. This can help to model the whole city travel demand as a whole and better serve the goal to make public transportation more attractive to riders. Table 4 summarizes the features, factors and strength of the typical machine learning algorithms were used for identifying of trip routing and planning.

As future research direction might be focusing more on the data-driven models and collecting more detailed data that might yield better and unexpected results, which worth to be explored.

VI. IDENTIFYING TRAFFIC PATTERNS AND BEHAVIOUR

Identifying vehicle movements, understanding traffic patterns, behaviour, how traffic congestions appear and increase in time and space can benefit the prediction of short- and long-term traffic situations, it also can reduce the congestion. There are several attempts that focus on analyzing and identifying traffic pattern and behaviour. Sekar and Shondelmyer [88] focused on detecting and analyzing traffic infraction based on traffic behavior. The authors proposed an approach in which an information handling system detects a traffic infraction of a driver driving a vehicle. In turn, the information handling system forms an infraction detection zone that includes a set of traffic control devices, and sends a set of configuration parameters to the set of traffic control devices. The information handling system then uses vehicle identification data in the set of configuration parameters to identify driving behaviors of the driver through the infraction detection zone and issues a citation based upon the identified driving behaviors.

Wang *et al.* [89] introduced a novel concept is called "shadow traffic" for modeling traffic anomalies in a unified way in traffic simulations. They transformed the properties of anomalies to the properties of shadow vehicles and then described how these shadow vehicles participate in traffic simulations, (i.e. a variety of traffic anomalies can be depicted in a unified way and well describe how the anomaly itself is evolving). They claimed that their model could be incorporated into most existing traffic simulators with little computational overhead. Moreover, experimental results demonstrate that the model is capable of simulating a variety of abnormal traffic behaviors realistically and efficiently. They recommended, as a future work, to build a real-time editing traffic anomaly simulation system in which users can introduce and edit anomalies whenever and wherever they need in traffic simulations, also to explore modeling of complex vehicle-crowd interactions.

Li *et al.* [90] proposed a system and method for traffic engineering in networks and in particular embodiments, for distributed traffic engineering in Software defined networks. In accordance with an embodiment, a network component for dynamic Zoning for traffic engineering (TE) in Software defined networking (SDN) includes a processor and a computer readable storage medium storing programming for execution by the processor. The programming including instructions to: receive network information from at least one SDN controller from a plurality of SDN controllers in a network; determine a plurality of TE Zones for the network, selecting a local Zone TE controller for each of the plurality of TE Zones, and selecting a master TE controller according to the network information and a Zoning scheme, wherein the local Zone TE controller is selected from one of the SDN controllers, and wherein the master TE controller is selected from one of the SDN controllers; and transmitting an indication of the Zone composition, the local Zone TE controllers, and the master controllers to at least some of the SDN controllers.

The master selection strategy provides the network zoning processor with a methodology for how to select the master controller from the controller candidates. Possible strategies include random selection, fixed selection, joint optimization with Zoning, etc. Selection preference/un-preference and other necessary data may be specified along with the selection strategy. The Zoning strategy indicates whether to perform node grouping or flow grouping. The former means to create Zones by associating nodes (routers, Switches, base stations, UEs, etc) to controllers; the latter implies to do so by associating flows (represented by their candidate routing paths) to controllers. In an embodiment, which strategy to use depends on network and traffic status. For instance, in stable flow network segments flow grouping is preferable over node grouping; whereas, in unstable flow segments the opposite is desired. Other parameters, for example, Zone border type, can be included in Zoning configuration. There are three border types: link sharing only, node sharing only, and link and node sharing.

VII. DETECTION AND EVALUATION OF DRIVER BEHAVIOUR

There are decent amount of approaches were proposed to detect and evaluate of driver behavior. We focused on the following areas: detecting and evaluating of driver distraction, capturing the driver behavior using speech model, and analyzing and predicting driver behavior.

A. DETECTION AND EVALUATION OF DRIVER DISTRACTION

Nowadays, many drivers get distracted from visual and cognitive distractions. In addition, the features that are equipped with the vehicles such as entertainment systems, driver fatigue or portable devices that are brought into the vehicles such as smart phones also cause the distraction. Driver distraction, especially among young drivers, is considered one of the most common causes of traffic accidents and congestion. Andrei Aksjonov et. al in [91] and [92] proposed a novel method for evaluating driver distraction and situation awareness while performing a secondary task using machine learning and fuzzy set theory. The evaluation results showed that the proposed method allows to recognize, detect and to calculate the level of driver distraction in percentage based on safe vehicle dynamic performance. The secondary task is examined as a chatting on a cellular telephone. The conducted driver-distraction experiments are done using simulation in laboratory and generate more accuracy compared to the old one as it involves more input measures.

For monitoring the driver attention, Nanxiang et. al. in [93] build statistical models in the form of Gaussian Mixture Models (GMMs) to quantify and analyze the actual deviations in driver behaviors from the expected normal driving patterns. The authors defined secondary tasks as operating with the radio, phone and a navigation system. They collected data from real world scenarios using different noninvasive sensors including the controller area network-bus (CAN-Bus), video cameras and microphone arrays. Their model achieves 77.2% accuracy and shows that certain tasks are more distracting than others. Building upon these results, the authors proposed a regression model to generate a metric that identifies and describes the driver's attention level to signal alarms, preventing collision and improving the overall driving experience [93].

All the previously proposed methods provide a distracted or non-distracted decision and require some additional devices, such as cameras. Consequently, suggested method could be developed and used as a practical tool for different evaluation and comparative analyses of the secondary tasks influence on vehicle safety. Examples of the applications of detecting and predicting the driver behavior are: lane changing, intersection decision-making, driver profiling, and router choice modeling.

B. CAPTURE THE DRIVER BEHAVIOR USING SPEECH MODEL

Another direction is to study the driver motion behavior which includes driver's body movements to obtain their motion parameters that have impact on the vehicle control and traffic safety while driving on the road. This can be used to analyze the impact of human fatigue and alcohol on their driving performance under different traffic conditions.

Modeling the driver behavior essentially emerged to predict the driver intent, vehicle and driver state, and environmental factors that are used to improve transportation safety, reducing traffic congestion and enhancing the driving experience as a whole [94].

C. ANALYZE AND PREDICT DRIVER BEHAVIOR

Researchers from different backgrounds such as car industry, transport engineering, and psychology have been trying to study and analyze human driving behavior in realistic situations to: (1) better understand the relations between the driver actions, the vehicle performance and the driving environment, (2) prevent road crashes and reinforce traffic safety, and (3) enhance drivers comfort. Afaf Bouhoute et. al. In [95] developed a methodology to process and analyze car-generated data. The proposed method used probabilistic graphical models combined with a machine-learning algorithm for building a formal model of the driver behavior. It also focused on two analysis goals: 1) automatic conformity of the drivers' behavior to traffic rules; and 2) visualization and comparison of drivers' behaviors. Early experimental results showed that the design of numerical domains considered influences hugely on the analysis results.

Najah and Hatem in [96] provided an overview of advances of in-vehicle and smartphone sensing capabilities and communication and recent applications and services of driver behavior modeling (DBM) such as cloud-based services. The components and stages involved in driver behavior modeling, the various forms of input and the primary modeling approaches were introduced and the use of the DBM with emphasis on Advanced Driver Assistance Systems (ADAS) and the emerging autonomous vehicles were described. Also, the authors provided different techniques for simulation-based and data-driven evaluation mechanism along with datasets for specific DBM objectives and applications. Finally, the authors highlight several research challenges and key future directions and open research issues that enabling researchers to develop more sophisticated DBM.

Fugiglando et. al in [97] proposed a near-real-time method to analyze and classify driver behavior into different groups using a selected subset of controller area network (CAN) bus signals. The proposed method uses unsupervised learning technique and information that are collected from different resources such as gas pedal position, brake pedal pressure, steering wheel angle, steering wheel momentum, velocity, RPM, longitudinal, and lateral acceleration. The authors offer a validation method to test the robustness of clustering in a wide range of experimental settings and to compute the minimal amount of data needed to preserve robust driver clusters.

Results showed that the optimal number of cluster can be identified, and specific combinations of signal-feature provide very high performances in terms of robustness. In addition, the authors showed that it is possible to reduce the size of the database as much as 99% without affecting the clustering performance.

Bashar et.al. in [98] provided an overview of latest approaches used for drivers and passengers recognition based on data collected from smart phones. The authors also proposed a probabilistic method that utilizes features based on smartphone inertial measurements and doors signal, such as user motion during entry and captures salient ingress, to identify and analyze the user behavior. Experimental results showed the usefulness, effectiveness and simplicity of the identification method.

Analyzing the impacts of drivers' characteristics on their driving performance under varying traffic conditions is helpful and significant to the research on traffic safety and in formulating the measures of traffic control. Also, it is important to many professionals such as who are working in traffic behavioral studies. Many factors affecting driver behaviors have been investigated extensively, such as driver distraction, experience, in-vehicle information, fatigue and alcohol. Capturing the driving motion is a process to record and track drivers' body movements and obtains their motion parameters in a three-dimensional space [99]. Drivers' motional behavior greatly impacts the moving operation of an individual vehicle. Jianjun et. al. in [99] presented a study to better understand the driver behaviors based on information captured from a driving motion capture system (MCS) which is crucial to highway traffic safety. The authors use of MCS to capture driving motion and MotionBuilder to reproduce the driving motion. Then the quaternion method is utilized to understand and calculate the efficiency of driver behaviors. the proposed method explores the relation between driving behaviors and traffic conditions. Simultaneously, it could be used in other fields such as ergonomics, behavior and athletic sports [99].

Generally, it is difficult to measure and quantify the cognitive workload of a driver because a set of factors should be considered, such as the driver characteristics, the driving conditions, the traffic conditions, and the weather and local environment. However, Hyun et. al. in [100] developed a model to predict the driver's electroencephalograph (EEG) level utilizing basic information obtained while the vehicle is being driven. The model extracts useful features from the vehicle driving information, such as engine RPM, vehicle speed, lane changes, and turns that are grouped into three groups; driving information group, driving conditions, and driving behavior information. These features are used to divide the EEG values into two classes, "normal" and "overload". The classification model uses the support vector machine (SVM) algorithm to predict normal and overload states during actual driving. The model uses actual driving data collected from driver on real roads. The authors evaluated the prediction performance after building a SVM model and found that better prediction performance was obtained for drivers who felt more overloaded during complex driving than during simple straight driving. In addition, this prediction model can be utilized in some existing human vehicle interface-based driver workload management system (HVI-DWMS), such as in [101].

There are several challenges remain unaddressed for identifying and analysis of traffic pattern and behavior; some of these are: detecting of traffic bottlenecks, automatically distinguish between different types of transportation infrastructure to be able to understand the relationship between them, understanding how vehicles and drivers deal with traffic sign especially when there are more than one lane options available for merging. In addition, developing a dataset that contains complete driver behaviors is a necessary. This data set should be labeled and annotated correctly and cover different driver styles, urban environments, and cultures.

VIII. ANALYSIS OF VEHICLE/PEDESTRIANS BEHAVIOUR

Dangerous and abnormal pedestrian behaviors are the main cause of many traffic accidents. On average, a pedestrian was killed every 1.6 hours and injured every 7.5 minutes in traffic crashes in the US [102]. More than 30% of the total number of people killed in traffic accidents were pedestrians [103]. Significant efforts are being made to understand pedestrians' behavior to develop more accident free traffic environments in several countries. Qianyin et. al. in [104] studied five kinds of dangerous pedestrian abnormal behaviors, which are: crossing road border, illegal stay, crossing the road, moving along the curb and entering road area. In addition, they built a behavior model between the pedestrian trajectory and the road to describe the above behaviors. The authors first extracted the background from the video frames to detect the pedestrian, and then the shadow is eliminated. Third, the aspect ratio characteristic and traditional tracking method based on features are used to recognize and track the pedestrians. Finally, the authors developed a mathematical model to detect the abnormal behavior of the pedestrians. Experimental results showed that the proposed model using surveillance videos, collected from real traffic monitoring system in Guangzhou, China, achieved more than 85% detection accuracy of abnormal behaviors. There are some problems need to be addressed in future research, such as tracking pedestrians covered by vehicle and detection of abnormal behavior of the pedestrian at night.

Zaki et. al in [105] used automated computer vision tracking approach to localize pedestrians in small groups via the MMTrack Algorithm. The authors used the walking behavior to identify possible commonality between nearby pedestrians. The authors used the spatio-temporal criteria and the introduced movement similarity measure to classify and counting pedestrians in groups. To show the feasibility and accuracy of the proposed method, the authors used video data collected at a moderately dense pedestrian crosswalk in Vancouver, British Columbia. Evaluation results showed that the proposed method achieves 77% accuracy. Avoiding collision could be done by studying the group behavior.

An unsafe pedestrian crossing at the signalized intersections is considered one of the most common sources of pedestrian fatalities. Iryo-Asano et. al. in [106] analyzed and modeled the probabilistic crossing behavior of pedestrians after the onset of the pedestrian flashing green (PFG) until the completion of crossing. The authors used the stop–go decision and speed distribution models to represent the sidewalk and the crosswalk behaviors. Sensitivity data analysis of the proposed model showed that the crosswalk length and the distance to the crosswalk from the pedestrian position at the onset of the PFG cause pedestrians to speed up while crossing or give up crossing. In addition, it successfully represented the percentage of illegal crossings and the speeds of pedestrians at different crosswalks.

Distracted drivers are responsible for more accidents than impaired drivers, but the ubiquity of smartphones, distracted pedestrian is also on the rise and leads to traffic accidents, especially while crossing the street. Dong et. al in [107] proposes a new algorithm to detect the pedestrian behavior who unconsciously using their phones during the crossing of the street. Experimental results show efficiency of the proposed algorithm in pedestrian detection using a PWUM dataset.

Nan and Hideki in [108] analyzed and examined the characteristics of heavy vehicle behavior. The authors empirically analyzed data observed at a single-lane roundabout in Japan and examined the headway characteristics of heavy vehicles using three headway parameters. The big sizes of heavy vehicles force them to behave differently and the headways are commonly greater than passenger cars only. These results could be used to evaluate the performance of roundabout such as roundabout entry capacity estimation.

Kaparias et. al. in [109] proposed a new behavioral analysis, which uses video sources to qualitatively presents the interactions between vehicles and pedestrians and classify these behaviors and reactions as a function of traffic parameters (e.g., speed, density, and frequency of pedestrian crossings). The method used video data collected from a number of critical locations in London to show the factors that affect the confidence and tolerance of road user. Results showed that pedestrians have increased their confidence when they interact with vehicles, but drivers have not changed their behavior. To generalize the proposed method, other sits have to be studied, more road users (e.g. cyclists) should be considered, and additional characteristics of road users (e.g., demographics and perceptions) should be covered. In addition, it would be attractive to explore other aspects of vehicle-pedestrian interactions, such as the behavior of disabled road users, the effect of weather conditions, and the impact on the surrounding areas.

Koji and Hiroki in [110] conducted observation surveys and developed linear regression models to analyze and clarify the risky behavior of both pedestrians and vehicles making left turns at five major intersections in Japan. In addition, the authors discussed the issues that prevent and reduce the pedestrian-vehicle conflicts at intersections based on the sensitivity analysis. Number of large-size intersections and other conflict patterns should be discussed as future works that might improve the accuracy of the proposed models.

Qualified human drivers are able to analyze the road traffic and choose a driving strategy that avoids accidents. However, automated vehicles need to be trained to be able to smartly perform the same task. Chen et. al in [111] proposed a new method for evaluating the safety and feasibility of the driving and passing strategies for automated vehicles at un-signalized crossings. Simulation tests were conducted to demonstrate the effectiveness of the proposed method. As an example, One Soft-Yield driver model is evaluated and the simulation results showed that it achieved more efficiency than nature human-driver using data collected from the Ann Arbor city in Michigan. Future work might include developing a more detailed pedestrian model and more behaviors and features can be considered.

Another attempt was done by Camara et. al in [112] in which the authors considered the interactions between pedestrian and autonomous vehicle as a game-theoretic interaction in which a pedestrian wishes to cross the road in front of the AV at an unmarked crossing. In this situation one agent must yield to another. The authors used and analyzed data collected from real-world pedestrians interacting with manual drive vehicles when crossing roads. The authors studies the time orders in which the results suggested that AVs should not act right away on detecting a road crossing interaction, but rather wait for first few informative features before acting (speed up or slow down). This implies that the first event features gains more attention to make a decision rather wait for late features, which may risk making a decision if it waits much longer. In addition, the authors suggested that studying the Optimal Stopping for AV controllers for pedestrian interactions would be a high impact research area.

There are different factors that potentially impact the way pedestrians behave; some of them are age, gender, group size, culture, education level, and economic. We believe that studying the impact of these factors and the relationships between them represent the next step to go. In addition, how pedestrians interact and communicate with autonomous vehicles should be addressed [108]. Moreover, understanding the pedestrians' intention is limited.

IX. SIGNAL CONTROL AND TRAFFIC LIGHT

Traffic light is the main element to control the movement of vehicles by specifying the waiting and going times; fixing the time for traffic lights is inefficient way to control vehicle movements and lead to imbalance system due to inconsistent number of vehicles on each side. Abu Zaid et. al. [113] proposed an algorithm to control the traffic light based on number of vehicles on each traffic light. The algorithm uses image data extracted from the captured video using a camera installed in the field and apply the artificial neural network and fuzzy logic to adapt the time length for each light. The algorithm is validated by comparing its results with manual results. The generated results will regulate traffic flow and reduce the waiting time wasted in the roads.

Video monitoring and surveillance systems have been widely used in traffic management and traffic light control systems. Several attempts have been made to develop smart traffic lights. Anurag et. al. [114] developed a method that uses images extracted from live videos feed from cameras installed at traffic junctions to calculate a real time traffic density. This method switches the light according to the traffic density aiming to reduce traffic density.

In general, these techniques that are based on videos and images require (1) good image quality that is weather dependent especially in case of rain and fog, (2) high rate of transmitted and received data, (3) sophisticated algorithms to model the various states of traffic that are based on fuzzy logic and genetic algorithms. To address these issues, many works have used the Programmable Intelligent Computer (PIC) microcontroller with transmitter and receiver IR sensors to evaluate the traffic density and accomplish dynamic timing slots. PIC and IR sensors require small amount of information to be transmitted and received and low installation cost.

Bilal Ghazal et. al. [115] proposed a smart traffic light system that control and manage the traffic light of a "+" junction of mono directional road. The system uses the IR sensors to estimate the traffic density posted in either side of the roads. Based on the density value, the green light will be either extended in case of traffic jam to allow large flow of vehicles or reduced in case of no cars are present to prevent unnecessary waiting time. In addition, the system allows emergency vehicles to pursue using a portable controller.

To handle emergency vehicles towards the junction, several attempts have been introduced. Some of them, such as [116], [117] use the RF emitters to send warning signals to the RF transceivers disposed at every traffic light intersection and provide a special route accordingly. Other attempts use the Global Positioning Systems (GPS) to provide preemption signals to both traffic light and hospitals [118], [119], [120]. To reduce the latency of emergency services for vehicles, the authors of [121] explored the effect of traffic congestion on the emergency services and proposed a framework that dynamically adjusts the traffic lights, changes related driving policies and drivers' behavior, and applies essential security controls based on the announced emergency level. However, the effectiveness of the proposed framework has not been evaluated.

When the drivers wait too much in the traffic light queue and the traffic light changes from green to yellow, most of the time the drivers cross the road during transitions from yellow to red, consequently, the possibility of accidents increases. This knows as a Red Light Running (RLR) phenomenon, which often occurs as a consequence of the fact that the traffic light is not well balanced. The authors in [122] proposed a technique that uses the information gathered through a wireless sensor network to dynamically optimize the waiting time in the road queue and to reduce the occurring of the RLR phenomenon in an isolated intersection. This is done by assigning a longer time of green light to the road that has a longest queue.

Automatic driving and parking, automatic traffic sign recognition, and automatic collision detection are some tasks that are provided by the Advanced Driver Assistance Systems (ADAS). Current developments aim to automate some of the drivers' tasks using computer vision and other technologies such as machine learning and robotic navigation. ADAS already have a huge impact on the industry and society, increase the safety of the drivers, and help in maintaining the vehicles as well. A survey that shows the current progress and future directions in the field of vision-based embedded ADAS that bridges the gap between theory and practice is shown in [123].In addition, the authors in [123] reviewed different hardware and software options used in the ADAS, and the design, development, and testing considerations are also discussed. Moreover, some outstanding challenges are also identified. The authors in [124] listed a set of vision-based ADAS with a consistent terminology and taxonomy. They also proposed an abstract model to formalize a top-down view of application development to scale towards autonomous driving system.

Several attempts have been made toward providing an energy efficient intersection service in order to optimize the way vehicles cross an intersection. To reduce the energy consumption and emission, energy efficient intersection service is developed to optimize the way vehicles cross an intersection and to avoid any un-necessary acceleration or braking by the drivers. LED Traffic Lights Reduce Energy Use in Chicago by 85% [125].

To investigate the potential of V2X communication technology in reducing road traffic congestion using smart traffic light controller, Cullen Rhodes and Soufiene Djahel [126] developed an efficient mechanism, called TRaffic Light Phases Aware Driving for REduced tRaffic Congestion (TRADER) to reduce the overall vehicle's travel time in smart cities. TRADER has been implemented and extensively evaluated using SUMO and TraCI. The evaluation results show that the performance varied based on network topology and traffic density.

Soufiene et. al. in [127] investigated the opportunities of improving the commuter's journey duration using the technology offered by V2I and proposed a Belief-Desire-Intention architecture that uses local knowledge and information collected from the surrounding infrastructures (vehicles and traffic light controllers (TLCs)) to model the way how vehicles behave in the road. This architecture exchanges beacons among vehicles to determine their optimal speed and position in the road segment in order to cross the intersection with minimum delays while ultimately avoid stoppages whenever possible. The initial simulation results show significant reduction of average travel time. however, the proposed architecture does not handle the selfishly acting vehicles or the reactive and proactive solutions in an efficient way.

Another attempt was done by Jagadeesh *et al.* [128] to enable the traffic light to switch from red to green based on traffic density. The authors combined existing technology with artificial intelligent to develop and implement a low cost real-time and sensor-based dynamic traffic light control system to reduce the Average Trip Waiting TIme (ATWT). Their proposed system uses Dynamic control, IR sensor, Low power embedded controllers, comparators and storage device.

Communications between vehicle to vehicle and vehicle to road (infrastructure), Khekare and Sakahra [129] proposed a framework called VENET that plays an important role in smart cities by transmitting information about the traffic condition and aiding divers to take smart decisions to prevent themselves from congestion. Another attempt that uses VANET was done by Bani Younes and Boukerche in [130] to estimate the vehicle stop time for each traffic light. However, their proposed method is not reliable because there is no synchronization between the simulation scenario and traffic flow, also it does not address the case when the vehicles accelerate or decelerate at the moment the signal light change [20].

Automatically moving the traffic to less crowded and adapting it to handle emergency scenarios are the ultimate goals of most traffic management systems. Researchers developed several intelligent traffic systems that capture the feature of surveillance via camera presents on the junction using image analysis techniques [131] and controlling traffic lights with the help of photoelectric sensors [132]. These systems use the relevant weight of each road to open traffic for roads that are more crowded and give them longer time compared to others less crowded. Limitations of VANET are: 1) Appropriate hardware should be installed in every vehicle and 2) Decisions should be made by users. Systems that are implemented on four-way junction and have no relation to every vehicle and limit the number of hardware required to be installed on every vehicle such as [114].

Inefficient traffic light systems trouble the transportation system which will badly affect the economic, health, financial, and environmental domain of citizens and governments [115]. The major problem of the existing traffic light systems is that the transition timing slots are fixed, which is known as Fixed Traffic Light Control (FTLC) system. FTLC systems are unable to solve the situations where the traffic congestion is only observed from one direction [115]. Other situation is when traffic flow is increased at intersection roads during rush hours and decreased at night. In these situations, the traffic light should be adapted to extend or reduce the green light activation based on traffic status and density, which is known as Dynamic Traffic Light Control (DTLC) systems. DTLC system reduces the average waiting time of vehicles on junctions and is the most suitable to the complexity of current traffic conditions [133].

Future effort should be made to address the influence of adjacent intersections on one junction to achieve a complete modeling, monitoring, and control for multiple synchronized junctions. Adaptive traffic light systems and synchronize multiple traffic lights at different junctions to reduce traffic congestion is required. To improve the safety, traffic efficiency, and fairness among vehicles at intersections, Wang *et. al.* [134] proposed a 3-level buffer based virtual traffic scheme for intelligent collaborative intersections. The authors divided the intersections into three adaptive areas according to the traffic flow of each lane and used the V2V, V2R, and V2I to improve the safety and fairness without involving traffic light. In addition, the authors proposed a Collaborative Collision Avoidance Predictive (CCAP) control algorithm to assist vehicles to go a cross next intersection without stopping through predicting the time conflict and generating an efficient traffic schedule for the entire road network. Their simulated results improve the fairness by 331%, decrease the average delay by 88%, and improve the ability to solve congestion by 12% compared with traditional algorithms.

Another attempt was done by Khamis and Gomaa in [135] to control and monitor the traffic lights that are operating in the adjacent intersections to reduce the jam and potential accidents, especially in the rush hours.

Some ITS uses Local Positioning System (LPS) instead of GPS (Global Positioning system) for locating a vehicle with the help of localized workstations or sensors situated at optimal points. The evolution of the Internet of Things, which requires to install as many sensors as possible to capture the detail from all different angels, allow smart cities to be real. Benefits of sensor-based data as input to traffic management systems are: 1) there is no special data base to store the huge volume of traffic data and to make proper queries and decisions, and 2) there is no special automated system that uses data warehouse and mining techniques for summarizing and cluster traffic data to make proper decisions for a particular time. However, more sensors mean huge and redundant data will be generated and storage and maintenance cost will be increased. Interaction between system supplier (traffic engineers) and system users (travelers) is less considered. Visual analysis provides suppliers the chance to make better decisions based on visual information.

In the vehicle type classification, instead of labeling the samples as positive and negative, multi-group classification (e.g., car, truck, bus, motorcycle, large/heavy vehicles) would further benefit the machine's understanding of traffic scene. This leads to develop a more general classification frameworks that improves the accuracy and the overall performances and will be further evaluated over a longer monitoring time and more complicated scenarios, such as low video quality (e.g., low resolution, motion blur), different lighting conditions, and more operational challenges. In addition, evaluate the proposed framework using heavily congested traffic conditions and different curved road segments, might realize the generated results. Directions to future researches can be as follows:

- More general classification approach based on data collected from more sites is required. The classification approach can categorize based on vehicles size (e.g., Grand saloons, Small vans, minivans, SUVs, bus, trucks and others), drivers behavior (normal, dangerous, aggressive, or conservative drivers), vehicle maximum speeds (luxury cars versus regular cars), driving mode (automated vehicles or human-driving vehicles), or vehicle models and make. Other vehicle classification methods can be examined to better approximate the real traffic flow [19].
- Uniform performance measurements are urgently needed for evaluating the overall performance and accuracy of the prediction algorithms, especially when

the two selected measures are showing different performances.
- Longer time intervals can be used to evaluate different online algorithms so as to extend their applicability to meet the requirements of more ITS applications.
- Using natural language processing in predicting traffic flow is an interesting and challenging problem which needs to be studied further. This could be done by representing the input of the main properties of traffic flow as vectors and trying to get the vector that is very close using some machine learning and artificial intelligence techniques [18], [136].
- Other data sets can be applied to test the online algorithms. These data sets cover more sites and at different time slots.
- Modeling flow in different situations, such as stretch of highway and diverge junctions.

Real-time information about traffic conditions and active information gathering methods that are collected using data from sensors installed in highways or average measured GPS and LPS speeds from mobile phones during the current time period. These methods might be used to guide both selective real time sensing of different portions of a road network and the bulk collection of data to reduce uncertainty about the flows over segments and routes.

X. CHRONOLOGICAL REVIEW OF INTELLIGENT TRANSPORTATION AND TRAFFIC MANAGEMENT SYSTEMS

Here we provide a chronological review for the recent survey papers in the areas of intelligent transportation and traffic management systems. In 2011, Baskar *et al.* [137] focused on reviewing the traffic management and control frameworks for Intelligent Vehicle Highway Systems (IVHS) to improve the traffic performance. IVHS represent the most promising solutions to the traffic congestion problems, which focus on applying intelligent techniques to allow vehicles to communicate with roadside infrastructure in order to shifts the driving tasks from the driver to the vehicles and make better driving decisions. Some of these tasks include activities such as braking, steering and making control decisions about speed and headways. The authors also described the ITS and IVHS, and difference between them and their relations with the Automated highway Systems (AHS) and the Intelligent Vehicles (IV). The IV represents the main component of the IVHS and AHS, and aims to achieve more efficient vehicle operation by helping the driver or by taking the complete control of the vehicle. In addition, the authors investigated the control design methods and their applications used for traffic control tasks, artificial intelligent techniques, IV and traffic control frameworks and architectures for freeway systems. Various traffic management architectures such as PATH, Dolphin, CVIS, SafeSpot, PReVENT, and Auto21 CDS were discussed and quantitatively compared to show how the current traffic control methodologies could fit in an IVHS-based traffic control set-up.

In **2012**, Partishtha *et al.* [138] presented various approaches for intelligent traffic systems and proposed a model for managing real time traffic system using CCTV cameras and WAN. The paper started by exploring the challenges in ITS such as the real time signal control, traffic load prediction and computation, vehicle tracking, vehicle routine and route optimization. Then it viewed a variety of approaches that are in use to explore and search the field of Intelligent Traffic Management such as the Geographical Information Systems, Artificial Intelligence, Graph Theory and Real time Systems. In addition, it explored the main technologies that can be used for ITS such as Wireless Sensor Networks, CCTV, RFID and GPS. The proposed model for real time traffic management relies on installing the CCTV cameras in the desired locations to capture images for real time traffic, then analyze and process these images to firstly obtain vehicles' plates numbers to track suspected vehicles and secondly compute the traffic load which can be used to control the green light signal timing. In addition, it suggested the use of other technologies such as WAN and mobile services that can help users to find emergency services and get the traffic information dynamically in real time.

In **2013**, Kashif and Abdul Hanan [139] presented the variety of Intelligent Transport System (ITS) areas, applications, and technologies. The ITS integrates the virtual technologies with transportation in order to reduce risks, accidents rate, traffic congestion, carbon emissions, air pollution and increase the safety, reliability and travel speeds. Authors firstly review the generation and the areas of ITS that provide solutions for cooperation and reliable platform such as: Arterial and Freeway Management Systems, Freight Management Systems, Transit Management Systems, Incident Management Systems, Emergency Management Systems and Regional Multimodal and Traveler Information Systems/Information Management (IM). In addition, they reviewed the application of ITS that used for transportation safety, efficiency and user services such as Electronic Toll Collection (ETC), Highway Data Collection (HDC), Traffic Management Systems (TMS), Vehicle Data Collection (VDC), Transit Signal Priority (TSP) and Emergency Vehicle Preemption (EVP). Finally, authors reviewed the different technologies of ITS that used to improve the transportation conditions, safety and services such as: wireless communications, computational technologies, floating car data/floating cellular data, sensing technologies, inductive loop detection, video vehicle detection and Bluetooth detection. The conclusion of the survey paper showed that the ITS covers many technologies that can help in improving safety, efficiency, mobility, accessibility and intermodal connections of transport systems.

In **2015**, Chepuru and Rao in [140] reviewed the current and research challenges and opportunities to the development of secure and safe IoT-based ITS applications. The authors also reviewed the current ITS architectures, requirements, and standards. They also classified and analyzed existing ITS threats and attacks. In addition, they offer a broad view on how recent and ongoing advances in sensors, devices, internet applications, and other technologies have motivated affordable healthcare gadgets and connected health care services to limitlessly expand the potential IoT-based ITS for further development.

In **2016**, Merrad *et al.* [141] provided a survey on how the researchers used WSN, simple sensors and/or analytical approaches to regulate the traffic around an intersection. Experiments show that a network of wireless magnetic sensors provides more flexibility, consumes lower energy, reduces the installation and maintenance costs, easy to deploy, and has smaller size than video, radar detection, and inductive loop systems [142]. The authors also presented the basic notations and the most important parameters that affect the traffic control. These parameters include: signal cycle, stage, split, and offset. The signal cycle is the repetition of the signal combination and has different stages, during one stage a set of streams can move securely. Split parameter represents the green duration of each stage. Offset is the phase that represents the difference between signal cycles of successive intersections that optimize the green wave along an arterial [141], [143], [144]. Some other parameters are travel time, travel delay, turning probabilities, queue length and delay. These parameters are of three types [141]: dynamic data, model parameters, and statistic data. Dynamic data are data that changed over a short period of time (i.e., second by second). Model parameters refer to parameters that are either constant or slowly changed over time. Statistics data represents data that are constant such as road_id, number of lanes in each road. In addition, the authors in [141] compared RHODES [145], a real-time traffic adaptive signal control system, with PREDICT [146] model that is used to predict the arrival time. The comparison results showed that the RHODES achieves slightly better throughput and significant decreasing in the delay.

In **2016**, Tendulkar *et al.* [147] proposed a traffic management system using IoT to manage the traffic signals by monitoring the traffic density[1] in order to avoid the traffic congestion on road using network communication. The architecture of the proposed system consists of wireless network sensors, RFID (Radio Frequency Identification) and GSM-GPS (Global positioning System). The wireless network sensors (i.e., sensor nodes) use sensors to communicate together, send information through the used network and record the environmental physical condition such as temperature, pressure, pollution etc. The RFID technology is used to identify, trace and count objects based on three parameters; the speed of vehicle, average waiting time and queue size. The GSM-GPS is used to track the current location of the vehicle, the distance between source and destination, information about stolen vehicles and any position such as land, sea, battlefield, and underground. The authors defined the problem with the proposed solution, and finally an initial test-bed prototype was developed.

In **2016**, Anaswara and Lakshmi [148] reviewed different traffic management schemes that use IoT in smart cities. Some of these schemes are (1) reservation-based system at intersections that perform better than normal traffic light by reserving a piece of roads to cross junction and used for both fully-automated and human-driver cars to create a reservation algorithm [149], [150], (2) automated intersection management systems that build a detailed communication protocol, through simulation evaluation, the system proposed in [151] outperforms current intersection technology that uses traffic light and stop signs, (3) different polices, such as FCFS, FCFS-light, and FCFS-Emerg polices, that communicate different kinds of vehicles such as automated and emergency vehicles with traffic light infrastructures and give some kinds of vehicles priorities than other vehicles without increasing their delay. Switching between these polices is done by learning from reservation history which policy is best for particular traffic state. (4) intelligent intersection and autonomous passing-through intersections especially with the emerging of driver less vehicles in which all the traffic components ()such as lane, path, critical section, and vehicles are modeled and evaluated. Other reviewed schemes are: online coordination of a continuous flow of connected and automated vehicles [152], traffic light control for multiple intersections [153], smart parking system for an urban environment [154].

In **2017**, Anand *et al.* [5] presented an extensive review on various data mining as well as clustering methods that model, predict, and plan transportation systems to facilitate Intelligent Transportation Systems (ITS). Around 50 research articles from the last decade were collected from the leading journals and reviewed in three stages. Firstly, the contributions that pertain to the ITS were reviewed chronologically. Secondly, the data mining approaches, involving predictive and descriptive concepts for managing transportation, were reviewed based on the adopted methodologies. In the third stage, the clustering models were categorized as supervised or unsupervised, and reviewed based on their usefulness over transportation data analysis. Finally, the paper discussed their findings from the review and summarized the research gaps as following: descriptive mining methods have aided in generating a real-time information system, identifying traffic patterns, developing travel speed calculation model, and investigating parking decisions. Predictive data mining techniques have helped in inferring the network topology, finding traffic bottlenecks, solving the multi-objective location inventory problem, constructing two data reduction algorithms, and predicting short-term traffic flow in heterogeneous conditions. Among the descriptive data mining methods, clustering models have extensive use in forming the single transportation system, calibrating the speed-density parameters, estimating the travel speed, and clustering the taxi-cab trips and route planning system. Especially, the unsupervised meth-

[1]Traffic density is defined as a number of vehicles in a specified length of a road in a given time period. Traffic density is the most commonly used parameter to indicate the level of congestion on a roadway.

ods have many applications in ITS. Traditional unsupervised models have drawbacks; however, these are rectified using the evolutionary approach. The presented evolutionary approach also has drawbacks. Thus, increasing the potential of the evolutionary model is rather challenging. Finally they recommended an effective evolutionary approach without drawbacks as a direction for future research that will certainly help in developing enhanced ITS.

Urban traffic system is a huge system that consists of many objects such as traffic lights, buildings, pedestrians, cyclists, cars, buses and other public transport vehicles. In order to estimate the traffic flow different methods are used to count the number of different objects during a specific time. The detection of anomalies (outliers) that represents the observations of inconsistent set of data in the traffic flow is an important method that can be used to analysis the urban traffic data using the traffic prediction or application scenarios such as spatial data [62], [158], [159].

For traffic prediction, in 2019 Yao *et al.* proposed a novel approach that tackles the spatial dependencies and temporal dynamics in a unified framework is called Spatial-Temporal Dynamic Network (STDN). The STDN mechanism is introduced to learn the dynamic similarity between locations, and a periodically shifted attention mechanism is designed to handle long-term periodic temporal shifting. Their experimental results on two datasets of real-world traffic verify the effectiveness of the STDN method [160]

Urban anomalies represent the disturbances in urban city environments. In 2017, Wu *et al.* focus on studying the future anomaly prediction problem in urban environments rather than studying the anomalies in existing urban data. They developed the Urban Anomaly PreDiction (UAPD) framework, which addresses a number of challenges, including the dynamic, spatial varieties of different categories of anomalies. Using up to date urban anomaly data, the UAPD first detects the change point of each type of anomalies in the temporal dimension and then uses a tensor decomposition model to decouple the interrelations between the spatial and categorical dimensions. Finally, the UAPD applies an auto regression method to predict which categories of anomalies will happen at each region in the future. The experimental results on two urban environments, demonstrate that UAPD outperforms alternative baselines across various settings, including different region and time-frame scales, as well as diverse categories of anomalies [161].

In 2018, Dejenouri *et al.* studied the impact of different conditions on traffic flow that lead to unusual patterns. They focused on studying the historical data of these conditions such as the festivals and events related to unusual patterns in the traffic flow in order to improve organizing both the layout of traffic and events. To handle the flow distributions, an established outlier detection method, the local outlier factor (LOF) is used instead of the individual observation. They applied the LOF to extend the database with new flow distributions and the results of their method on a real urban traffic data as a case study finds meaningful outliers in the traffic flow data [162]. Similarly, Wang *et al.* in 2018 used the Local Outlier Factor (LOF) algorithm basis to combine the extracted features of different types of traffic data and developed a grid-based LOF algorithm to detect the abnormal area in Beijing. Their extensive experiments on taxi and bus trips shows the effectiveness of the proposed approach [163].

Sun in his doctoral dissertation developed an application is called transit-hub. He used data mining and machine learning techniques for context sensitive prediction of long-term, short-term and real-time delays in sparse public transit networks. He integrated neural network models, heuristic search algorithm, deep learning techniques and sensitivity analyses of the hyper-parameters algorithms to analyze the performance of public transit networks, optimize the on-time performance under uncertainty of traffic and weather conditions, detect the operations of transit networks over a large metropolitan area and identify non-recurring traffic congestion and explain its causes. It efficiently convert traffic data in Traffic Message Channel (TMC) format to images, as well as a data augmentation mechanism using crossover operators for class balancing. In addition, the application provides set of experiments to understand how advanced decision support tools improve the utilization of the transportation infrastructure [164].

Bhowmick and Narvekar studied the trajectory outliers in urban traffic data and classified them into distance based, density-based, and motifs-based outliers based on the used method in processing steps [165]. Djenouri and Zimek presented a tutorial on outlier detection in urban traffic data and classified them into statistical techniques that employ statistical models to identify anomalies in traffic data, similarity-based techniques that use distance measures and neighborhoods to derive local density estimates, and techniques based on pattern analysis that explore the correlation between traffic flow values by using concepts from pattern analysis [162]. Djenouri *et al.* in 2019 reviewed the use of outlier detection approaches in urban traffic analysis and divided them into two main categories: flow outlier detection that detects flow outliers and includes statistical, similarity and pattern mining approaches, and trajectory outlier detection that includes offline processing for trajectory outliers and online processing for sub-trajectory outliers [166].

XI. INTELLIGENT TRAFFIC PUBLIC DATA SETS AND TOOLS

Table 5 shows a list of open source tools that are used by researchers in the area of traffic and transportation management and here we provide a set of public datasets used by researchers in the area of traffic management systems.

A. MULTI-MODAL INTELLIGENT TRAFFIC SIGNAL SYSTEMS GPS - DEPARTMENT OF TRANSPORTATION (USDOT)

Data were collected during the Multi-Modal Intelligent Transportation Signal Systems (MMITSS) study. MMITSS is a next-generation traffic signal system that seeks to provide

TABLE 5. Open source tools that are used by researchers in the area of traffic and transportation management.

Open Source Tools	Description
Traffic Intelligence Tool	Tools for transportation analysis, in particular road traffic, including a video analysis tool that extract the trajectories of moving objects from video data -automated video analysis (tracking) **URL**: https://www.openhub.net/p/trafficintelligence
OpenTraffic	OpenTraffic is a global data platform to process anonymous positions of vehicles and smartphones into real-time and historical traffic statistics. **URL**: http://opentraffic.io/
MOTUS	MOTUS is an open-source microscopic traffic simulation package that was developed in java. It is especially aimed at reasearchers that need full knowledge of everything in simulation as well as the ability to extend the capabilities with new technologies, algorithms or models. **URL**: http://homepage.tudelft.nl/05a3n/
Waze	Waze is the world's largest community-based traffic and navigation app. Join other drivers in your area who share real-time traffic and road info, saving everyone time and gas money on their daily commute. **URL**: https://www.waze.com/
CARTO-Waze connector	For the modern city looking to improve its mobility infrastructure and assess traffic systems, modern, real-time data streams are a powerful tool. A CARTO-Waze connector tool can provide key insights to urban data scientists and planners. It can be used to pull the JSON file into CARTO every two minutes for further mapping and analysis. **URL**: https://carto.com/blog/announcing-carto-waze-open-source-connector/
SUMO	"Simulation of Urban MObility", or "SUMO" for short, is an open source, microscopic, multi-modal traffic simulation. It allows to simulate how a given traffic demand which consists of single vehicles moves through a given road network. The simulation allows to address a large set of traffic management topics. It is purely microscopic: each vehicle is modelled explicitly, has an own route, and moves individually through the network. URL: https://sumo.dlr.de/userdoc/Sumo_at_a_Glance.html

a comprehensive traffic information framework to service all modes of transportation. The GPS data set catalogs the vehicle operation data of the test vehicles that used for the MMITSS field testing. The data contains the performance and operation details of vehicles. This file contains a number of fields detailing elements such as vehicle position and speed, fidelity measures of GPS-based data elements, and vehicle operation data.

B. INTELLIGENT TRANSPORTATION SYSTEMS RESEARCH DATA EXCHANGE - PORTLAND

The Portland data environment provides the following data: (a) Freeway data consisting of two months of data from dual-loop detectors deployed in the main line and on-ramps of a Portland-area freeway (I-205), (b) Incident data from the Oregon Department of Transportation Advanced Traffic Management System database and planned event data from the ODOT Trip-Check Traveler Information Portal information web site, (c) Weather data from two sources: NOAA data and Remote Weather Information System (RWIS) station data, (d) Three types of arterial data: (1) Volume and occupancy data from four single loop detectors on 82nd Ave., (2) Signal phase and timing data for 32 signals along the 82nd Avenue corridor, (3) Travel times on 82nd Ave., computed from data collected by two Bluetooth readers, and (e) Transit data provided from TriMet, the Portland-metro area transit agency, including schedule, stop event and passenger counts data for both bus and light rail.

C. LIVE TRAFFIC DATA SENSOR FEEDS (REACTOR) - STATE OF IOWA: DEPARTMENT OF TRANSPORTATION

Iowa Department of Transportation's Intelligent Transportation System (ITS) Detector Sensors. Sensor Feed: Includes location of sensors, current travel speed, traffic counts, occupancy counts, and more. Work Zone Alert Feed: Includes work zones that have dropped below the normal speed and are determined to have a critical traffic speed abnormality.

D. ACTIVE TRANSPORTATION DEMAND MANAGEMENT (ATDM) TRAJECTORY LEVEL VALIDATION

The ATDM Trajectory Validation project developed a validation framework and a trajectory computational engine to compare and validate simulated and observed vehicle trajectories and dynamics. The field data were used to demonstrate how on-site instrumented vehicle data can be used to validate simulated vehicle dynamics using the validation framework.

The vehicle trajectory data were collected in a separate task of the Active Transportation Demand Management (ATDM) Trajectory Level Validation project. The primary project objective was to develop a methodology to validate simulated vehicle dynamics at the trajectory level. Microscopic and macroscopic performance measures were calculated from the trajectory data and used in a number of validation tests related to safety, vehicle limits, driver comfort levels, and traffic flow.

E. MULTI-MODAL INTELLIGENT TRAFFIC SIGNAL SYSTEMS VEHICLE TRAJECTORIES FOR ROADSIDE EQUIPMENT

Data were collected during the Multi-Modal Intelligent Transportation Signal Systems (MMITSS) study. MMITSS is a next-generation traffic signal system that seeks to provide a comprehensive traffic information framework to service all modes of transportation. The Vehicle Trajectories file is populated with basic safety messages received from equipped vehicle within the communication range of an Roadside Equipment (RSEs).

The data also contains elements that communicate additional details about the vehicle that is used for vehicle safety applications, and elements that communicate specific items of a vehicle's status that are used in data event snapshots which are gathered and periodically reported to an RSEs. These data are transmitted at a rate of 10 Hz.

F. INTELLIGENT NETWORK FLOW OPTIMIZATION PROTOTYPE BASIC SAFETY MESSAGES

Data is from the small-scale demonstration of the Intelligent Network Flow Optimization (INFLO) Prototype System and applications in Seattle, Washington. Connected vehicle systems were deployed in 21 vehicles in a scripted driving scenario circuiting this I-5 corridor northbound and southbound during morning rush hour. Basic Safety Messages (BSM) sent by connected vehicles (CVs) through either the cellular network or Dedicated Short Range Communication (DSRC) when the vehicle is in the range of Roadside Units (RSU). These messages were received by the traffic management center (TMC).

G. VEHICLE AWARENESS DEVICE DATA FROM LEESBURG, VIRGINIA

The files in this data environment were produced using the Vehicle Awareness Device (VAD) installed on one test vehicle over a two month period. The VAD installed in the test car is identical to the VADs installed in over 2800 vehicles participating in the Safety Pilot Model Demonstration conducted from August 2012 through August 2013 by the National Highway Traffic Safety Administration (NHTSA) in Ann Arbor, Michigan.

This legacy dataset was created before data.transportation.gov and is only currently available via the attached file(s). Please contact the dataset owner if there is a need for users to work with this data using the data.transportation.gov analysis features (online viewing, API, graphing, etc.) and the USDOT will consider modifying the dataset to fully integrate in data.transportation.gov.

H. INTELLIGENT NETWORK FLOW OPTIMIZATION PROTOTYPE TRAFFIC MANAGEMENT ENTITY-BASED QUEUE WARNING

Data is from the small-scale demonstration of the Intelligent Network Flow Optimization (INFLO) Prototype System and applications in Seattle, Washington. Connected vehicle systems were deployed in 21 vehicles in a scripted driving scenario circuiting this I-5 corridor northbound and southbound during morning rush hour. This data set contains queue warning messages that were recommended by the INFLO Q-WARN algorithm and sent by the traffic management center to vehicles to warn drivers upstream of the queue. The objective of queue warning is to provide a vehicle operator sufficient warning of impending queue backup in order to brake safely, change lanes, or modify route such that secondary collisions can be minimized or even eliminated.

I. NHTSA PRODUCT INFORMATION CATALOG AND VEHICLE LISTING (VPIC) - MODIFIER DB

The NHTSA Product Information Catalog and Vehicle Listing (vPIC) is a consolidated platform that presents data collected within the manufacturer reported data from CFR 49 Parts 551 - 574 for use in a variety of modern tools. NHTSA's vPIC platform is intended to serve as a centralized source for basic Vehicle Identification Number (VIN) decoding, Manufacturer Information Database (MID), Manufacturer Equipment Plant Identification and associated data. vPIC is intended to support the Open Data and Transparency initiatives of the agency by allowing the data to be freely used by the public without the burden of manual retrieval from a library of electronic documents (PDFs). While these documents will still be available online for viewing within the Manufacturer Information Database (MID) module of vPIC one can view and use the actual data through the VIN Decoder and Application Programming Interface (API) modules.

J. VEHICLE TRAVEL INFORMATION SYSTEM (VTRIS) - DATA DOWNLOAD TOOL

The VTRIS W-Tables are designed to provide a standard format for presenting the outcome of the Vehicle Weighing and Classification efforts at truck weigh sites. The data that appears in the W-Tables comes from the Summary files that are generated by the Summary subsystem.

XII. PROPOSED MODEL

Based on the above mentioned approaches and techniques, we found that there are limited researches that:

A. Investigate the usage of cloud-based frameworks to enhance the performance of the traffic management systems.
B. Develop a real-time application that captures the relationship between different traffic components, such as traffic lights, road signs, and road intersections.

Therefore, as a future direction, we encourage researchers to propose a general framework that address the above limitations to enhance the performance of traffic management systems. Figure 4 shows the conceptual proposed model of the future work due to the limitations of some existing work. In the model, we divided the city into regions and each region has some road intersections; each intersection has a traffic light. In the proposed mode; there is a relationship between these regions and the road intersections. In addition, the model specifies the relationships between road intersections, in which the traffic lights that are close to each other contribute to each other. For example, in region 1, there are two intersections: A and B. while in region 2 there is one intersection, which is C. It is clear that the relationship between intersection A and B is stronger than the relationship between A and C, meaning that vehicles in intersection B may contribute more and affect the traffic status in intersection A than what intersection C does. Assume that there are x vehicles in intersection A, y vehicles in intersection B and z vehicles in intersection C. After a specified amount of time;

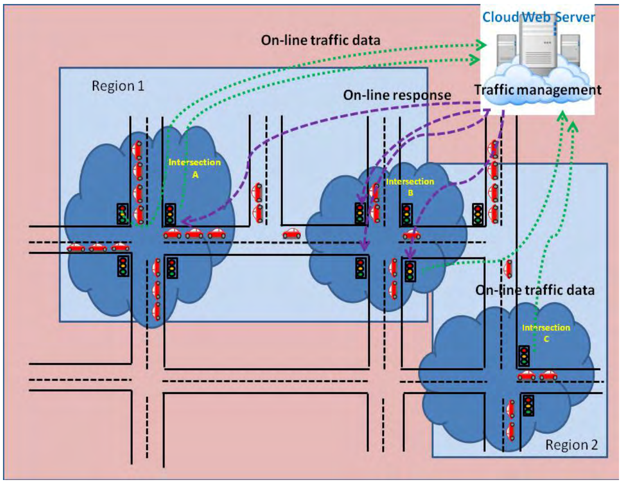

FIGURE 4. The proposed traffic management conceptual model.

some vehicles a where $a <= y$ that were originally located at intersection B moved to intersection A and after a specified amount of time, some vehicles b where $b <= z$ that were originally located at intersection C moved to intersection A. In other words, a/y and b/z will be the contribution from intersection B and C to intersection A, respectively.

Imagine that traffic congestion occurs at intersection A and considering the above relationships, building these relationships help the traffic lights to communicate to each other in order to increase/decrease the green interval so the traffic congestion might be minimal. In addition to the relationship between traffic intersections (lights); the proposed model includes the following sub-systems:

1. Traffic lights control sub-system. This system located in Cloud-based server and controls the traffic lights that located in a specific region by determining the green and red intervals for these traffic lights based on current traffic status.
2. Traffic communication sub-system that receives on-line traffic data, updates traffic status and send updated traffic data to the main cloud-based server.
3. Intelligent sub-system that use artificial intelligent and data mining techniques to processes on-line traffic data and extracts useful decisions and triggers the traffic lights control system with the best action.
4. Storage sub-system that stores historical traffic data to be used in the future.

XIII. CONCLUSION AND FUTURE DIRECTIONS

This research aimed at improving the understanding of the state of art of traffic management technologies specially using data mining and machine learning. Our review has categories the existing studies into approaches that depended on traffic parameters in real time measurement, approaches that work on detecting moving objects, approaches depended on identifying routing, other approaches worked on identifying the pattern and behaviors of drivers and pedestrians and finally approaches that focused on the traffic light signals. Our future work will focus on proposing a new traffic management approach.

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