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TOPICAL REVIEW

Driver Behavior Classification: A Systematic Literature Review

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ABSTRACT Driver behavior is receiving increasing attention because of the staggering number of road accidents. Many road safety reports regard human behavior as the most important factor in the likelihood of accidents. The detection and classification of aggressive or abnormal driver behavior is an essential requirement in the real world to avoid deadly road accidents and to protect road users. The automatic detection of a driver's behavior aids in the prevention of dangerous situations for the driver and all other participants in the driving environment, as well as the implementation of corrective measures. This paper presents a systematic literature review (SLR) of driver behavior classification. This study aimed to highlight and analyze the different types of driver behavior, types of studies, data sources, datasets, features, preprocessing techniques, and artificial intelligence algorithms used to classify driver behavior and its performance. Based on the results obtained from the analysis of the selected works, we aim to identify the key contributions and challenges of studying driver behavior classification and propose potential avenues for further directions for practitioners and researchers.

INDEX TERMS Driver behavior, intelligent transport system, systematic literature review, machine learning, deep learning.

I. INTRODUCTION

The intelligent transport system (ITS) concept emerged first in 1991, when transportation experts realized that electronic technologies could start to play a crucial role in optimizing surface transportation. The National ITS Program was also legally established by the US Congress [1]. Intelligent Transportation Systems are technology-based systems that aim to solve various road traffic problems [2], such as traffic accidents, congestion, and conflicts, by analyzing data collected from sensors or digital technology [3], [4]. ITS is a general term that refers to the application of communication, control, and information processing technologies to vehicle networks [5]. An ITS covers everything related to a transport system, including the vehicle, infrastructure, driver, and road users. They assist the driver in making the best decisions in real time to avoid dangerous situations [5]. There are three objectives of ITS: mobility, sustainable transport, and convenience [6], [7]. Mobility deals with the transportation system's effectiveness and capacity, while sustainable transport focuses on road safety and environmental respect, and convenience ensures service accessibility.

ITS is now used for more than just traffic control and information, but also for road and vehicle safety, infrastructure utilization efficiency, and the reduction of accidents, injuries, and fatalities [8].

Every year, road safety officials set up campaigns to raise awareness of road accidents through interventions in schools and visual and audiovisual information; additionally, public policies take measures to reduce the rate of road accidents, for example by lowering the speed limit on the roads [9]. Despite these efforts, road deaths are still too high worldwide. The World Health Organization (WHO), through the Global Status Report on Road Safety; found that an average of 3,700 people died every day in traffic-related incidents in 2016, and 1.35 million traffic-related deaths occur worldwide each year [10]. It is therefore essential to analyze the various factors and driver behavior that have a direct impact on road accidents.

Advanced Driver Assistance Systems (ADAS) are an example of in-vehicle ITS that are designed to assist drivers in a variety of ways, including improving safety, reducing

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the risk of accidents, and making driving more convenient. ADAS technologies can include features such as lane departure warning systems, adaptive cruise control, automatic emergency braking, reversing cameras, and more. These systems typically use a combination of sensors, cameras, radar, and other technologies to gather information about the vehicle and its surroundings, and to provide the driver with warnings, alerts, or other forms of assistance as needed [11], [12]. However, the accuracy of these sensors can sometimes decrease considerably, and the ADAS system cannot predict potential danger at the right time [13].

Artificial intelligence techniques play a crucial role in research. Machine Learning (ML) and Deep Learning (DL) are powerful technologies that are widely used in different contexts and applications, such as in robotics [14], natural language processing (NLP) [15], image classification [16], [17], and disease diagnosis like COVID-19 [18]. In recent years, machine learning and deep learning techniques have accelerated the development of intelligent transport systems (ITS) while making them more efficient, especially for traffic anomaly prediction and detection [19], accident detection and classification [16], accident severity prediction [20], and other traffic problems. According to [21], the human factor plays a primary role with a rate of 95% in road accidents. As a result, driver behavior analysis has become a necessity to ensure the safety of all road users. Understanding and analyzing driver behavior are essential to identifying and addressing potential safety concerns and developing strategies to reduce the likelihood of accidents or other road incidents. Driver behavior is a complex concept that is influenced by a range of factors, which can make it challenging to accurately describe and analyze. These factors may include psychological, social, cultural, and environmental influences, as well as the individual characteristics of the driver.

Therefore, in parallel to ADAS and artificial intelligence, researchers are working hard to understand, detect, identify, and predict driving styles and behaviors. This knowledge is crucial because driving is a common daily activity for many people [22]. By analyzing driver behavior with ML and DL techniques, we can better understand and address the factors that contribute to risky driving and work towards improving safety on the road. DB describes the driver's actions as they relate to the driving scene and the general environment [23] (see Fig. 1). DB is generally evaluated in terms of environmental variables such as traffic signs, road geometry, and pedestrians as well as vehicle variables such as distance, speed, acceleration, and other related variables [24]. The connections between the driver, the car, and the environment must be investigated to understand driver behavior. Therefore, three contexts have to be considered [25]:

- Driver context such as driver status, facial expression, and distraction.
- Car context like speed, acceleration, and orientation.

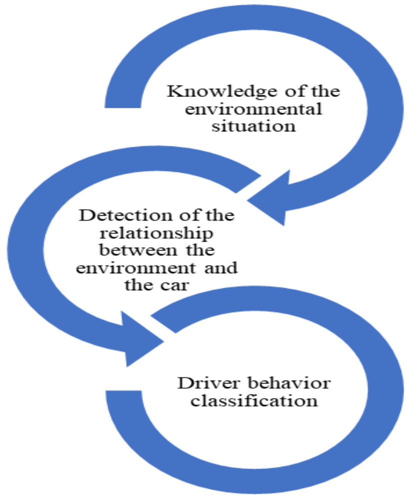

FIGURE 1. Driver behavior processes.

- Environmental context like traffic conditions, geometry, obstacles, and weather conditions.

In recent years, various commercial and research systems have been proposed to analyze driver behavior and develop systems to evaluate driver performance and assist drivers [26]. A common infrastructure shared by all these systems is the driver surveillance system [27].

This paper aims to provide a systematic literature review (SLR) on driver behavior classification. It covers research published between 2015 and 2022, provides a comprehensive overview of existing approaches to study, and analyzes driver behavior using artificial intelligence techniques. The objective is also to offer a guide for researchers on proposed approaches, performance classification techniques, datasets, and features selected to classify driver behavior. The following contains the contributions of this research:

1) We provided an overview of the most recent academic papers on classifying driver behavior.
2) A new taxonomy of different types of behaviors to classify behaviors in a systematic way, which can be useful for identifying trends or patterns in behavior, and for designing interventions. In addition, an in-depth analysis to identify the various approaches that have been used to identify driver behaviors studies.
3) Finally, we identify the data sources, datasets, features, and preprocessing techniques such as feature extraction and selection methods, and we provide a complete analysis of different ML and DL techniques involved and performance obtained.

The remainder of this paper is structured as follows. Section II presents a literature review of works related to our context. Next, Section III presents the research methodology that we used to select and study the papers analyzed. Section IV presents the main results of this study in a comprehensive overview. Section V provides an overall discussion of the main results according to the research questions. Finally, Section VI presents the conclusion of the study and its limitations.

II. RELATED WORKS

In general, any behavior while driving that could endanger the car or its occupants, pedestrians, other drivers, or roadside facilities may be regarded as dangerous behavior. This state of the art is organized according to the type of driver behavior which includes five categories: Abnormal driver behavior is defined as unsafe behavior on the road (risky and negative); then there's aggressive driving, which is defined as being aggressive and intolerant; line deviation, which describes driver deviations on the road; stopping vehicles, which is a behavior of drivers behaving at controlled stop intersections; and driver status, which describes driver behavior like a distraction. In addition, we process and analyze the impact of context on driver behavior.

A. ABNORMAL DRIVER BEHAVIOR

Monitoring of abnormal driver behavior is the cornerstone for improving driving safety. The paper [28] proposed a real-time intelligent system that can detect abnormal vehicle behaviors using traffic cameras and the You Only Look Once (YOLO) algorithm for object detection in video images. Then the Kalman filter tracks the location of the vehicle through successive images, and anomaly detection is carried out using the images in which a vehicle appears (depending on its speed). Article [29] presents a framework based on the Strategic Highway Research Program 2 (SHRP 2) and Naturalistic Driving Study (NDS) datasets to calculate a driver's risk profile (normal or abnormal) using a Random Forest (RF) algorithm. They were able to achieve 90% of accuracy. In paper [30], the Serial-Feature Network (SF-Net) algorithm was proposed for normal and abnormal driver behavior recognition based on smartphone inertial sensors like GPS and gyroscope. The approach reached an accuracy of 97.10% and a recall rate of 98.4%. A proposed system in [31] classifies driver behaviors and road anomalies as normal, abnormal, or bump. Based on smartphone sensors data were collected and the k-Nearest Neighbor (KNN) and Dynamic Time Warping (DTW) algorithms performed an accuracy of 78.06% and 96.75% respectively for classification.

Papers [32], [33], and [34] classified driver behavior as positive and negative. The paper [32] presents a mobile application called "Project Drive" that bridges the gap between detecting negative driver behavior and motivating users to safer driver behavior. They used the clustering k-means algorithm on GPS data. In [33], the study examines how the presence of road signs affects young drivers' behavior in nighttime conditions using simulator and camera data. The authors of [34] used simulator data and the MANOVA statistical technique to investigate the effects of optical circles and chevron patterns on driver behavior and speed when entering a bend on a rural two-lane road.

Papers [35], [36], and [37] distinguished between safe and unsafe driver behavior. In [35], they classified driver behavior using smartphone sensors via an optimal path detection algorithm and Bayesian classification. The method achieved 93.3% of correctly classified instances. For safe driving, [36] suggests a system that uses two traffic datasets called Local and LARA to give drivers advice based on traffic light conditions. The system obtained 95.52% precision. The paper [37] proposes a smartphone-based system to provide important information for the analysis of driver behavior at intersections using a camera, an accelerometer, and gyroscope data. They proposed Long Short-term Memory (LSTM) and Convolutional Neural Network (CNN) models and reached 0.36 for the mean percentage error (MPE).

The paper [38] used the Next Generation Simulation (NGSIM) dataset to propose an LSTM-based car tracking model that captures realistic traffic flow features and detect asymmetric driver behavior (which is a critical feature of human driver behavior). The effectiveness of road signs on driver safety is studied in [39] using GPS and video data. The Logistic Regression (LR) algorithm was trained to detect visible and non-visible driver activity.

Some articles go further than abnormal behavior and assessed how much the behavior presents a risk road safety. This latter is one of the main concerns of mobility and urban planning, so it is often important to recognize risky driver behaviors. A Support Vector Machine (SVM) and Artificial Neural Networks (ANNs) are used to recognize safe and dangerous driver behaviors using in-vehicle sensor data [40]. The classification results indicate an average accuracy of above 90% for both classifiers. The paper [41] used the SHRP 2 dataset and the SVM algorithm to study the probability that left-to-right lane changes are dangerous. The method ensured an accuracy of 90%. In [42], a method for detecting risky driver behaviors by analyzing vehicle speed with time in real-world driving is proposed. The k-means and SVM algorithms achieved 95% for classes correctly classified. Papers [43] and [44] focused on the detection of driving risk levels based on data collected by mobile sensors. The SVM model used in [44] performed with an accuracy higher than 70%, while in [43], SVM was combined with an auto-encoder algorithm and achieved 83.03% accuracy. In [45], the authors classified the driver's risk level as low, medium, and high using a decision tree "CART algorithm" and simulator data a with statistical package for the social sciences (SPSS). The characteristics of driver behavior were used to assess the risk of a vehicle-pedestrian collision based on video data [46]. This method was archived at over 85% with high discrimination accuracy. The paper [47] proposed an ensemble learning system for evaluating normal, low, high, and very high-risk driving styles on a smartphone data using the combination of the following algorithms: SVM, Multi-Layer Perceptron (MLP), and KNN. The system succeeds in finding at least 94% accuracy in the driver's style evaluation. Based on GPS and ADAS data, authors in [48] suggested a system for categorizing driving risks into low and high risks and obtained 80% accuracy. They focused on the unbalanced time series sample problem when evaluating driving behavior, which can be alleviated by MeanShift clustering. The authors of the article [49] proposed a real-time classification of driving behavior based on k-means clustering, hierarchical clustering, and model-based clustering algorithms to identify the number of behavioral classes as normal, high, and low risk. Then SVM, Decision Tree (DT), and Naive Bayes (NB) algorithms were applied to evaluate these risk behaviors and test the performance of the clustering methods. The algorithms attend 95.3%, 99.6%, and 84.3% accuracy respectively. In another paper [50], they analyze the high or low skills of drivers using sensor data from a driving simulator, and an SVM algorithm was used, which performed with an accuracy of 95.7 %. Additionally, [51] classifies driver behavior as skilled or non-skilled using the hidden Markov model (HMM) and the model's archived 80.37% accuracy.

B. AGGRESSIVE DRIVER BEHAVIOR

Among the most well-known driver behaviors in the literature is aggressive behavior. In [52], the authors determined whether the driving style is safe or aggressive, involving signs, speed, and maneuver estimation. They used the CNN algorithm for detection, which performed with 88.02% accuracy. A system based on SVM was presented in [53] to classify the various types of aggressive drivers using a few annotated simulator data points and a semi-supervised approach. The classification accuracy of the method was about 86.6% using S3VM. The paper [54] proposed a system for normal and aggressive driver behavior classification based on a combination of Fully Convolutional Network (FCN) and LSTM algorithms. Using the UAH-DriveSet dataset, the system reached an F1-score of 95.88%. In [55], authors used the Random Forest method to find motion-based factors that can predict aggressive driving. The model achieves a 97.10% Area Under the Curve (AUC). While in the work [56], they presented a significantly improved anomaly detection mechanism using Recurrent Neural Networks (RNNs) based on simulator data. This method achieves 78.6% precision and 36.4% recall.

In order to identify driving maneuvers and classify aggressive, normal, and cautious driving styles, the research [57] examines how driving habits change depending on the task performed for online car-hailing services using k-means clustering. The paper [58] proposed a system for aggressive or smooth driving style detection using the Gaussian mixture model (GMM) and data from the gyroscope. The experiment analyzed the driving habits of older and younger people under the same environmental tests and requirements. A supervised method based on Labeled Latent Dirichlet Allocation (LLDA) is proposed in [59] to understand driver behavior and latent driving styles. It integrates prior knowledge via the Safety Pilot Model Deployment (SPMD) dataset to classify drivers into three categories: aggressive driving, moderate driving, and careful driving. The average accuracy of this model was 60.5%, outperforming SVM, NB, and KNN. This research [60] collected real data from the vehicle accelerometer and gyroscope to identify aggressive driver behaviors using statistical regression, time series analysis, and the following machine learning algorithms: GMM, Partial Least Squares Regression (PLSR), wavelet transformation, and SVR. The method achieved 77% of the F1-score using the PLSR model. The paper [61] examined dangerous driving events and how they are connected to traffic accidents using video and GPS data with correlation analysis. In [62], authors predicted the driving style of drivers based on driver activities and environmental data. Driver physiological data before and during the driving start, car door opening and closing data, and acceleration data were collected. This approach used both Bayesian Networks (BN) and Sequential Minimal Optimization (SMO) algorithms, with accuracy values ranging from 72.7% to 90.9% for the aggressive driving recognition rate.

Other researchers categorize aggressive driving behavior by stating the types of aggressiveness. For example, [63] and [64] classified seven driver behaviors as aggressive: braking, acceleration, left turn, right turn, left lane change, right lane change, and non-aggressive. Data were collected from an accelerometer sensor on an Android smartphone, and various models were investigated, including RNN, LSTM, and Gated Recurrent Unit (GRU) models. The experiments showed that the GRU model produced the best accuracy results, at 95%. In [65], five driver states are classified as driver behaviors (aggressive-stable, non-aggressive-stable, non-aggressive-instable, aggressive-instable, and normal) using driver behavior and EEG data. They combined k-means, SVM, and KNN to perform an accuracy of 83.5%, with an average accuracy of 69.5% across all tested traffic states.

On the other hand, some researchers were interested in classifying the level of aggressiveness of drivers, such as [66], [67], [68], and [69]. They have classified drivers' behavior with scores that express the levels of aggressiveness from lowest to highest using SVM and LSTM algorithms. The results achieved 86.67% and 92.8% accuracy, respectively. Tracking the driving style of each driver without classification was also an objective, as in the case of [70] where the authors illustrate car-following behaviors in various driving situations using the Next Generation Simulation (NGSIM) dataset and genetic algorithm (GA).

C. LINE DEVIATION

Real-time monitoring of driver events or driving style is the cornerstone of improved driving safety. In these parts, we summarize research on line deviation detection. Papers [71], [72], and [73] classified six types of driver behaviors as weaving, swerving, side slipping, fast U-turn, turning with a wide radius, and sudden braking. Acceleration and orientation data were collected, and the algorithms SVM, Neural Networks (NN), and composition between SVM and NN were applied for classification. The models attend 95.36%, 96.88%, and 95.7% accuracy, respectively. In [74], authors presented a system to identify risky driving actions, such as illegal lane occupation, abrupt double lane changes, illegal U-turns, and others. Based on video surveillance data, the suggested method obtains an average detection accuracy of 88.62% using the hybrid algorithm Particle Swarm Optimization-Support Vector Machine (PSO SVM). In this paper [75], a behavior analysis technique based on the Hidden Markov Model (HMM) was proposed. The aim was to assess the driving behavior of moving cars and identify unusual driving events like approaching, braking, lane keeping, and lane changing. The Conditional Monte Carlo Dense Occupancy Tracker (CMCDOT) framework was used to determine the speed and location of nearby vehicles in real time. The results show that the proposed method successfully detects moments of risk. In [76], they classified the behaviors using traffic data into free lane changing, non-free lane changing, successful lane changing, and unsuccessful lane changing. This approach used SVM, and the prediction accuracy reached nearly 90%.

D. VEHICLE STOPPING

The behavior of the driver in certain critical areas, such as stop zones is considered one of the most crucial issues in road safety. When a yellow indication is triggered, the dilemma zone is investigated and modeled as a binary decision problem to stop or go [77]. Many papers conducted binary classification of driver behavior in the dilemma zone such as [78], [79], [80], [81], [82], [83]. In [78], [79], [80], [81], they classified the behavior using SVM, BN, Stochastic Model Predictive Control (SMPC), and combinations of DT and Mixed Logit panel model algorithms, respectively, that were trained with simulator data respectively. While the SVM model predicted 92.9% accuracy, BN achieved 82.9% precision. In a study [82], the SVM model was proposed and trained with data collected from GPS, accelerometers, and sensors and achieved an accuracy of 90.02%. The video data is used in [83] with a Binary Logistic Regression model. The developed model showed that the prediction accuracy of the model is 83.3%.

Understanding how drivers behave at stop-controlled intersections is of crucial importance for the control and management of an urban traffic system. Based on real data, the paper [84] classified driver behavior at minor street stop sign intersections as no-stop, rolling stop, or complete stop using binary and ordinal LR classifiers. In [85], the behavior is classified into a full stop, slight rolling stop, ruling stop, slow down without stopping, and running through stop-controlled intersections using k-means and camera data. On the other hand, a statistical analysis (Chi-squared test) was used to define the types of driver behavior into complete stops, rolling stops, and non-compliant stops at rail level crossings (RLX) in the paper [86].

E. DRIVERS' STATUS

When a driver is distracted, drowsy, or has a special feeling the driving behavior changes and affects the driving style. In [87], two non-linear regression methods, ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS) were independently designed to predict the driver's ability to maintain the middle lane and speed limits from simulator data. The average error between predicted speed limit maintenance and real vehicle speed is 2.72, and the average error between predicted and real middle line-keeping ability is 0.27. The paper [88] examines the effect of passenger presence and driver distraction on young drivers' behavior using simulator data and an analysis of covariance with ANCOVA. In [89], authors proposed a system based on a Full Convolutional Network (FCN) to find effective features for real-time cognitive distraction detection at the wheel, and the model performed with 91% for accuracy. In [90], authors presented a review to separate and analyze the two primary categories of inattentive driving behaviors: driver distraction and driver weariness or drowsiness. Further, [91], [92], and [93] classified the drivers' conditions as drowsy using simulator data via RF, Dynamic Bayesian Network and ANN algorithms respectively. The results of these classifiers have an accuracy of 84.8% for RF and 0.22 MSE for ANN. The paper [94] exploited driving signals to analyze normal, aggressive, distracted, drowsy, and drunk driver behavior using the CNN algorithm. The model achieved 99.76% accuracy. Drowsiness behavior is also detected in [95] and [96] using the UAH-DriveSet dataset and LSTM algorithm. The algorithm archived 91% and 99.49% of the F1-score, respectively. While in [97], they established a new model based on autoencoders for the detection of abnormal driving: drunkenness or fatigue, recklessness, and phone use while driving. The accuracy of the model was 98.33%. Also in [98], they detected driver fatigue based on the perspective of traffic psychology. Using the SHRP 2 dataset and RF algorithms, the paper [99] categorizes driver behaviors as using cell phones, moving, adjusting, monitoring objects, passenger interaction, talking, drinking, or eating, and personal hygiene. The classifier obtains 98.5% concordance and a 6.5% MSE. Eating and drinking, talking, phone use while driving, and preparing are the behaviors classified in [100] with the interCNN algorithm. The archived model had 81.66% accuracy. Distracted behavior is classified in papers [101], [102] as texting with the right and left hands, talking on the phone using the right and left hands, drinking, reaching, applying makeup, and talking to passengers using CNN based algorithms. The algorithm achieved 99% accuracy. In the paper [103], eating and texting are the two distracting behaviors classified with the RF algorithm and achieved with 85.38% accuracy. In [104], they proposed to identify the different types of secondary tasks with the SHRP 2 NDS dataset in which drivers are engaged in activities, such as hand-held cellphone calling, cellphone texting, and interaction. Using the combination of DT and RF algorithms, the method achieved 99.2% accuracy at level 1 and 82.2% accuracy at level 2.

To further clarify the status of driving behavior, the paper [105] applied several different types of classifiers, such as LR, RNN, LSTM, and Deep Neural Network (DNN), for detecting driver confusion using data collected from sensors, GPS, and video. In [106], a technique is proposed to robustly classify driving styles using the Support Vector Clustering approach into defensive, aggressive, and normal. Another type of style is detected in [107] via a wearable glove system. It detects driver stress events in real-time using SVM, with 95% model accuracy. Moreover, in [108], the authors detected driving anger using Linear Mixed Models (LMM) and trained the model with SHRP 2 NDS dataset. The paper [109] proposed a model to measure driver behavior via the driver behavior questionnaire (DBQ) and social media, as well as drug and alcohol use, which were also used to measure driver behavior.

F. ANALYSIS OF THE IMPACT OF CONTEXT ON DRIVER BEHAVIOR

The objective of a driving behavior analysis is a very complex issue that depends on several divergent parameters and is not restricted to a classification of driver type or driving style. Other studies focus more on analyzing the impact of different factors or attributes regarding the driving environment on driver behavior. These factors can influence driver behavior, cause incorrect reactions, and lead to accidents. Like in [110], they studied explicit and implicit attitudes toward traffic climate and their relationship with drivers' self-reported behaviors. Additionally, authors in [111] examined how driving skills affected the association between traffic conditions and drivers' behavior. To determine the extent to which cognitive functioning contributes to the previously identified connections between driving attitudes and personality traits, the article [112] proposed an analysis of variables related to the high-risk driving behavior of young people in the early stages of their study. Speed control is investigated in [113] to analyze the different influence factors on the functioning and observation of right-turn drivers. In order to determine the best strategy for slowing down, [114] investigates how various perceptual treatments affect driving speed. Another factor highlighted in [115] is the effect of longitudinal pavement markings with varying levels and widths of deterioration on a driver's ability to maintain lane position. Reference [116] analyzed the impact of the color contrast of a waistcoat worn by cyclists on the visibility of drivers. Reference [117] examined whether motor vehicle drivers' behavior changes when there are more bicycles on the road. In addition, an important factor in the analysis of driver behavior is the weather condition, such as clear or foggy, which is studied in [118]. Other measures can be used to detect driver behavior or even help avoid collisions. In [119], they seek to detect the driver's intentions with respect to surrounding vehicles. In [120] the authors explored whether it is possible to identify traffic congestion based on several parameters, including delay constraints, and available speed via the GPS vehicle trajectory, while in [121] authors analyzed conflicts between vehicles and pedestrians and also driver behavior. To classify the conflict into potential, mild, and severe, a model for driver yielding behavior was developed using binary logistic regression.

III. RESEARCH METHODOLOGY

A literature review is an essential component of academic research. In this review, we use the Systematic Literature Review (SLR) technique to study and analyze driver behavior at the levels of behavioral classification types, types of studies, data sources, features, preprocessing, and algorithms. An SLR identifies, picks, and critically assesses research to respond to a formulated question [122]. We organized, carried out, and reported the review using the SLR method in [123].

A. RESEARCH QUESTIONS

The main research inquiries that need to be answered in order to conduct the SLR for the suggested study are as follows:

RQ1: What are the objectives and types of driver behaviors classified in the selected research studies?

RQ2: What are the types of driver behavior studies?

RQ3: What data sources, datasets, and features are used?

RQ4: What data preprocessing techniques are applied to improve data processing?

RQ5: What feature selection and extraction techniques are implemented to support the training and precision of the model?

RQ6: What types of models are used to classify DB and what is their performance?

B. SEARCH STRATEGY

We use five digital databases, namely: ScienceDirect, the IEEE Xplore digital library, SpringerLink, the DBLP database, and Google Scholar. We defined a set of keywords for the search process as "driver behavior", "driver behavior classification", "classification of driver behavior", "types of studies for driver behavior", "datasets for driver behavior classification", "algorithms for driver behavior", "data preprocessing for driver behavior", and we repeat the research with the same keywords, replacing "driver behavior" with "driver behaviour" as British spelling in the context of the research area. Then, the search process was performed to identify relevant articles to answer the search questions based on predefined keywords using Boolean operators in the above databases.

C. STUDY SELECTION AND QUALITY ASSESSMENT

To choose pertinent studies, we used the inclusion and exclusion criteria to evaluate candidate articles that might contain information that could be used to address the research questions.

Inclusion criteria:

- The articles published from 2015 to 2022.
- The research papers are from journals publications, or conferences.
- The works published in IEEE Xplore, DBLP, Science Direct, Springer and google Scholar.
- The articles are written in the English language.
- The research focuses on the classification of driver behavior.

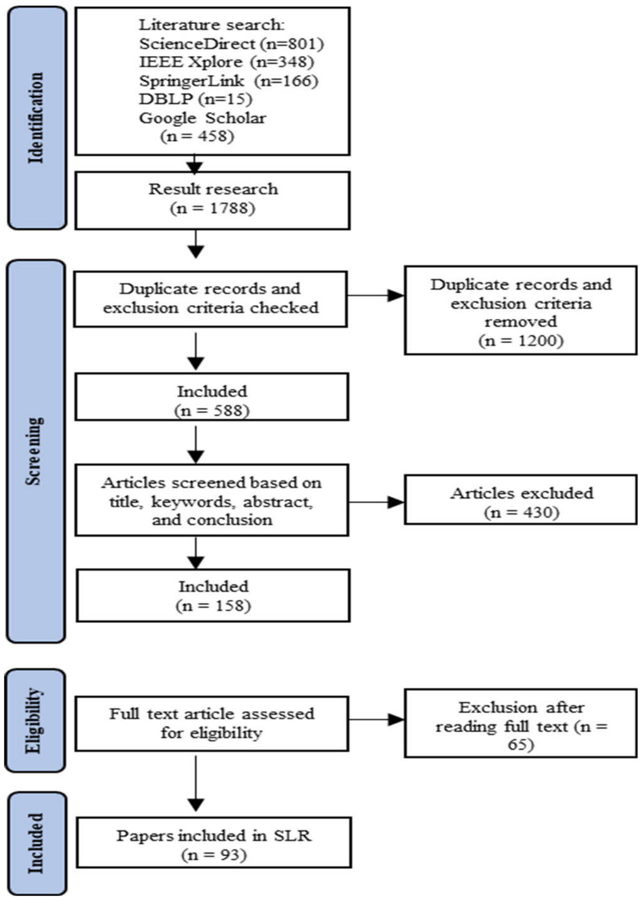

FIGURE 2. PRISMA flow diagram.

- The article uses machine learning or deep learning algorithms or descriptive or preliminary statistics techniques in the study.

Exclusion criteria:

- The articles are not in the range of 2015 to 2022.
- Irrelevant articles to our topic and research questions.
- We excluded duplicate articles.
- Articles that had a tenuous connection to the study's questions.

Next, the selected articles were assessed using firstly the title, abstract, conclusion, and keywords. Articles unrelated to the contemplated study were excluded. We then applied the quality assessment criteria to the remaining articles to assess their reliability, integrity, and relevance. In the review, quality assessment plays an important role in the SLR protocol. The selected articles perfectly answer the predefined key research questions based on inclusion-exclusion criteria. They are evaluated by all authors after the analysis and evaluation of the abstracts and conclusions of the selected articles (see Fig. 2).

D. DATA ANALYST

We identified 93 studies (Table 1) in the field of driver behavior classification that were published during the period

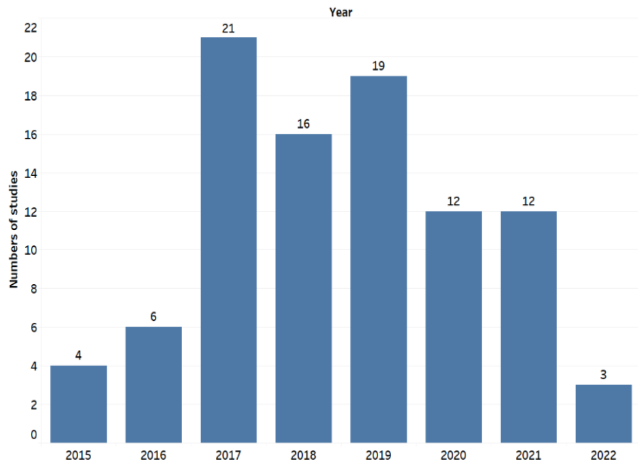

FIGURE 3. Distribution of the studies over publication year.

2015-2022. Of these, 26 (28%) were published in conference proceedings, and 67 (72%) articles were published in journals. Table 1 presents the publication venues of the chosen studies, and Fig. 3 displays the distribution by year.

IV. DRIVER BEHAVIOR: A COMPREHENSIVE OVERVIEW

In this section, we present all the answers to the research questions and the results concluded from the state of the art.

A. THE OBJECTIVES AND TYPES OF DRIVER BEHAVIORS CLASSIFIED IN STUDIES (RQ1)

To fully understand the types of driver behavior in literature, we have attempted to categorize them into five categories: abnormal driver behavior, aggressive driver behavior, stopping driver behavior, line deviation, and the driver's status, as shown in Table 2 and Fig. 4.

- Abnormal driving behavior includes behaviors like abnormal, dangerous, negative, risky, high-risk, and low-risk.
- Aggressive driving behavior includes aggressive behaviors and their types and levels of aggressiveness.
- Vehicle stopping for driver behavior includes behaviors in intersections and dilemma zones like stop, and go.
- Line deviation includes behaviors such as weaving, swerving, side slipping, quick u-turns, turning with a large radius, abrupt braking, and so on.
- Driver's status such as distraction, drowsiness, stress, use of cell phones, talking, eating, and drinking.

We note that the driver behaviors related to abnormal driver behavior are studied at 30%, and the driver's status are studied at 28%, in the selected papers. Therefore, we can deduce that the study of driver behaviors outside the car is less studied and more difficult, such as the cases of line deviation 8%, and vehicle stopping 12% (see Table 2), as they are related to the vehicle and the driving environment, such as road signs and pedestrian crossings.

This work aims to understand how drivers behave on the roads, which is of crucial importance for the control,

TABLE 1. Publication venues.

Source	Publication venue	References
Journal Article	Accident Analysis and Prevention	[57], [65], [82], [86], [88], [92], [93], [104], [115]
	Transportation Research Part F: Traffic Psychology and Behavior	[39], [45], [103], [108], [110], [112], [114], [121]
	IEEE Access	[60], [90], [96], [99], [100], [102]
	Journal of Safety Research	[111], [113], [117], [118]
	Transportation Research Part C: Emerging Technologies	[38], [47]
	Transportation Research Interdisciplinary Perspectives	[70], [109]
	PLoS ONE	[64], [80]
	Journal of Intelligent Transportation Systems: Technology, Planning, and Operations	[74], [79]
	IEEE Transactions on Intelligent Transportation Systems	[29], [55]
	IEEE Transactions on Human-Machine Systems	[42], [53]
	IEEE Sensors Journal	[30], [107]
	Expert Systems with Applications	[40], [94]
	Transportation Research Record	[84]
	Transportation Research Procedia	[83]
	Transportation Letters	[66]
	Traffic Injury Prevention	[34]
	Sustainability (Switzerland)	[85]
	Sensors (Switzerland)	[62]
	Safety Science	[116]
	Safety	[33]
	Procedia Manufacturing	[78]
	Pattern Recognition Letters	[101]
	Journal of Psychology in Africa	[98]
	Journal of Network Communications and Emerging Technologies (JNCET)	[73]
	Journal of Modern Transportation	[50]
	Journal of Advanced Transportation	[59]
	International Journal of Intelligent Transportation Systems Research	[44]
	International Journal of Automotive Technology	[91]
	International Journal of Ambient Computing and Intelligence	[31]
	IFAC-Papers On Line	[87]
	IEEE Transactions on instrumentation and measurement	[97]
	IEEE Open journal of intelligent transportation systems	[72]
	IEEE Transactions on Vehicular Technology	[48]
	IEEE Transactions on Mobile Computing	[49]
	IATSS Research	[46]
	Analytic Methods in Accident Research	[81]
Conference Proceedings	Transportation Research Procedia	[61], [76]
	Procedia Computer Science	[43], [120]
	2019 IEEE International Conference on Mobile Data Management	[36]
	International Conference on Future Internet of Things and Cloud Workshops, W-FiCloud 2016	[32]
	Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	[28]
	International Conference on Intelligent User Interfaces, Proceedings IUI	[67]
	2017 IEEE Global Communications Conference	[51]
	2019 IEEE International Symposium on INnovations in Intelligent SysTems and Applications (INISTA)	[54]
	2019 IEEE International Conference on Cybernetics and Intelligent Systems (CIS) and IEEE Conference on Robotics, Automation and Mechatronics (RAM)	[75]
	2019 IEEE Intelligent Vehicles Symposium (IV)	[56]
	2018 IEEE Intelligent Vehicles Symposium (IV)	[69]
	2015 IEEE Intelligent Vehicles Symposium (IV)	[58]
	2019 IEEE 10th International Conference on Awareness Science and Technology (iCAST)	[89]
	2019 International Conference of Electrical and Electronic Technologies for Automotive (AEIT AUTOMOTIVE)	[68]
	2018 IEEE International Conference on Consumer Electronics (ICCE)	[37]
	2018 3rd IEEE International Conference on Intelligent Transportation Engineering (ICITE)	[106]
	2017 International Joint Conference on Neural Networks (IJCNN)	[63]
	2017 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS)	[119]
	2017 International Conference on Computer Science and Engineering (UBMK)	[52]
	2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)	[95]
	2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)	[41]
	2016 IEEE International Conference on Multimedia and Expo (ICME)	[105]
	2015 IEEE International Conference on Sensing, Communication, and Networking (SECON)	[71]
	2012 IEEE Intelligent Vehicles Symposium	[35]
	Total	93

minimization, and even avoidance of accidents; the management of an urban traffic system; and many other benefits. In general, each paper in Table 2 identifies and classifies types of driving behavior. Some types of driver behavior are very common, and others are related to the study itself. To better understand and facilitate the driver behavior types analysis we regroup these types on tree levels as explained in Fig 4. First, we categorized drive behavior types into five categories: Abnormal, aggressive, line deviation, stopping vehicles, and driver status. Then, for each category, we divided these types (targets) into normal or not normal, and finally; we added all targets used in the articles studied.

We have abnormal DB present in 19.08%, which includes, for example, abnormal, negative, unsafe, and risky. We then have aggressive driver behavior and her types with 18.42%, drivers' status with 35.53%, line deviation with 19.74%, and

TABLE 2. Articles related to the type of driver behavior.

Type of behavior	Papers
Abnormal driver behavior	[28], [29], [30], [31],[32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [108]
Aggressive types	[52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [65], [67], [66], [68], [69], [70], [63], [64], [94], [108], [106], [95], [96]
Line deviation	[71], [72], [73], [74], [75], [76]
Vehicle stopping	[81], [83], [80], [82], [78], [79], [84], [85], [86]
Driver's status	[87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [99], [100], [101], [102], [103], [104], [105], [106], [107], [108], [109], [98]

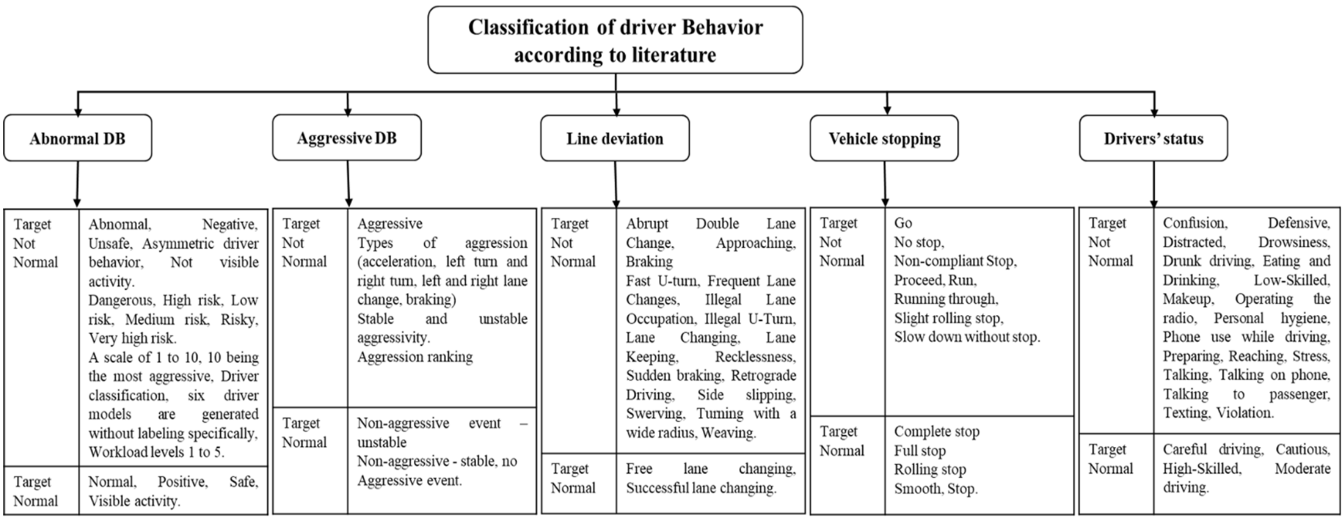

FIGURE 4. Driver behavior categorization objectives.

vehicle stopping with 7.24% as shown, in Fig. 5. Generally, 63 types of driver behavior are identified for the not normal driver behavior type (targets) and 18 types of driver behavior for the normal targets.

B. DRIVER BEHAVIOR STUDIES TYPES (RQ2)

Research on driver behavior focuses on two aspects: objective and subjective measurement.

Typically, subjective conduct measurements are derived based on individual viewpoints and beliefs. It represents the driver's unique experience and is described from their point of view. These subjective measures can be used to evaluate driver behavior through the questionnaire study. We can note that the questionnaire survey is simple to administer and analyze, but it may introduce subjectivity because respondents occasionally fail to recognize when they engage in risky behavior [124], [125].

Objective driving ratings are based on quantifiable data. It is based on experiments via simulators or a limited sample of real cars. The principal sources of acknowledged objective driving data are driving simulator studies, field driving studies, and naturalistic driving studies. In objective measure, the naturalistic driving study (NDS) uses unobtrusive measurements to record detailed information about drivers, vehicles, and their surroundings in order to study driver behavior on the road [126]. Field driving studies (FDS) monitor driver behavior using instrumented vehicles; even with the use of monitoring equipment, instructors are frequently present in the vehicle to record measurements and code driving performance [127], [128]. The driver behavior data under the precise control of the experiment could also be obtained in the driving simulator test (driving simulator study) [129].

From previous studies, we concluded that the field driving study is most commonly used for studying driver behavior either with cameras, sensors, etc., with 51.55% compared to the studies included in the state of the art, because it is principally based on field studies, where human intervention is always present to determine the types of driver behavior and to collect data from all data sources. Followed by the driving simulator study with 26.80%, the naturalistic driving study with 14.43%, and finally the questionnaire study with 7.22% (see Fig. 6).

The main problem with the first method (subjective measure) is that the questionnaire usually reflects the subjective opinions of the driver rather than the driver's actual performance on the road. The second method (objective measure) usually involves manually controlling the driving environment to induce more aggressive driver behavior. In contrast, the second method of analysis avoids the deviation caused by the drivers' attitudes.

At the same time, in research involving naturalistic driving, the cars of the test subjects have equipment that, over

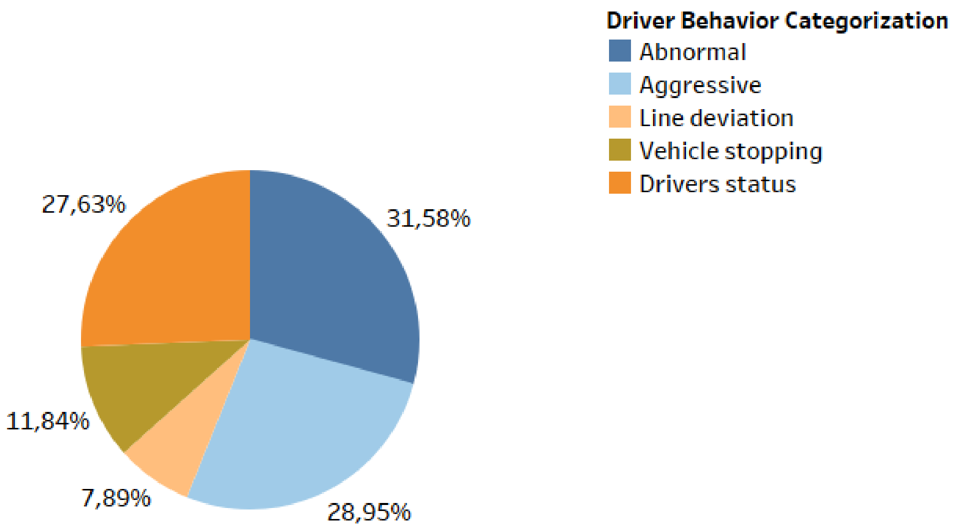

FIGURE 5. Driver behavior categorization.

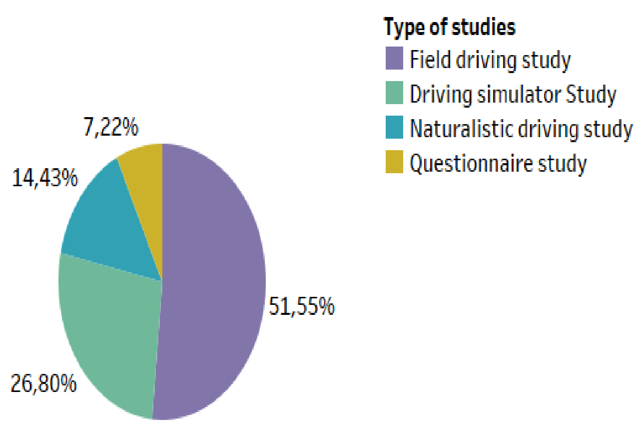

FIGURE 6. Type of studies for driver behavior.

time, continuously monitors various elements of their driving behavior in an unobtrusive manner in the absence of a test supervisor. The strategy offers data that is challenging or impossible to gather using existing research techniques.

C. DATA SOURCES, DATASET AND FEATURES (RQ3)

1) DATA SOURCES

To classify driver behavior, a different data sources (see Table 3) are used to collect data. A data source is simply the origin of the data. It can be a file, a particular database, or even a live data stream with sensors, cameras, etc. In our selected studies, the data source types used are smartphone sensors, GPS, accelerometers, cameras, simulators, etc. The most used data source type is the simulator, with 25% of the number of selected studies, followed by cameras with 17%, GPS with 13%, smartphone sensors with 10%, and the other sources as shown in Table 3.

From the various data sources, several different types of behavior can be extracted, depending on the researcher's objective and type of data source. In general, the types of driver behavior classification are associated with different data sources. From Table 4 we can classify abnormal behavior from cameras, GPS, simulators, accelerometers, and gyroscope data. In addition, we can classify aggressive behavior from the data of simulators, smartphone sensors, gyroscopes, GPS, etc. The vehicle's stopping behavior is studied mainly from the camera and simulator data. Thus, we can classify the driving events mostly from the sensor data (accelerometer and orientation sensors). The classification of the risk level is done mainly from the sensor, simulator, and GPS data.

TABLE 3. Data source for driver behavior classification.

Data source	Papers	Percentage of studies
Simulator	[53], [45], [65], [88], [89], [75], [81], [80], [46], [33], [34], [68], [78], [103], [79], [56], [69], [91], [107], [92], [93], [50], [87], [49]	25%
Camera	[28], [37], [39], [52], [74], [83], [105], [106], [33], [76], [76], [76], [76], [85], [86], [102]	17%
GPS	[30], [32], [39], [42], [44], [57], [61], [66], [67], [82], [105], [48]	13%
Smartphone sensors	[43], [44], [47], [52], [62], [63], [82], [94], [105]	9%
Accelerometer	[31], [35], [37], [60], [67], [71]–[73], [82]	9%
Gyroscope	[30], [31], [35], [37], [58], [60], [67]	7%
Questionnaire	[61], [81], [82]	3%
Orientation sensor	[71], [72], [73], [97]	4%
Recorder system	[66], [106]	2%
OBDII Sensor	[67], [94]	2%
EEG	[65], [69]	2%
ECG	[33], [69]	2%
Radar	[106]	1%
Magnetometer	[35]	1%
Data collectors–observers	[84]	1%
EDA	[69]	1%

2) DATASETS

To classify the driver's behavior, some datasets are used in the selected articles. These datasets contain a combination

TABLE 4. Data source for driver behavior classification with target.

Data source	Target
Smartphone sensors	Normal, Safe, Aggressive, High risk, Low risk, Risky, very Hight risk Confusion, Distracted, Drowsiness, Drunk Run, Stop
Simulator	Normal, Agressif-instable, Agressif-stable, Non agressif-instable, Non agressif-stable Distracted, Drowsiness, Eating and Drinking, High-Skilled, Low-Skilled, Stress, Texting Six driver models are generated without labeling specifically. Workload levels 1 to 5 Proceed, Run, Stop
Orientation sensor	Normal, Fast U-turn, Side slipping, Sudden braking, Swerving, Turning with a wide radius, Weaving, Drunk driving, Phone used
Gyroscope	Abnormal, Normal, Safe, Unsafe Aggressive, Bump
GPS	Abnormal, Normal, Safe, High risk, Risky Confusion, Run, Stop
Camera	Safe, Unsafe, Aggressive Confusion, Eating and Drinking, Phone use while driving, Preparing, Reaching, Talking, Talking on phone, Texting Abrupt Double Lane Change, Free lane changing, Frequent Lane Changes, Illegal Lane Occupation, Illegal U-Turn, Lane Changing, Retrograde Driving, Successful lane changing Go, Stop
Accelerometer	Abnormal, Normal, Safe, Unsafe, Aggressive Fast U-turn, Side slipping, Sudden braking, Swerving, Turning with a wide radius, Weaving Run, Stop

TABLE 5. Datasets for driver behavior classification.

Dataset	Papers	Percentage of studies
SHRP 2	[29], [41], [99], [104], [108]	28%
UAH-DriveSet	[54], [95], [96]	17%
SPMD	[55], [59]	11%
NGSIM	[38], [70]	11%
Driver Behavior Dataset	[63], [64]	11%
100-CAR Naturalistic driving Data Set	[41], [51]	11%
LOCAL and LARA	[36]	6%
Driving dataset	[40]	6%

TABLE 6. Datasets for driver behavior classification with target.

Dataset	Target
UAH-DriveSet	Normal, Aggressive, Drowsiness
SPMD	Aggressive, Careful driving, Moderate driving
SHRP2	Abnormal, Normal, Dangerous Drivers' status: (Eating and Drinking, Personal hygiene, Phone use while driving, Reaching, Talking, Talking to passenger, Texting)
LOCAL & LARA	Safe
Driving dataset	Safe, Dangerous
Driver Behavior Dataset	Aggressive: acceleration, left and right turn, left and right lane change, braking, and non-aggressive event
100-CAR Naturalistic driving Data Set	Normal, Dangerous, High-Skilled, Low-Skilled

of smartphone sensor data, monitoring system data, transport agency data, and other data sources. In the following section, we describe an example of datasets used in selected papers.

The**Strategic Highway Research Program** 2 (SHRP 2) NDS database includes data from 50 million vehicle miles and 5.4 million trips. SHRP 2 was collected by 3,100 volunteers at six different sites in the United States: Tampa, Florida; central Indiana; Durham, North Carolina; Erie County, New York; central Pennsylvania; Seattle, Washington [130].

The**UAH-DriveSet** is a dataset used for the analysis and classification of driving behavior. It was collected from six distinct drivers and cars. Three separate driving behaviors, normal, drowsy, and aggressive were included in the data produced [131].

The**Next Generation Simulation** (NGSIM) Vehicle Trajectories and Supporting Data [132] datasets are gathered on Peachtree Street in Atlanta, Georgia, eastbound I-80 in Emeryville, California, and U.S. Highway 101 in Los Angeles, and California. A network of synchronized digital video cameras was used to gather the data.

The **Safety Pilot Model Deployment** (SPMD) [133] includes data on driver-vehicle interactions, vehicle trajectories, basic safety messages (BSMs), and contextual data that specifies the environment in which the model deployment data was gathered. Over 2,700 automobiles outfitted with CV technology were used to collect the data between October 2012 and April 2013.

The **100-Car Naturalistic Driving Study database** [134] contains several examples of excessive driver behavior and performance, such as extreme weariness, impairment, mistakes of judgment, risk-taking, aggressive driving, and traffic violations [135].

The **driver behavior dataset** [63] is gathered across four car excursions that last, on average, 13 minutes. The types of driving events and behaviors in this dataset are: aggressive acceleration, aggressive left and right turn, aggressive left and right lane change, aggressive braking, and non-aggressive event.

According to our selected paper, eight datasets are used to classify driver behavior, as shown in Table 4. The most used dataset is SHRP2 with 28%, followed by UAH-DriveSet with 17%, as presented in Table 5.

In addition, Table 6 presents the targets related to each dataset. From UAH-DriveSet, we can extract normal, aggressive, and drowsy driver behavior. Normal, abnormal, and drivers' status (eating and drinking, personal hygiene, phone use while driving, reaching, talking, talking to passengers, and texting) are extracted from SHRP2. Safe and dangerous situations are extracted from the driving dataset. More specific types of aggressiveness are found in the driver behavior dataset.

3) FEATURES

Every data source or dataset contains a set of features. Each feature or column, in the dataset, represents measurable data that can be used for analysis. Through this study, we categorize a set of variables or features according to the different data sources and datasets. We have grouped these features into 39 general characteristics, presented in Table 7.

TABLE 7. Features for driver behavior classification.

Features	Number of studies
Vehicle speed	50
Acceleration/Deceleration	44
Rotation rate/angle	32
Pedal/Throttle/Accelerator	30
Time/ time to intersection/stop line/lane crossing	24
Acceleration (Lateral and Longitudinal)	22
Traffic condition	20
Personnel information	19
Steering	16
Physiological and psychological signals	15
Distance to ahead vehicle/lane/yellow line/pedestrian/traffic flow	13
Velocity	11
Vehicle position	11
Location	10
Engine speed/load/output torque/RPM	8
Turn signals	7
Vehicle type	6
Orientation	6
Traffic light	5
Phone Tasks	5
Image	5
Detected vehicles	5
Stroke	4
Pedestrian	4
Lane change/deviation	4
Gap	4
Environmental conditions	4
Traffic sign	3
Gyroscope data	3
Passengers	2
Meteorological data	2
Magnetometer	2
Crosswalk/Crossing	2
Acceleration noise (or variation)	2
Wiper on/off	1
Intensity of the car door movement	1
Gravity	1
Direction	1
Clutch	1

The ten features most commonly used to classify driver behavior are: vehicle speed, acceleration/deceleration, rotation rate, and rotation angle; pedal, throttle, and accelerator; acceleration (lateral and longitudinal); time; time to an intersection; time to a stop line; and time to a lane crossing; traffic condition; personnel information; steering; and physiological and psychological signals. Other features are also used in DB classification, Table 7 presents these different features.

We find that several features describing the acceleration are used: lateral, longitudinal, vertical, and linear acceleration. Lateral acceleration represents driving events such as left turns and lane changes; longitudinal acceleration corresponds to braking and acceleration of the vehicle; vertical acceleration represents road anomalies such as bumps and potholes; and linear acceleration quantifies the force of acceleration applied to a vehicle in all three dimensions (x, y, and z), excluding the force of gravity. Gravity and acceleration inputs from all three axes are required to calculate linear acceleration. In addition to acceleration features, several others are extracted from data sources and used many times in the articles studied. The following Fig. 7 and Fig. 8 show the must-used features that can be extracted from each data source and dataset. From these figures, we can derive features that allow drivers to describe and identify their behavior; furthermore, these features can be exploited to create classification models of driver behavior.

Fig. 7 allows us to deduce that: The simulator helps extract a lot of information, such as acceleration, deceleration, acceleration (lateral and longitudinal), throttle, direction, vehicle position, and vehicle speed. GPS can be used to measure the speed and acceleration of a vehicle. The accelerometer can provide acceleration on three axes, which gives us an accurate indication of driver behavior and road anomalies. The gyroscope can provide the angular velocity (speed of rotation) on the three axes (x, y, and z). Moreover, the combination of vehicle speed and throttle opening can capture the acceleration characteristics of the driver. With the camera, we can capture images of vehicles, drivers, and surroundings and detect the angle of rotation, vehicle speed, acceleration, deceleration, gap, pedestrian, traffic sign, etc.

Regarding the datasets in Fig. 8, SHRP2 contains well-known feature sets used to study driver behavior such as acceleration (lateral and longitudinal), personal information of drivers (gender and age), passengers, turn angle, traffic conditions (construction zone, environmental factors, intersection influence, road geometry, secondary tasks, surface condition, traffic density, traffic flow), velocity, turn signals, vehicle speed, and other features. The 100-CAR Naturalistic Driving Data Set contains acceleration (lateral and longitudinal), vehicle heading (GPS), accelerator pedal position, rotation rate, vehicle speed, velocity, and other features. The UAH-DriveSet includes acceleration, distance to the vehicle ahead, distance to the vehicle ahead in the current lane, turn rate and turn angle, vehicle position (angle of car relative to lane curvature, position of car relative to lane center), vehicle speed, and other characteristics.

To provide additional orientation for future work and experimentation, we provide through this SLR for each type of driver behavior the features most commonly used to describe that type. This helps researchers to choose the most important features to achieve a better classification and, at the same time, link each type of driver behavior with the features that can more efficiently describe it. Table 8 presents the most commonly used features to describe the main types of driver behavior.

Acceleration and deceleration, vehicle speed, rotation angle, and acceleration (lateral and longitudinal) are the features that should be used to classify driver behavior as aggressive and abnormal. For vehicle stopping behavior, we need personnel information (age, driving experience, education, gender, license type), vehicle speed, time to an intersection, time to the stop line, and time of day. To study and classify drivers' status, we need traffic conditions, acceleration, vehicle speed, acceleration (lateral and longitudinal), the image of the driver, rotation angle, and steering. Finally, to recognize line deviation features commonly utilized are: rotation angle, acceleration and deceleration, acceleration (lateral and longitudinal), orientation, speed, gap, and velocity.

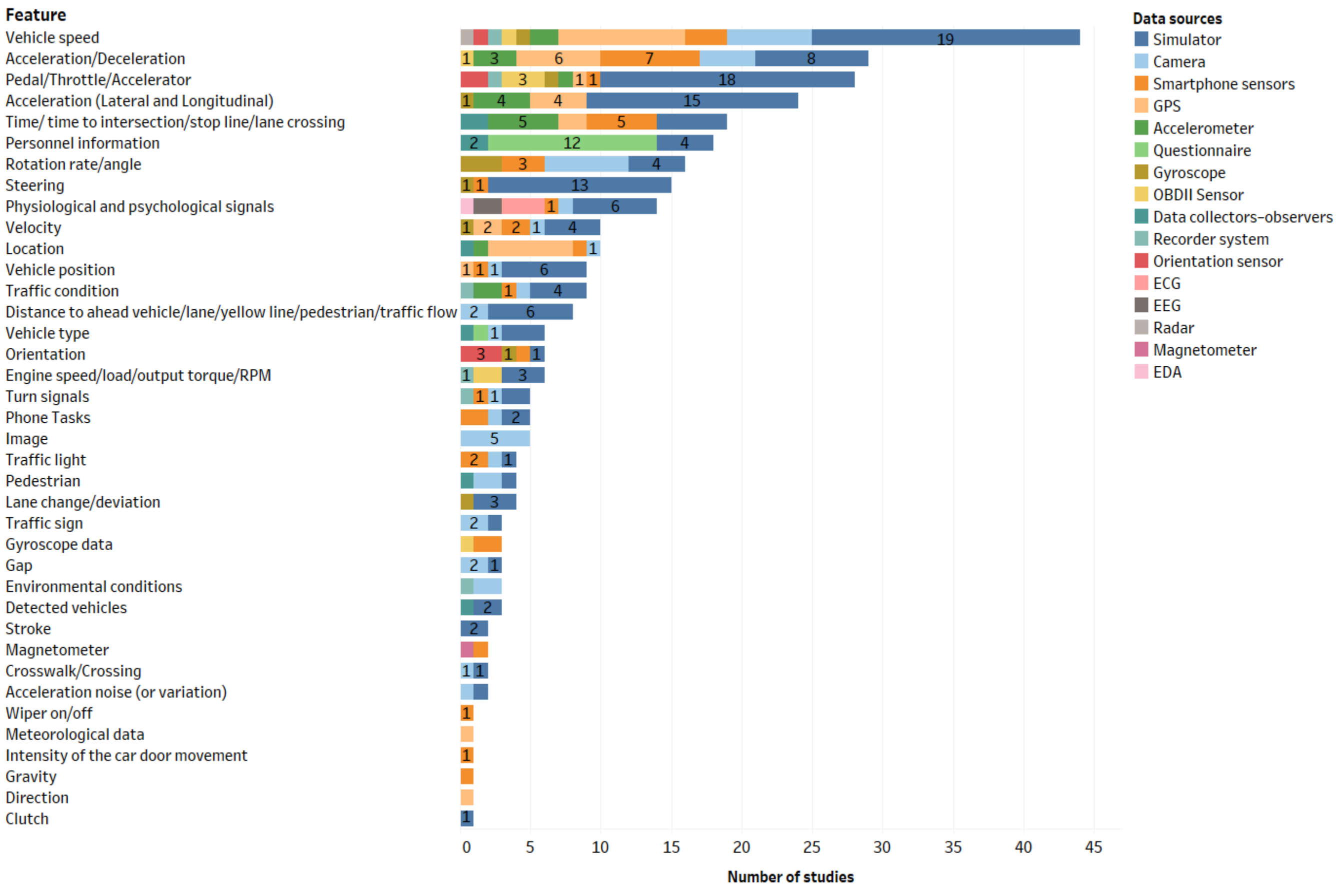

FIGURE 7. Data source vs features for driver behavior classification.

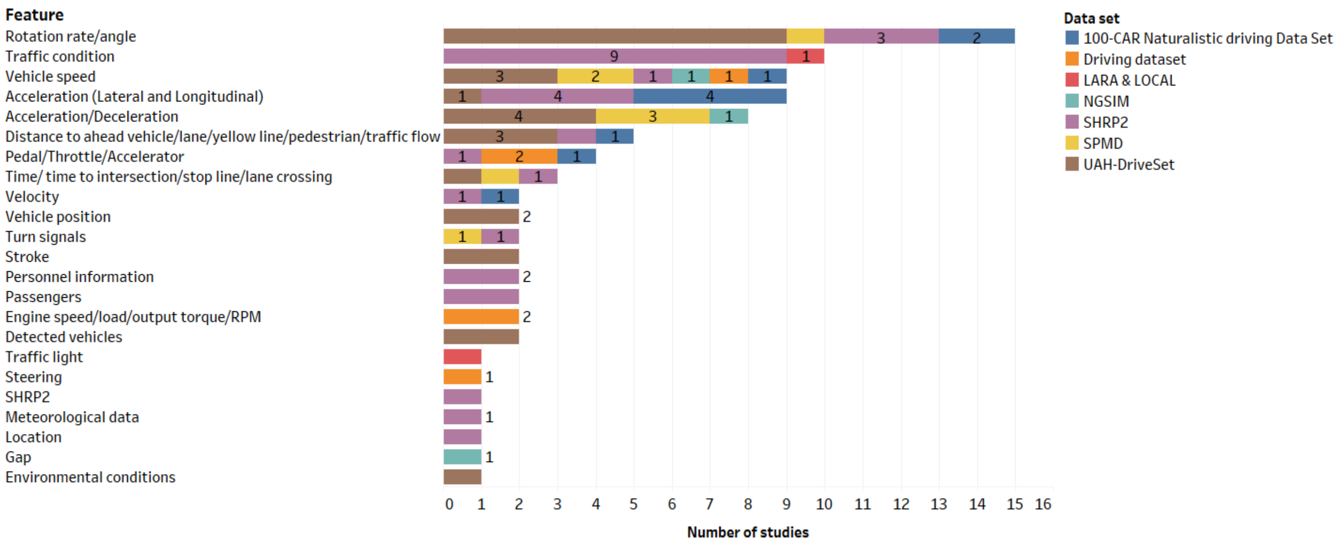

FIGURE 8. Dataset vs features for driver behavior classification.

D. DATA PREPROCESSING TECHNIQUES (RQ4)

One of the most challenging keys to a performant machine learning or deep learning model is the quality of the training data. Therefore, data preprocessing is a phase in the necessary data mining and analysis process that converts raw data into a format that can be comprehended and examined by

TABLE 8. Features related to driver behavior categorization.

Driver behavior type	Features
Abnormal	Vehicle speed, Acceleration/Deceleration, Rotation rate/angle, Acceleration (Lateral and Longitudinal), Pedal/Throttle/Accelerator Steering, Time/ time to intersection/stop line/lane crossing, Physiological and psychological signals, Velocity, Traffic condition, Vehicle position, Engine speed/load/output torque/RPM, Image, Location, Distance to ahead vehicle/lane/yellow line/pedestrian/traffic flow, Lane change/deviation, Stroke, Meteorological data.
Aggressive	Acceleration/Deceleration, Vehicle speed, Time/ time to intersection/stop line/lane crossing, Rotation rate/angle, Acceleration (Lateral and Longitudinal), Pedal/Throttle/Accelerator, Physiological and psychological signals, Distance to ahead vehicle/lane/yellow line/pedestrian/traffic flow, Gyroscope data, Magnetometer, Traffic condition, Lane change/deviation, Steering, Location, Vehicle position.
Line deviation	Rotation rate/angle, Acceleration/Deceleration, Acceleration (Lateral and Longitudinal), Orientation, Time to intersection/stop line/lane crossing, Vehicle speed, Acceleration noise, Velocity, Distance to ahead vehicle/lane/yellow line/pedestrian/traffic flow, Traffic condition, Vehicle position.
Vehicle stopping behavior	Personnel information, Vehicle speed, Time/ time to intersection/stop line/lane crossing, Location, Traffic condition, Phone Tasks, Vehicle type, Distance to ahead vehicle/lane/yellow line/pedestrian/traffic flow, Pedestrian, Environmental conditions, Traffic sign, Pedal/Throttle/Accelerator, Traffic light, Crosswalk/Crossing, Detected vehicles, Rotation rate/angle, Acceleration noise (or variation), Velocity.
Drivers' status	Traffic condition, Pedal/Throttle/Accelerator, Vehicle speed, Acceleration (Lateral and Longitudinal), Image, Rotation rate/angle, Personnel information, Steering, Acceleration/Deceleration, Velocity, Engine speed/load/output torque/RPM, Physiological and psychological signals, Distance to ahead vehicle/lane/yellow line/pedestrian/traffic flow, Turn signals, Vehicle position, Location, Stroke, Gravity, Time to intersection/stop line/lane crossing, Detected vehicles, Passengers.

algorithms. In fact, to obtain good results, the data must be pre-processed to remove any impurities, solve the problems inherent in the data, and improve its quality.

For a more efficient study of the various research proposals undertaken to preprocess and improve the data quality, we analyze the data preprocessing techniques used, the image and video preprocessing techniques adopted, the imbalanced data problems, and the data labeling techniques studied separately.

1) DATA PREPROCESSING

The data preprocessing techniques used in the state of the art are cleaning and removing noise, resampling or synchronization, normalization, rolling window or data augmentation or segmentation and imbalanced data. Fig. 9 shows that normalization is the most commonly step in data preparation, followed by cleaning and noisy data elimination and data augmentation to improve the performance of the models. Data resampling is a dominant step in this problem where we have different sources of data, as well as data imbalance processing.

- Data cleaning and remove noise

The cleaning process is required to eliminate redundant data from the raw data, such as correlated and identical features, duplicate rows with the same timestamp, and then substitute missing values.

The researchers use machine learning techniques to impute missing values such as KNN. The KNN algorithm is used to replace missing values by approximating a point value using the nearest points based on other features. In another study, missing data is approximated by linear interpolation. Because temporal data frequently suffers from noise, features cannot be extracted directly from it since noise frequently skews measurements of things like speed. Other research uses statistical methods to replace missing values such as mean, median, and standard deviation.

Position and speed errors in Controller Area Network (CAN) buses, GPS receivers, and inertial sensors all impact the driver behavior classification model in addition to the measured data. Researchers use preprocessing of the raw speed time series before training the model. Meanwhile, others use preprocessing of the data via a smoothing filter to remove the effect of noise. Moreover, the Kalman filter is adopted to remove noise in some papers. Also, it's used to reduce measurement errors in abnormal acceleration and deceleration values in the NGSIM dataset [38].

- Resampling stage

The sampling rate at which the traffic features are collected is not uniform. For example, a 10 Hz camera, a 10 Hz sensor, and a 1 Hz GPS sensor. Features can be downsampled at a lower sampling rate or the lower-sampled features can be upsampled at a higher sampling rate to overcome this problem. Some researchers applied an oversampling technique based on a finite impulse response (FIR) filter well-known in the field of signal processing research for its ability to do oversampling (interpolation). Others solve the problem by oversampling the sampled data below the highest sampling frequency via linear interpolation filtering.

- Data normalization

Data normalization is an important step to achieve a model's performance, as the features have different scales. For data normalization, researchers generally used the linear scaling technique, as normalization technique for resampled time series sensor data. Another method was used for data normalization by performing the FTP-72 (speed) driving test in advance to guarantee the results.

- Data augmentation

Data augmentation is frequently used as a preprocessing method to help increase the size of the dataset, which in

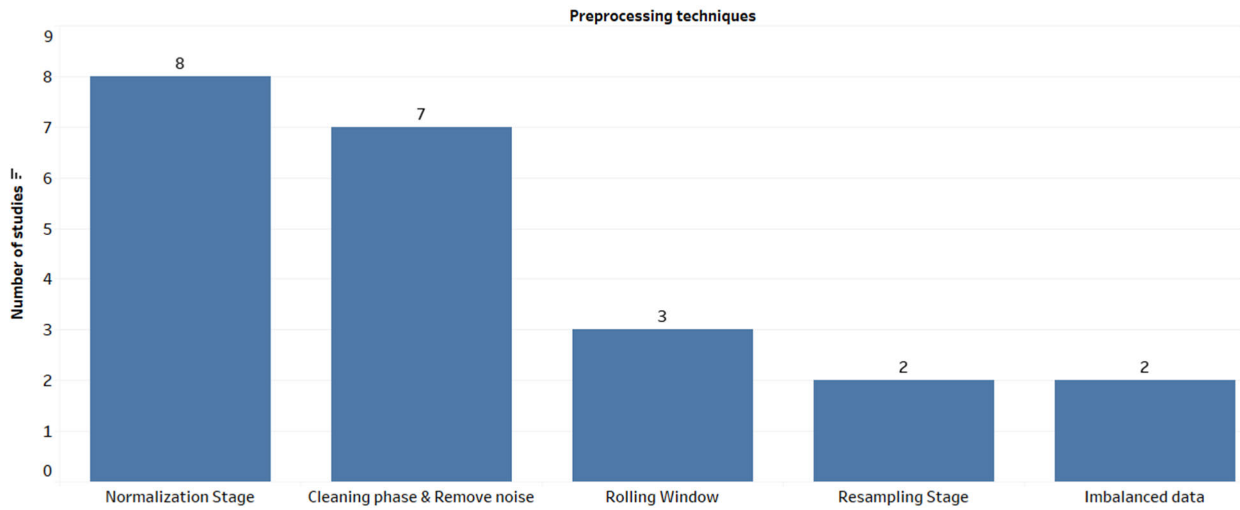

FIGURE 9. Preprocessing techniques used to classify driver behavior.

turn improves the accuracy of the model by providing a better classification of the driver's behavior. This technique allows extracting more information from the raw data than by picking random data segments. Using a sliding window with a set length, the data was separated into overlapping parts.

- Imbalanced data

The distribution of abnormal and normal driver behavior in the data is generally imbalanced (impedance data), and as long as the dataset has time series characteristics, most performant data balancing techniques are needed. Furthermore, additional data filtering cannot be used when processing the data, as this step will not only result in the loss of temporal information but will also not fit the situation in which the algorithm has to be processed. This problem is a challenging one, and because of the data imbalance in most datasets, the evaluation metrics precision, recall, and F1-score are introduced, nevertheless, it is not sufficiently addressed in the selected papers. To tackle this problem, some researchers consider that the normalization of temporal data is sufficient and that the problem of unbalanced classes can be resolved by the algorithm itself. The MeanShift method is also used to expand the samples of low-risk factors and solve the problem of unbalanced samples.

2) PREPROCESSING OF VIDEOS AND IMAGES

Images and videos are important sources of driver behavior data. The preprocessing of an image or video is the set of operations carried out on the image that consists, on the one hand, of modifying the appearance of the image to extract information more easily and, on the other hand, to remove useless information such as image noise to improve the data quality [136].

Analyzing video can be done by frames or by paths divided into segments of one minute or more. In general, all of the videos were cropped using fixed selection frames, the backgrounds were removed, and then the videos were resized to produce lower-definition copies. This is because employing high-resolution photos inherently adds storage, computing, and data transmission overheads, which would make the model's design more challenging. This method also lessens the conflicting effects of background and lighting changes on the classification task, which can frequently occur in actual driving situations. In addition, considering the optical flow (OF) at the input of an image-trained model can effectively improve accuracy. The cubic B-spline method is used to represent the vehicle motion in the video.

Image augmentation is also an important task that not only helps provide a diversified dataset and prevent the classifier from overfitting but also assists in the development of a more robust classifier that could classify much more effectively.

In most cases, manual observation models were used to identify traffic and environmental conditions to extract features that trained the model. Also, the mean RGB value is used as a subtractor to center the data. The trajectories can be extracted from the video to solve some problems using the shared source traffic vision analysis platform TvaLib.

For an imbalanced data problem, the downsampling of the collected video can be solved by storing only every third frame, which reduces data redundancy.

3) DATA LABELING

The first problem encountered in the driver behavior classification study is the labeling of the data. The data labels must be very accurate in order to teach the model to make correct predictions. There are many methods used to label the data: manually, automatically, and based on indicators in the data that allow us to directly label and understand the type of driver behavior.

In most cases, the data labeling is done manually, but the problem becomes complex when the data increases. The method requires much time and many humans to label that data.

Automatic labeling refers to any data labeling technique that is not done by humans. This could mean labeling by machine learning models, heuristic approaches, or a combination of both. The most commonly used technique in the selected studies is clustering. The K-means clustering algorithm is the most used one. It is based on several forms to measure similarity, like Euclidean distance and log-likelihood distance. For example, in [53], speed was the key to labeling driver behavior; in [42], the speed range was used; and in [65], driving characteristics were the clustering base. Generally, we use clustering only for continuous and categorical variables [45]. Three clustering algorithms are proposed in [49], including k-means clustering, hierarchical clustering, and model-based clustering, to choose the optimal number of clusters for each and then label the data based on the speed data.

The other method used in the studied papers is based on the analysis of the datasets. They labeled aggressive behavior as occurring in drivers who prefer greater longitudinal acceleration and deceleration. Also, for the level of risk, they categorize behavior by the minimum acceleration, average acceleration, and kinetic energy reduction ratio, which are connected to the accident rate. The driver's behavior at intersections is detected based on the decreasing probability of stopping through the increasing speeds of the approaching vehicle and the increasing yellow duration at the signal.

E. FEATURE SELECTION AND FEATURES EXTRACTION TECHNIQUES (RQ5)

The objective of feature selection is to find the best set of features to build performant models of the phenomena studied. According to previous research, the selection of relevant features is done either automatically or manually using context knowledge. To select the most relevant feature, ML learning techniques were widely used such as, SVM [65], LR [105], and RF [48]. According to [96], acceleration and jerk based on timestamp and speed, which are provided by GPS sensors, are the most often used features in the classification of driver behavior. For video data in [74], authors used minimum redundancy and maximum relevance (mRMR). This approach performs better than conditional mutual information maximization (CMIM), mutual information maximization (MIM), and ReliefF when evaluating the best representative trajectory histograms. A sensitivity metric, mean square error (MSE), was employed to determine the bare minimum number of events or features required to study driver behavior. In general, few papers have proceeded to the feature selection section.

Feature extraction refers to the process of constructing derived values (features) that are more informative and can facilitate subsequent learning steps. Two techniques were applied: feature engineering to create a new feature from existing ones and dimension reduction.

TABLE 9. Features extraction methods.

Feature extraction technique	Papers
Mean	[57], [106], [71], [72], [40], [103]
Standard deviation	[57], [106], [71], [72], [40]
Maximum value	[55], [57], [106], [71], [72], [40]
Minimum value	[55], [57], [106], [71], [72]
Median value	[40]
Variation	[40], [103]
Second-Order Taylor	[103]
Hjorth parameters	[40]
kurtosis	[40]
Skewness	[40]
Threshold based algorithm	[57]
Point detection algorithm	[57]
SVM algorithm	[65], [73]
Cubic B-spline	[74]
Plot technique	[94]
TvaLib platform	[85]
PCA	[29], [57], [103], [104], [106]

It is very important to extract static characteristics from the data to study driver behavior. These characteristics can be used to make straightforward behavioral classifications. The methods used for feature extraction, are mean, maximum, standard deviation, minimum, PCA, and others, as shown in Table 9. Time series data is used in papers [51] and [99], to extract statistical parameters of the attributes mean, standard deviation, maximum value, and minimum value to represent the maneuvers. The minimum and maximum values of speeds and acceleration were used in [55]. While in [71] and [72], the statistical parameters were used such as maximum, minimum, the range of values, the mean, and the standard deviation, and they present the main difference between the different driver behaviors. In addition, in [40], feature extraction was applied based on the following basic statistical descriptors: mean, maximum value, standard deviation, and median value. In [103], mean and variation are used to find effective trends then Predicted Error (PE) - It was calculated using Second-Order Taylor. Article [57] uses a threshold-based algorithm to extract driving maneuvers from the path. The point detection algorithm is used to estimate the time range of the signal in search of important events [35]. The papers [65], [73] use SVM to extract stability features. In [94], they proposed converting the signals into images using the recurrence plot technique. Consistent misuse of control or propensity to drive can be determined from the mean and median values. The maximum value, for instance, denotes abnormal or aggressive behavior when it is higher than the speed limitations that are presented. Furthermore, a fast rate of change may be indicated by the standard deviation, which frequently denotes aggressive behavior. The engine is being driven aggressively if the standard deviation of the engine speed or throttle position is high. The major properties of a signal in the frequency domain can be captured using Hjorth parameters, which are frequently employed in feature extraction. Hjorth activity reflects the signal's strength, the mobility of its average frequency, and the complexity of its frequency variation [40]. The degree of dispersion and symmetry of the data are each described using kurtosis and skewness,

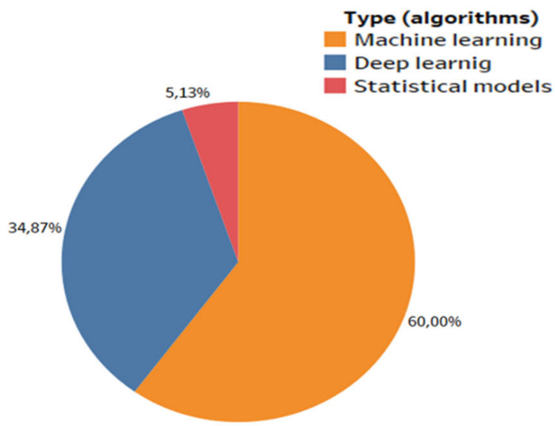

FIGURE 10. Type of algorithms.

respectively. Particularly, Skewness measures how much the data deviate from a perfectly symmetric distribution, whereas Kurtosis assesses how heavy or light-tailed the data are in comparison to a normal distribution [40].

A feature extraction procedure was required to minimize the dimensionality of the feature space and obtain the most representative parameters from a large number of modified features. Dimension reduction purposes in papers [29], [57], [103], [104], [106] use principal component analysis (PCA) to reduce dimensionality, improve model overfitting performance, and reduce computational complexity. For video data, the length of the vectors was fixed to reduce the data dimension.

F. APPROACHES FOR DRIVER BEHAVIOR ANALYSIS (RQ6)

In this section, we will identify and analyze the applications of machine learning, deep learning, and statistical techniques and algorithms in the field of driver behavior assessment and classification. Fig. 10 presents in percentage form the number of papers that have developed ML, DL, or statistical analysis. It shows that machine learning (ML) algorithms are the most used; they are present in 60% of previous studies. Then deep learning (DL) algorithms took 34.87%. Finally, statistical methods are less used, with 5.13%. In this SLR, we have extracted twenty machine learning (ML) algorithms used to classify driver behavior. We have SVM, LR, RF, KNN, k-means clustering, BN, DT, AdaBoost, and other algorithms presented in Fig. 11. In addition, twenty deep learning (DL) algorithms, we have LSTM, CNN, ANN, RNN, DNN, SF-Net, FCN, autoencoders, and other algorithms presented in Fig. 11. Six statistical techniques used, such as the T-test, ANOVA, and ANCOVA. The algorithms SVM, LR, LSTM, ANN, KNN, RF, and CNN are the most commonly used, they present 49.72% of the articles studied. Fig. 11 shows the interest that each algorithm received in previous studies.

1) DRIVER BEHAVIOR CLASSIFICATION ALGORITHMS

We have analyzed the algorithms used in the selected studies according to the dataset, data source, type of algorithm, and type of driver behavior study.

At the level of the dataset, Fig. 12 shows for each dataset the classification algorithms used to predict and classify driver behavior. LSTM is the most commonly used algorithm for UAH-DriveSet with 11.42%. Then, SVM, RF, and DT algorithms are often used in the SHRP2 dataset, with 5.71% in each one. SVM and ANN are used with 2.87% in the Driving dataset, and RNN, LSTM, and GRU are used in Driver Behavior Dataset with 2.85% in each one. In general, the LSTM algorithm is the most used in driver behavior classification from the extracted dataset, with almost 17.14%, followed by SVM with 14.29%, and RF with 11.43%, and the other algorithms percentages are shown in Fig. 12. We can also conclude that ML algorithms are the most commonly used to classify driver behavior from datasets, accounting for 51.43% of the total, while DL algorithms account for 42.86%.

In addition, from Fig. 13, SVM and LR algorithms are mostly used to analyze smartphone sensor data. Also, for simulator data the SVM algorithm is recommend. In general, the SVM algorithm is the most used in the data source for the classification of driver behavior with 19.60%, then LR and LSTM with 9.49 and 8.23%, respectively, and the percentage of other algorithms is shown in Fig. 13. ML algorithms account for 62.66% of the algorithms used for the classification of driver behavior based on different data sources, followed by the DL algorithm with 32.91% and the statistical method with 4.43%.

2) DRIVER BEHAVIOR CLASSIFICATION PERFORMANCE MEASURES

Measuring model performance is crucial to understanding and quantifying its effectiveness. Through this process, we can determine which model is the best to use for a classification or regression task. The Fig. 14 show that the most popular performance metrics considered in the chosen studies are accuracy, F1-score, recall, and precision.

In fact, as accuracy is the most common evaluation metric in classification modeling, it is adopted 48.75% of the selected studies, followed by the F1-score in 12.50% of papers. The harmonic mean of the recall and precision values is represented by this metric. 11.25% used recall or sensitivity metrics to measure the fraction of correctly classified positive patterns, while 8.75% used precision metrics to measure the fraction of correctly predicted positive patterns in a positive class. False-positive rate, MSE, ROC curve, and AUC are each used at 3.75%, followed by MPE at 2.5%, specificity, MCC, MAE, and Concordance at 1.25% each.

3) DRIVER BEHAVIOR CLASSIFICATION PERFORMANCE

In terms of the best performing algorithm, we cannot decide exactly which of the algorithms illustrated above (see Fig. 11) performs better than the others, as in most of the studies selected above, their data source, features, sample size, study environment, number of participants, metrological data, and other factors are all different. To analyze the model's performance, we project in Table 10 the algorithm used in the datasets detailed in Table 5 and its measured performance.

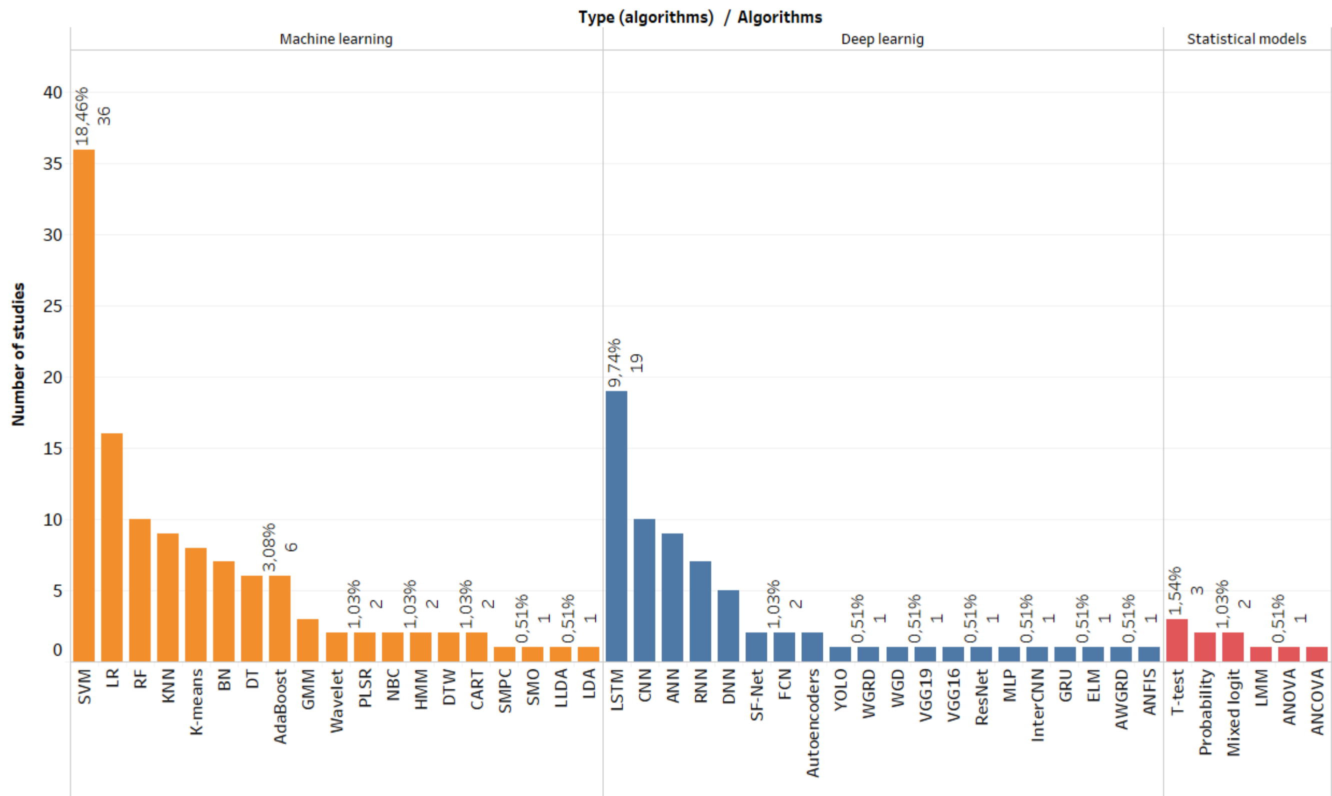

FIGURE 11. Distribution of algorithms.

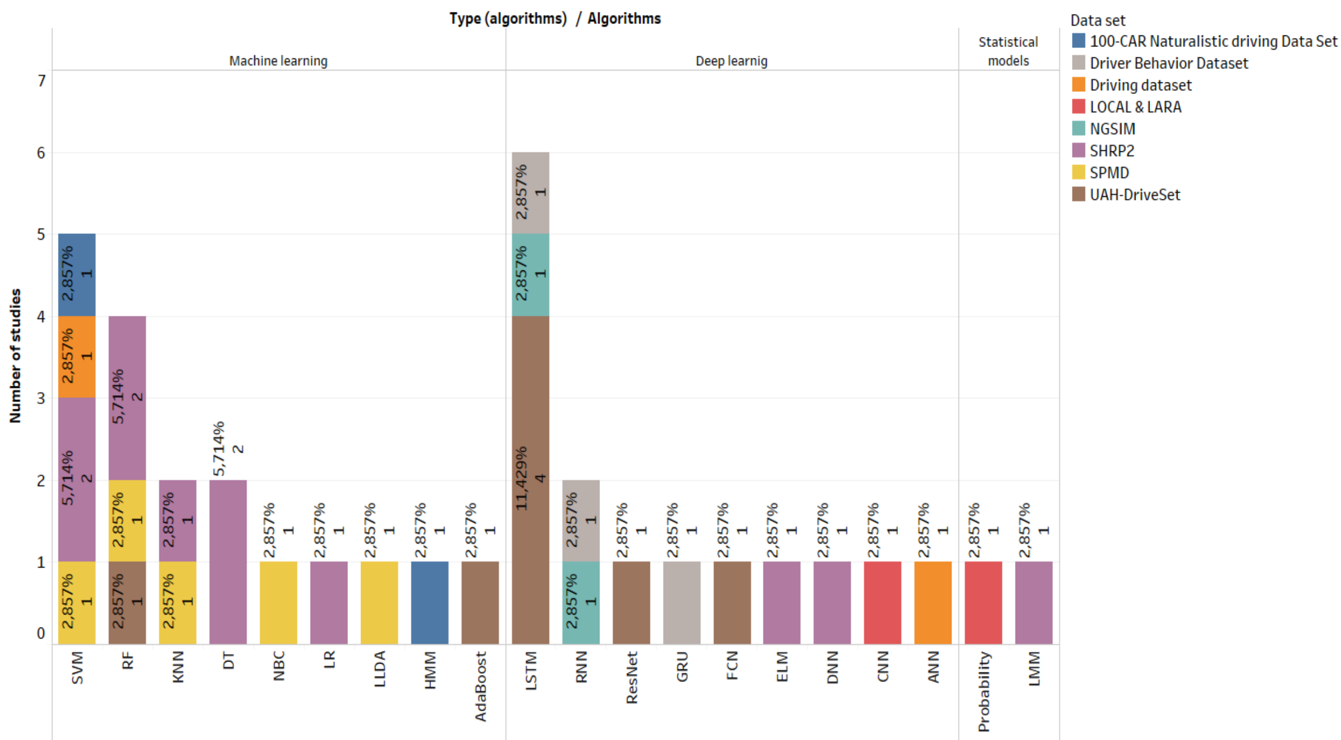

FIGURE 12. Distribution of driver behavior algorithms used in the dataset extracted from selected studies.

We note that in UAH-DriveSet the highest score obtained is 99.49% F1-score with the LSTM algorithm and the three output classifications: aggressive, drowsy, and normal. The SPMD achieves an accuracy of 60.5% with the LLDA algorithm, and the extracted behavior types are aggressive driving, cautious driving, and moderate driving. Then 98.5%

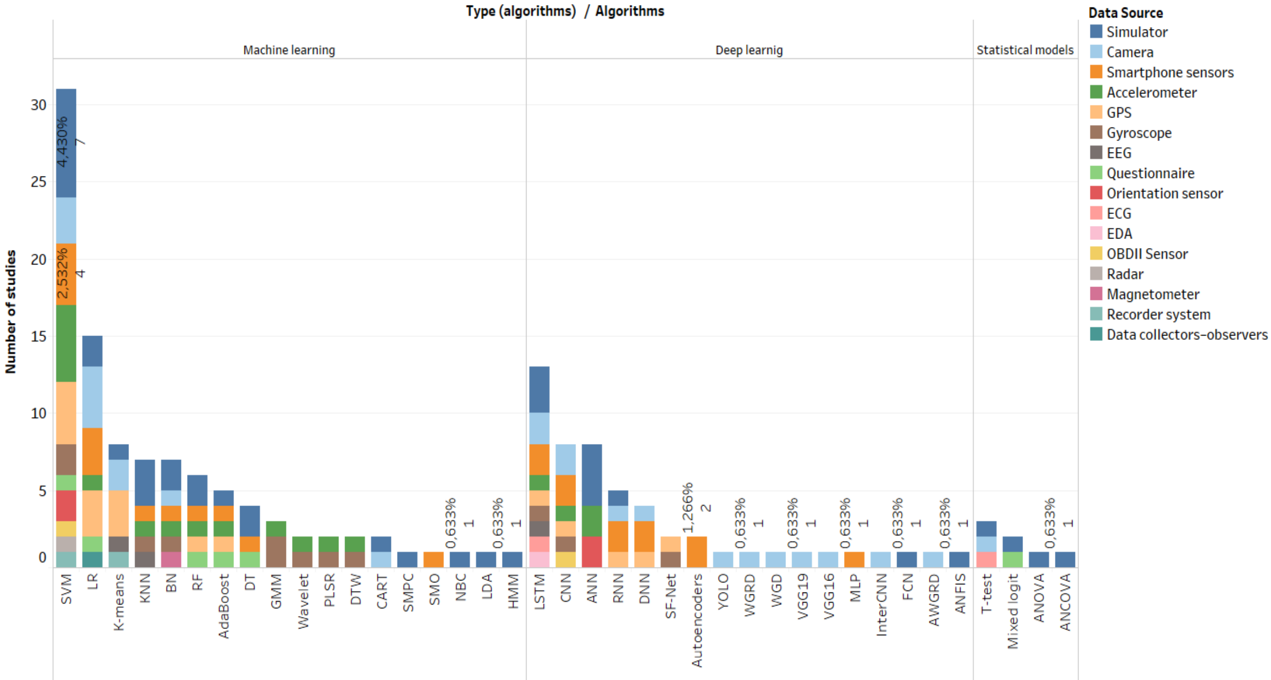

FIGURE 13. Distribution of driver behavior algorithms used in the data source extracted from selected studies.

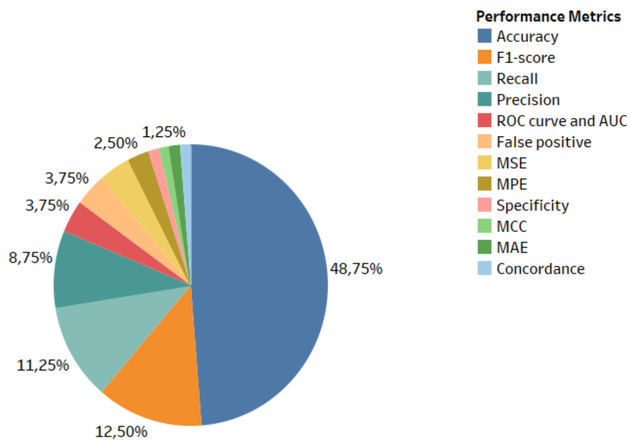

FIGURE 14. Performance metrics.

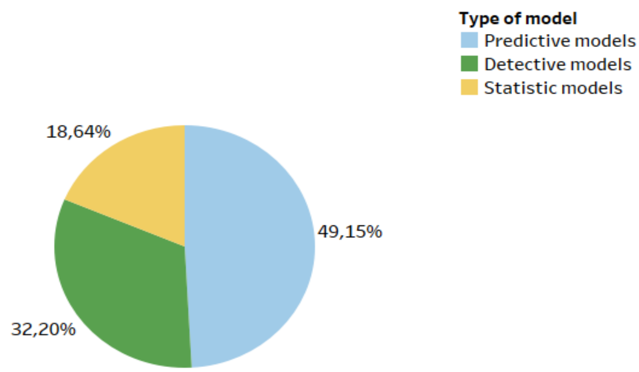

FIGURE 15. Type of models.

concordance is obtained in the SHRP2 dataset with the RF algorithm and the following outputs: eating and drinking, personal hygiene, phone use while driving, reaching, talking, and talking to passengers. In addition, 90% accuracy is found in SHRP2 with both abnormal and normal behaviors and the RF algorithm. Furthermore, the driving dataset with the SVM algorithm, and the types of dangerous and safe driver behavior obtained 90% accuracy. With the GRU algorithm and Driver Behavior Dataset, 95% accuracy is attained, and the driver behavior is classified as aggressive in acceleration, braking, left and right turns, left and right lane changes, or non-aggressive events. Finally, the 100-CAR Naturalistic.

Driving Data Set and the SVM algorithm found a result of 90% accuracy for the types of dangerous and normal driver behavior.

4) DRIVER BEHAVIOR APPROACHES

The algorithms identified earlier were used to assess driver behavior generally in three forms: (1) detecting driver behavior; (2) predicting and classifying driver behavior; and (3) using statistics to study driver behavior. Fig. 15 is plotted to describe the driver behavior study techniques and models. 49.15% of studies use algorithms to predict driver behavior, followed by 32.20% that use detection models, and 18.64% that use statistical models.

In addition, in the detection models, the authors use 54% ML algorithms and 44% DL algorithms. The same thing happens in prediction models: ML algorithms account for 64.29%, DL algorithms for 33.67%, and statistical models for 2.04%. While in statistical models, researchers also use more ML algorithms with 57.14% and statistical algorithms like ARIMA and others with 42.86% (see Fig. 16).

TABLE 10. The results of the algorithms based on the targets for each dataset.

Types	ALGORITHMS	Dataset	Result	Performance Metrics	Target
DL	FCN and LSTM	UAH-DriveSet	95,88	F1-score	Aggressive, Normal
	CNN architectures	LOCAL & LARA	97,9	Accuracy	Safe
	GRU	Driver Behavior Dataset	95	Accuracy	Aggressive acceleration Aggressive breaking Aggressive left turn Aggressive right turn Aggressive left lane change Aggressive right lane change Non aggressive event
	LSTM	UAH-DriveSet	99,49	F1-score	Aggressive Drowsiness, Normal
			91	F1-score	
ML	DT and RF	SHRP2	82,2	Accuracy	Normal Phone use while driving Talking, Texting
	HMM	100-CAR Naturalistic driving Data Set	80,37	Accuracy	High-Skilled, Low-Skilled
	KNN	SPMD (Safety Pilot Model Deployment)	35,6	Accuracy	Aggressive Careful driving Moderate driving
	LLDA	SPMD (Safety Pilot Model Deployment)	60,5	Accuracy	Aggressive Careful driving Moderate driving
	LR	SHRP2	79	Concordance	Eating and Drinking Personal hygiene Phone use while driving Reaching Talking Talking to passenger
			16,1	MSE	
	NBC	SPMD (Safety Pilot Model Deployment)	46,3	Accuracy	Aggressive Careful driving Moderate driving
	RF	SHRP2	98,5	Concordance	Eating and Drinking Personal hygiene Phone use while driving Reaching Talking Talking to passenger
			6,5	MSE	
	SVM	SPMD (Safety Pilot Model Deployment)	18,3	Accuracy	Aggressive Careful driving Moderate driving
Statistic	Probability	SHRP2	90	Accuracy	Dangerous, Normal
		Driving dataset	90	Accuracy	Dangerous, Safe
		100-CAR Naturalistic driving Data Set	90	Accuracy	Dangerous, Normal
		LOCAL & LARA	91,87	Accuracy	Safe
			90	Accuracy	Abnormal, Normal

For each type of driver behavior study, we need to know the most commonly chosen type of algorithm (Fig. 17). Machine learning algorithms are the most frequently used algorithms in driving simulator studies, field driving studies, naturalistic driving studies, and questionnaire studies, with 60.98%, 62.82%, 54.17%, and 64.29%, respectively. Then, with 37.50% in naturalistic driving studies and 34.62% in field driving studies, deep learning algorithms are used. In the questionnaire study, 35.71% presented statistical techniques.

V. DISCUSSION

The purpose of the SLR protocol used in this article is based on the following objectives:

RQ1: The classification of driver behavior is a complex and difficult objective. It has not yet been addressed in detail in previous studies, in part because the types of driver behavior (targets) are not unified and many interferences and interdependencies can be detected between the terms used to target the same goal. To attempt this goal, we extracted driver behaviors (DB) from papers studied in this SLR, analyze the dependencies and relations between them and categorize them into abnormal DB, aggressive DB, vehicle stopping for DB, line deviation, and driver's status. In each category, there are types of DB included like abnormal DB (normal, abnormal, safe, dangerous, positive, negative, high risk, etc.), aggressive DB (aggressive behaviors and their types and levels of aggression), vehicle stopping (stop, run, go, rolling stop, etc.), line deviation (swerving, side slipping, fast U-turn, successful lane changing, etc.), driver's status (drowsiness, stress, use of cell phone, talking, eating, etc.). An accurate study allows us to group and categorize the types of driver behavior, which is an inevitable goal.

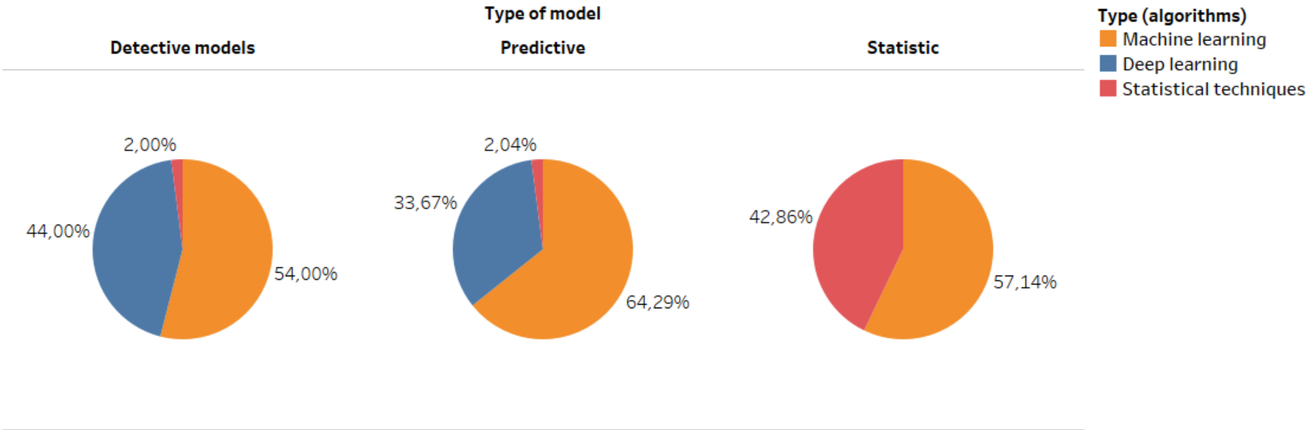

FIGURE 16. Classification of model types according to algorithm types.

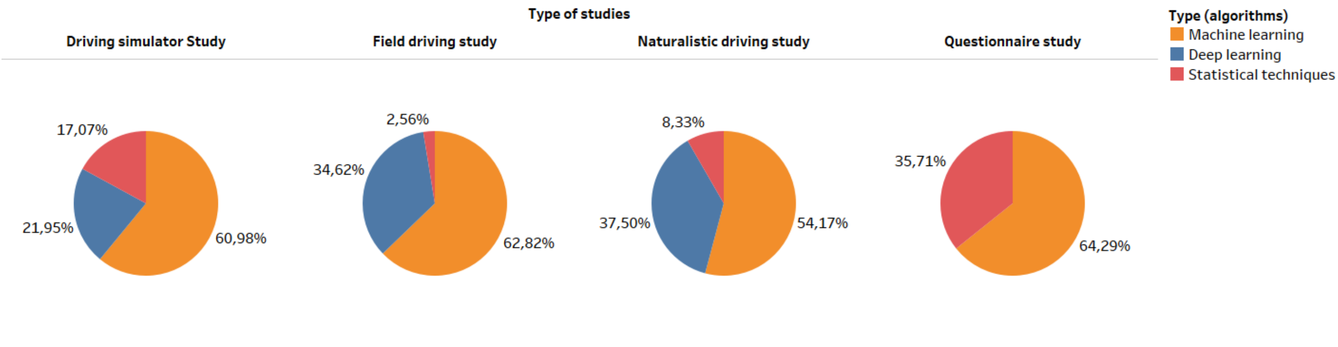

FIGURE 17. Classification of types of studies according to algorithm types.

RQ2: In the selected papers, four types of studies were extracted to classify driver behavior: questionnaire study, naturalistic driving study (NDS), field driving studies (FDS), and driving simulator study. The questionnaire reflects the subjective opinions of the driver rather than the driver's actual performance on the road, and the other types involve manual control of the driving environment to induce a specific driver behavior. In addition, field driving studies are the most commonly used to study driver behavior either with cameras, sensors, etc.

RQ3: From this SLR, we identified the different data sources used to extract data and classify driver behavior. These data sources are classified in Table 3, we find: a simulator, camera, GPS, smartphone sensors, accelerometer, gyroscope, and other data sources (Table 3). In addition, we have synthesized datasets used in several articles, such as SHRP2 (Strategic Highway Research Program 2), UAH-DriveSet, SPMD (Safety Pilot Model Deployment), NGSIM (Next-Generation Simulation), Driver Behavior Dataset, 100-CAR Naturalistic Driving Data Set, and other datasets (Table 5). From these sources and datasets, several different features are extracted. Due to the complexity of the problem and the different sources and datasets, the number of extracted features is abundant (39 large feature categories and 225 sub-features). Among the important features (the most frequent ones from the selected articles) are vehicle speed, acceleration/deceleration, rotation rate, pedal, acceleration (lateral and longitudinal), time (time to the intersection, time to a stop line, and time to a lane crossing), traffic condition, personnel information, steering, and physiological and psychological signals. Due to the different sources of data, the mass of data, and the different traffic characteristics, the problem of classification of driving behavior is more and more complex. However, due to these data, which are large and of different types, the research potentials in this area are promising, especially with the development of ML, DL, and statistical techniques.

RQ4 and RQ5: Data preprocessing techniques in the field of driver behavior discussed in selected articles are: the cleaning phase, noise removal, resampling phase, normalization, data augmentation, and imbalanced data. We find that these techniques are not used extensively and sufficiently to achieve the objective of driver behavior classification. For example, the number of features extracted in each article is too high to allow us to specify the features that are important for classifying driver behavior. Furthermore, because the data in this topic is typically temporal, it requires a complex structure and preprocessing to yield significant results. Let us not forget the problem of unbalanced data, which is not sufficiently covered in the selected papers. In addition, data labeling is a topic that most researchers do not address, and others do not clearly and adequately discuss. From the papers studied, we found a set of feature extraction techniques with mathematical forms like minimum, maximum, variance, and others, and using artificial intelligence algorithms like SVM, RF, and PCA. At the level of feature selection, we have found that most of the papers use the knowledge of the domain in the choice of features. However, ML and DL techniques offer enormous potential for feature selection, many techniques are available for this purpose and allow for attribute selection that improves the performance of the models.

RQ6: The SVM, LR, and LSTM algorithms are most commonly used in various datasets to classify driver behavior. In general, ML algorithms are more applied in different types of studies, while DL algorithms are also less used. Therefore, the question that arises is why machine learning algorithms are more widely used than deep learning algorithms, even though we have data that changes over time, has a large number of features, and comes from heterogeneous data sources. We can say that the potential of DL techniques is not sufficiently exploited for DB study.

In general, we have synthesized from various literature on driver behavior a set of factors that relate to the external environment of the car that can influence driver behavior. Such as road conditions, traffic conditions, weather conditions, and the presence of pedestrians, vehicles, motorcycles, and cyclists. Beyond that, we need a global system that allows us to classify driver behavior according to the external environment of the car.

The use of real-time driver behavior classification in road vehicles has many implications for road security, for example: First, in-car warning systems can alert the driver to unusual driving behavior and encourage him to be cautious. Secondly, we can use it to create a police warning system for abnormally driving vehicles by identifying, for example, vehicles that are likely to be dangerous or unsafe. This is achieved by analyzing the vehicle's distance traveled, speed, and other approaches. This system permits us to stop a person before an accident occurs, allowing governments to impose penalties on reckless drivers to maintain road safety and traffic control. Thirdly, it helps companies make better decisions about hiring drivers and predict the behavior of their employees. Finally, to detect areas of abnormal behavior to assist the government in making decisions to improve road safety in those areas. All of these applications can help prevent accidents and reduce the cost of repairs.

VI. CONCLUSION

The aim of this review is to identify existing classification systems for driver behavior. Using SLR guidelines and procedures, we analyzed and evaluated past reviews in the field of driver behavior. We followed the systematic literature review approach in this study and used digital databases such as ScienceDirect, the IEEE Xplore digital library, SpringerLink, the DBLP database, and Google Scholar to extract the information. This systematic review examined the literature on driver behavior classification from 2015 to 2022. Finally, we find 93 primary empirical studies that are relevant to the research questions (RQs) posed in this review. The results showed that field driving studies are the most widely used to study driver behavior classification. In addition, this SLR states that there are many types of driver behavior classifications. We have classified driver behavior as abnormal DB, aggressive DB, vehicle stopping for DB, line deviation, and driver status. We then identified the data sources and datasets utilized to analyze and predict driver behavior. The Strategic Highway Research Program 2 Data Set (SHRP2) and the UAH-DriveSet are the most commonly used datasets in driver behavior classification. The simulator and the camera are the most popular data sources for this problem. We explored preprocessing, feature selection, and feature extraction techniques used in the papers studied. Additionally, the SVM, LR, and LSTM algorithms are widely used in training data to classify driver behavior. In general, machine learning algorithms are most present in this problem of driver behavior classification with 60%, followed by deep learning algorithms with 32.73%.

This study possesses some limitations in searching for articles, as only journals and conferences indexed in Scopus between 2015 and 2022 were used. Additionally, only articles based on a system, method, or machine and deep learning algorithms based on driver behavior classification were selected and analyzed. We concentrated mostly on articles dealing with the study of driver behavior from the outside of the car, i.e., the external environment.

For future research, we will first focus on studying the different data sources that allow us to extract drivers' features in order to propose a semantic categorization of these features to provide more accurate description of the driver's behavior. Furthermore, we attempt to propose a DB classification system capable of classifying driving behavior using multiple data sources and leveraging the potential of deep learning algorithms for time series. Finally, we need to reduce the problems of driver behavior and study how this behavior is related to the environment, such as intersections, pedestrians, and weather.

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