Technologies for Vehicle Classification in Intelligent Transportation Systems: Advances, Challenges, and Perspectives

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**Abstract**

Intelligent Transportation Systems (ITS) are crucial for modern transportation infrastructure. These systems, powered by advanced technologies, are the key to optimizing traffic flow, enhancing safety, and reducing environmental impact. Among the many components of ITS, vehicle classification stands out as a crucial element. By accurately classifying vehicles based on their size, type, and behavior, tailored strategies for traffic control, lane assignment, and toll collection can be developed. With the advent of Artificial Intelligence (AI), new opportunities have emerged to enhance the performance of vehicle classification systems. This chapter aims to provide an overview of recent advances, current challenges, and future perspectives in vehicle classification technologies within ITS. It delves into implementing AI techniques in vehicle classification systems, analyzing their effectiveness, limitations, and potential applications. The conclusion highlights the need for robust algorithms, data diversity, and secure communication protocols. It also explores the need for explainable AI to enhance trust in classification decisions and integration with other ITS components for a comprehensive transportation ecosystem. Recent developments in deep learning techniques have led to high accuracy in vehicle classification. However, the complexities of traffic environments, diverse weather conditions, and privacy concerns pose significant challenges that need attention. Nevertheless, the future of vehicle classification for ITS is promising, with the potential to build more intelligent and efficient transportation systems, thereby contributing to a safer and more sustainable future.

1. Introduction

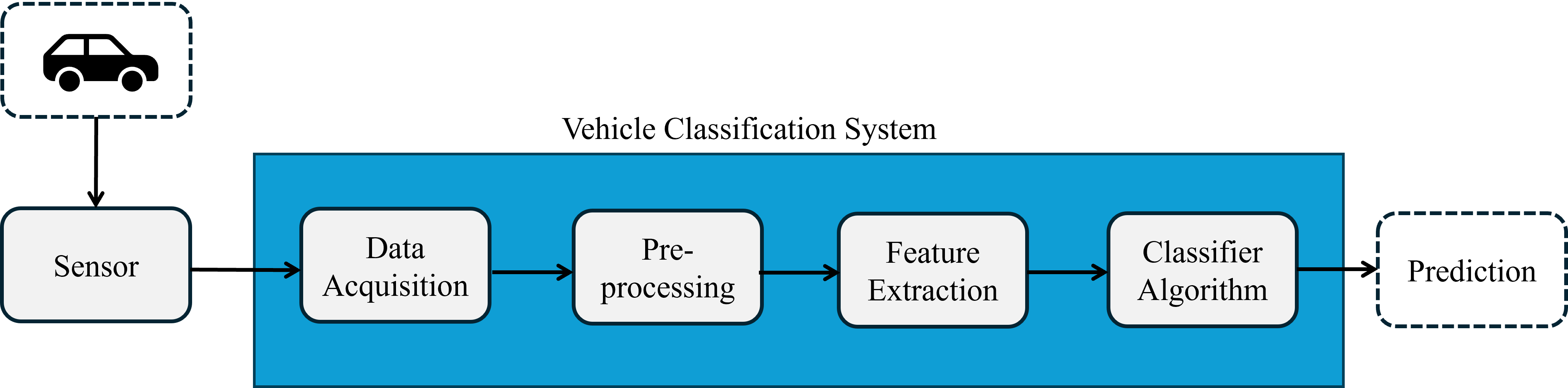
The increasing number of vehicles frequently overwhelms urban infrastructure and management, resulting in recurrent traffic congestion and compromised road safety. Therefore, it is crucial to prioritize the implementation of Intelligent Traffic Systems (ITS). A well-designed and implemented ITS ecosystem can significantly transform urban mobility, making it safer, more efficient, and more sustainable (Lv et al., 2023). Diverse components are combined in ITS, including sensors, communication networks, and data analytics techniques, all working together to enable real-time data collection, smart decision-making, and improved traffic management (see Figure 1).

Vehicle classification is a crucial element of any ITS. Methods for classifying vehicles are typically localized and can identify vehicles passing through fixed sensors or short-range monitoring areas. Classification of vehicles by size, type, and behavior is essential for real-time traffic monitoring. Classifying vehicles based on size, type, and behavior is essential to effectively monitor real-time traffic. It is also important for the development of smart cities and Advanced Driver Assistance Systems (ADAS). Recent advancements in sensor, communication, and machine learning (ML) technologies have created new opportunities to enhance traffic management by improving vehicle classification systems (Gholamhosseinian et al., 2021; Shokravi et al., 2020; Won, 2020; Zhihan et al., 2023; Kadłubek et al., 2022; Khalil et al., 2024). However, selecting the most suitable solution for specific vehicle classification needs can be difficult, given the unique technologies and criteria involved.



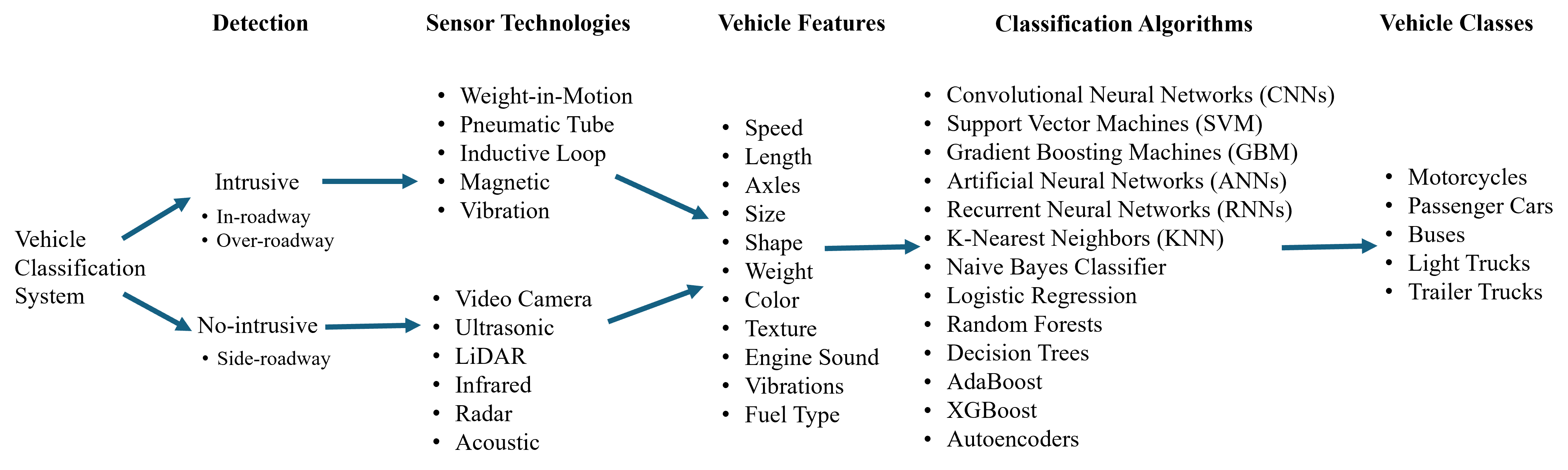
**Fig 1.** An ITS ecosystem includes sensors, communication networks, and advanced data analytics techniques, all working together to enable real-time data collection, informed decision-making, and improved traffic management [Created with Microsoft Designer].

A vehicle classification system has several components, each with a specific role in the overall process (see Figure 2). The system starts with sensors like inductive loops, cameras, radar, LiDAR, magnetic, and weigh-in-motion (WIM). These sensors detect characteristics of vehicles, such as presence, size, speed, and weight. The data from the sensors goes to a data acquisition system, which turns the sensor outputs into digital data for further processing. In the preprocessing stage, the raw data undergoes noise reduction, normalization, and synchronization to ensure quality. After this, the system identifies and isolates important vehicle features like the number of axles, vehicle size and shape, axle spacing, weight, and speed. Then, a classifier algorithm processes these features to categorize the vehicles into predefined classes such as light-duty, medium-duty, or heavy-duty. Examples of classifier algorithms include decision trees, support vector machines (SVM), neural networks, k-nearest neighbors (KNN), and, more recently, those based on deep learning architectures. This structured approach helps with ITS traffic management, road safety, and real-time vehicle identification.



**Fig. 2.** Vehicle Classification Architecture.

This chapter provides an overview of the recent technologies used in vehicle classification within ITS. The discussed technologies include sensors, artificial intelligence (AI), machine learning (ML), and novel processing algorithms. We analyze the effectiveness, limitations, and potential applications of these technologies based on literature reviews from Gholamhosseinian et al. (2021), Shokravi et al. (2020), Won (2020), Alghamdi et al. (2023), Zhihan et al. (2023), Kadłubek et al. (2022), and Khalil et al. (2024). Our search is based on the taxonomy shown in Figure 3, which is a modified version derived from previous review papers by Gholamhosseinian et al. (2021), Shokravi et al. (2020), and Won (2020).



**Fig. 3.** Methods and cutting-edge technologies for classifying vehicles within ITS.

Our research categorizes vehicle classification into two groups: Intrusive and Non-intrusive, and further divides each category into subcategories based on sensor technology. We also discuss innovative approaches, particularly those using AI and ML techniques for feature extraction and vehicle classification. Additionally, the chapter addresses challenges, limitations, and potential solutions such as sensor fusion and real-time processing. Finally, it outlines future directions, emerging trends, and the need for innovation to improve transportation system efficiency and safety.

2. Vehicle classification in ITS

In the 1980s, the Federal Highway Administration (FHWA) established a standardized vehicle classification schema to address traffic data needs, including pavement designers and the safety community. This schema was designed to work with electronic equipment and sensors available at that time, such as road tubes and inductive loops, to effectively categorize passing vehicles. The FHWA categorizes vehicles into distinct groups primarily based on their features, such as size, weight, speed, axle count, and intended use (Gupte, 2002). This categorization is vital for various purposes, including traffic surveillance, infrastructure development, and regulation adherence.

Table 1 summarizes the FHWA vehicle classification, organizing vehicles into categories based on type, number of axles, description, applications, and examples. It covers light-duty, medium-duty, and heavy-duty categories. Light-duty vehicles include motorcycles, passenger cars, pickup trucks, minivans, and SUVs for personal transportation and light commercial purposes. Medium-duty vehicles include buses, two-axle trucks for local deliveries, and three-axle trucks for heavier cargo transport. These vehicles attend public transport, local delivery, and construction needs. Heavy-duty vehicles have four or more axles, including single-unit trucks, single-trailer trucks, and multi-trailer trucks for various freight transport purposes. This classification system helps understand different vehicle types and their specific uses in transportation and logistics.

The classification of vehicles has gained significant interest in recent years. The ability to automatically detect and classify vehicles is crucial for improving traffic management, surveillance, and overall transportation efficiency. Researchers have developed advanced methods for vehicle classification within ITS, using technologies such as deep learning, computer vision, and sensor-based systems (Won, 2020; Lin et al., 2021). These methods incorporate static appearance features, motion features, magnetic field measurements, and ensemble deep learning techniques to accurately detect and classify various types of vehicles on the road (Yang et al., 2015; Won et al., 2020; Yang et al., 2023). These technologies not only support real-time traffic monitoring but also enhance the overall effectiveness of ITS by providing essential data for decision-making processes (Ennehar, 2023). The ongoing progress in vehicle classification methodologies underscores their importance in optimizing traffic management and improving road safety.

**Table 1.** Vehicle classification according to Federal Highway Administration (FHWA).

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Group** | **Class** | **Vehicle Type** | **Axles** | **Samples** |
| Light-Duty | 1 - Motorcycles | Two- or three-wheeled motorized vehicles | 2 | Motorcycles, scooter |
| 2 - Passenger cars | Standard cars designed for personal use | 2, 3  or 4 | Sedans, coupes, station wagon |
| 3 - Other Two-Axle, Four-Tire Single Unit | Vehicles other than passenger cars, including light trucks and vans with GVWR up to 14,000 | 2, 3  or 4 | Pickup trucks, minivans, SUVs |
| Medium-Duty | 4 - Buses | Vehicles designed to transport more than 15 passengers, with two axles and six tires or more | 2  or  3 | Greyhound buses, school buses, airport shuttles |
| 5 - Two-Axle, Six-Tire, Single Unit Trucks | Single-frame vehicles with two axles and dual rear wheels, with GVWR between 14,001 and 26,000 pounds | 2 | U-Haul trucks, delivery trucks, box trucks |
| 6 - Three-Axle, Single Unit Trucks | Larger trucks with three axles and GVWR between 26,001 and 33,000 pounds | 3 | Large box trucks, dump trucks, beverage trucks |
| Heavy-Duty | 7 - Four or More Axle Single Unit Trucks | Heavy trucks used for larger loads with GVWR above 33,000 pounds | 4 or  more | Heavy-duty trucks, large utility trucks |
| 8 - Four or Fewer Axle Single Trailer Trucks | Single-trailer combination trucks with up to four axles | 3 or 4 | Small semi-trailers, flatbed trucks |
| 9 - Five-Axle Single Trailer Trucks | Standard configuration for large freight trucks with a single trailer and five axles | 5 | Typical 18-wheelers, large semi-trailers |
| 10 - Six or More Axle Single Trailer Trucks | Single trailer trucks with more than five axles for very heavy loads | 6 or  more | Heavy-duty semi-trailers, large tankers |
| 11 - Five or Fewer Axle Multi-Trailer Trucks | Combination trucks with multiple trailers and up to five axles | 4 or 5 | Short-haul multi-trailers, doubles |
| 12 - Six-axle multi-trailer Trucks | Multi-trailer combination trucks with six axles | 6 | Double trailers, bulk commodity transporters |
| 13 - Seven or More Axle Multi-Trailer Trucks | Largest combination trucks with multiple trailers and seven or more axles | 7 or  more | Triple trailers, oversized load carriers |

[<https://www.fhwa.dot.gov/publications/research/infrastructure/pavements/ltpp/13091/002.cfm>].

The importance of the classification of vehicles in ITS extends beyond traffic monitoring and control to encompass aspects such as energy consumption, driving safety, and road traffic. By utilizing information from multi-sensor fusion and blockchain-based architectures, ITS can enhance the accuracy and reliability of vehicle classification systems, contributing to a smarter and more efficient transportation network (Song et al., 2023). Furthermore, the analysis of traffic stability, capacity, and flow characteristics in mixed traffic environments with intelligent connected vehicles has provided valuable insights into optimizing traffic operations and enhancing overall system performance (Luo et al., 2023; Liu, 2024).

3. Sensor technologies for vehicle classification

The first pneumatic tube detectors for traffic control were introduced in 1920 and are still used today for the short-term collection of vehicular data. Over the years, magnetic loop detectors have been implemented for traffic control, allowing the detection of vehicle length. Additionally, piezoelectric sensors are utilized to detect vehicle weight and axle configuration independently or in conjunction with Weight-In-Motion (WIM) systems. Radar sensors are widely used for vehicle classification based on length, size, and height. Infrared sensors measure the reflected infrared light from each vehicle and compare the data with a database to identify the best-matched profile. Lastly, acoustic sensors use speed-independent acoustic signatures to determine vehicle classes.

Vehicle classification systems are typically categorized based on their placement; the two main types are intrusive (in-roadway) detectors and non-intrusive (over-roadway or side-roadway) detectors:

* **Intrusive detectors** (see Table 2) involve the installation of sensors on or under the pavement of a roadway. These sensors collect various information from passing vehicles, such as vehicle length, axle count, and unique signal features. Examples of these sensors include pneumatic road tubes, inductive loops, piezoelectric, magnetic, vibration, and capacitive. While these systems are highly accurate in classifying vehicles, they are associated with high installation and maintenance costs. The sensors need to be placed underneath the road pavement, requiring saw cutting and resulting in increased expenses due to lane closures for the safety of road workers. They are also susceptible to damage from traffic and weather conditions, and there is limited available data on vehicle classification using these techniques.
* **Non-intrusive detectors** (see Table 3) are positioned above the roadway surface or on adjacent poles, minimizing disruption to traffic flow during installation and maintenance. There are different types of non-intrusive detectors, including side-roadway and over-roadway systems. Side-roadway sensors are positioned along the roadside, eliminating the need for lane closures and construction. The commonly utilized sensors include magnetometers, accelerometers, and acoustic. More advanced sensors such as Laser Infrared Detection and Ranging (LIDAR), infrared, and Wi-Fi transceivers have also been integrated. Although the installation process for non-intrusive detectors is simpler and costs are reduced, precise positioning and direction of the sensors are required. Significant challenges include accurately classifying overlapping vehicles and minimizing noise's impact on classification accuracy. Over-roadway systems use sensors positioned above the road to monitor multiple lanes simultaneously. Camera-based systems are the most common technology in this category, providing high classification accuracy. However, their performance can be affected by weather and lighting conditions, and there are concerns about driver privacy. Alternative sensors such as infrared sensors and laser scanners are used in some over-roadway systems to address these privacy concerns.

Tables 2 and 3 summarize various sensor technologies used for vehicle classification in ITS (Shokravi et al., 2020; Won, 2020; Gholamhosseinian et al., 2021). They detail the advantages and disadvantages of each sensor technology and provide examples of use cases for ITS applications.

**Table 2.** Intrusive sensor technologies for vehicle classification.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Sensor** | **Detection** | **Advantages** | **Disadvantages** | **Use in ITS** |
| Inductive Loop | Embedded wire loop, changes in inductance | Reliable presence  detection, axle counting | Disruptive  installation and  maintenance | Traffic flow monitoring, axle count |
| Magnetic | Changes in Earth's magnetic field | Reliable presence  detection, axle  counting | Limited classification accuracy | Pre-screening, parking detection |
| Weight-in-Motion | Deformations (Strain gauges, Piezoelectric) | Valuable data for  weight enforcement, road usage | High installation and maintenance costs | Weight enforcement, traffic management |
| Pneumatic  Tube | Air-filled Tubes | Reliable presence detection, axle counting | High installation and maintenance costs | Traffic flow monitoring, axle counting |
| Piezoelectric | Pressure Variations | Axle counting, basic classification | Requires careful installation, limited classification | Traffic flow monitoring, weight estimation |
| Capacitive | Changes in Capacitance | Potential for low-cost presence detection | Limited data on  vehicle classification | Pre-screening, lane change detection |
| Vibration | Vibrations | Valuable data for  structural health  monitoring | Disruptive  installation and maintenance | Bridge monitoring, traffic volume estimation |

**Table 3.** No-intrusive sensor technologies for vehicle classification.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Sensor** | **Detection** | **Advantages** | **Disadvantages** | **Use in ITS** |
| Video  Camera | Uses visible light spectrum for image capture | Relatively inexpensive, wide availability, high-precision classification | Affected by lighting conditions, requires processing for image analysis | Traffic monitoring, lane violation detection |
| Radar | Emits radio waves and measures reflections to detect objects | Provides data on the presence, speed, and direction of vehicles, long-range detection capability | Limited information for detailed classification, susceptible to interference from other sources | Traffic flow, collision avoidance |
| LiDAR | Emits laser pulses and measures reflected light to create 3D point clouds | Highly accurate for vehicle dimensions and location, excellent performance in low-light and adverse weather | More expensive than cameras, data processing can be computationally intensive | High-precision classification, autonomous navigation |
| Infrared | Detects heat signatures emitted by vehicles | Functions well at night but may struggle with classification | Sensitive to weather conditions (fog, rain), limited range | Low-light traffic monitoring |
| Ultrasonic | Emit high-frequency sound waves to detect and measure vehicles | Relatively inexpensive, good for basic presence detection | Short range compared to other options, susceptible to interference from wind and other sound sources | Traffic light optimization, parking detection |
| Acoustic | Detect and analyze sound waves generated by vehicles | Can provide information on speed and potential classification based on engine/exhaust sounds | Highly susceptible to environmental noise (traffic, wind), requires advanced signal processing for accurate classification | Traffic flow, speed estimation |
| Sensor Fusion | Combines data from multiple sensors (e.g., camera + LiDAR) | The highest accuracy in classification handles diverse conditions | Requires complex algorithms, high computational power | Advanced traffic management, security |

Among the proposed methods, the effective classification of vehicles by type and model seems exclusive to vision systems or aerial image detection. However, the use of video cameras for this purpose is quite expensive, especially for large-scale applications. They require several computational resources and involve the invasion of users’ privacy by capturing their faces and/or vehicle plates. Furthermore, video systems are affected by various environmental factors such as glare and shadows from direct sunlight, distortion, and reduced visibility due to rain, lens coverage from snow and ice, reduced visibility from fog, camera movement caused by wind, and equipment damage and data transmission disruption from changing atmospheric conditions. To address these issues, specific technologies such as weather-resistant cameras and adaptive processing algorithms have been proposed (Muhammad et al., 2021; Neupane et al., 2022; Yang et al., 2023).

Ensuring accurate and reliable data from sensors is crucial for effective vehicle classification. Regular maintenance and calibration are essential to keep sensor performance over time, which can be challenging in large-scale deployments. Mitigating interference from external factors like weather conditions and electromagnetic interference is crucial to ensure consistent and reliable data collection. Addressing the critical challenges in sensor technologies for vehicle classification systems is fundamental for developing optimal solutions in intelligent traffic monitoring applications.

Cost considerations are important, with in-roadway systems ensuring close contact with passing vehicles for accurate data capture and side-roadway systems offering cost advantages but requiring precise sensor placement adjustments. Camera-based systems raise privacy concerns, encouraging the use of alternative sensors like infrared, magnetic, or acoustic. Vehicle occlusion is a challenge faced by side-roadway-based systems, as overlapping vehicles can disturb sensors, leading to inaccurate classification. Strategies such as explicitly placing sensors at different heights to cover each lane can help overcome this challenge. Furthermore, machine learning techniques are increasingly used for classification accuracy, but collecting large data for training models and the manual labeling process can be time-consuming and resource-intensive. Integration of different sensor types and deployment methods can enhance classification accuracy. Over-roadway systems, primarily based on cameras, cover multiple lanes but may be affected by weather and lighting conditions. Finally, achieving nearly 100% classification accuracy for many vehicle types remains challenging.

4. Developments in Vehicle Classification within ITS

4.1 Recent Survey Papers

The field of vehicle classification has made significant advancements in recent years, thanks to the integration of advanced algorithms and sensor technologies. One example is the use of computer vision techniques combined with deep learning algorithms to achieve real-time and accurate vehicle classification based on factors such as type, size, and other relevant attributes. Deep learning models like convolutional neural networks (CNNs) have demonstrated promising results in tasks such as vehicle detection and classification, offering high levels of accuracy and reliability. These advancements enable ITS to achieve improved traffic management and overall system performance. Additionally, the integration of intelligent sensors and IoT devices in vehicles has facilitated data collection for vehicle classification purposes. These sensors can capture various data points such as speed, acceleration, and vehicle dimensions, which are then processed using machine learning algorithms to classify vehicles.

The paragraphs that follow provide a descriptive analysis of survey papers found in the literature:

* Boukerche et al. (2017) reviewed automated vehicle classification (AVC) systems. It delves into the challenges, techniques, and future research directions in this field. The main focus of the study is to detect vehicles, identify regions of interest (ROIs), and classify them by type, make, or make-and-model. It identifies three major modules: features extractor, global representation generator, and classifier. The study highlights the challenges of vehicle diversity, class ambiguity, varying viewpoints and conditions, occlusions, and modified appearances. It also outlines future research directions, including robust systems for varying lighting conditions, camera calibration-free systems, comprehensive real-world AVC datasets, 3D approaches, mobile real-time systems, and Vehicle Make, Model, and Generation Recognition (VMMGR). The study underscores the need for further research, as current AVC systems are not robust for real-world conditions and do not perform in real-time applications. The study classifies AVC systems by the level of classification granularity, and the mentioned technologies include computers, sensors, control systems, communications, electronic devices, digital image sensors, and computer vision techniques.
* Won (2020) presented a comprehensive review of advanced traffic monitoring systems with a focus on vehicle classification techniques and the associated challenges. The study categorizes vehicle classification systems into three main types: in-roadway-based, side-roadway-based, and over-roadway-based, further distinguishing them by the specific sensors utilized. Key challenges include the high installation and maintenance cost for in-road-based systems, precise sensor placement difficulties, privacy concerns for camera-based systems, and the complexity of detecting and classifying overlapping vehicles. The study highlights the potential of MEMS, machine learning, wireless communication technologies, and Vehicle-to-Everything (V2X) technology to address these issues. It underscores the necessity for a universally accepted standard, the development of closed-loop self-learning systems, and the exploration of hybrid sensor systems for improved classification accuracy. At last, vehicle classification is deemed essential for traffic monitoring and transportation planning, with the survey offering guidelines for selecting appropriate technologies.
* Shokravi et al. (2020) studied the use of Vehicular Ad Hoc Networks (VANETs) to overcome the limitations of current vehicle classification methods. They aim to provide real-time, global information on vehicle mobility and physical parameters. The paper identifies challenges with existing methods, such as their local nature, lack of physical vehicle parameter data, and dependence on unreliable GPS devices. It proposes leveraging VANETs, smart vehicles, onboard units (OBUs), roadside units (RSUs), and V2V and V2I communication to overcome these issues. The study emphasizes the importance of cross-disciplinary collaboration and the need for future research to focus on developing collaborative systems using vehicular sensors and VANET technology, offering a breakthrough in real-time vehicle detection and classification.
* Gholamhosseinian et al. (2021) thoroughly examined vehicle classification methods and their respective capabilities. The methodologies discussed include intrusive sensors (e.g., loop detectors, magnetometers), non-intrusive sensors (e.g., LiDAR, accelerometers), off-road sensors (e.g., satellite, UAVs), and hybrid methods (e.g., WIM, VANETs). Key challenges identified include the lack of a common dataset for evaluation, the need for broader performance metrics, sensitivity to environmental conditions, vehicle occlusion, and ensuring reliable communication in VANET-based systems. Future directions emphasize developing hybrid solutions that leverage multiple sensor types and utilizing VANET technology for real-time, global vehicle classification, addressing challenges like secure communication and technology integration. The main findings highlight that current vehicle classification methods cannot provide mobility and physical information globally in real-time applications, but VANETs offer a promising solution. The paper concludes that despite advancements, challenges remain in standardizing datasets, improving performance metrics, and advancing technologies like VANETs.
* Tippannavar et al. (2023) presented an overview of real-time vehicle identification and traffic management techniques and technologies without providing a specific research methodology. The paper highlights various challenges, such as issues with low-cost cameras in low-light conditions, a 9% error rate in distinguishing between small and large vehicles, signal mixing in ultrasonic sensor-based methods, and the limitations of experiments conducted in controlled environments. The study emphasizes the use of image processing, machine learning, Internet of Things (IoT), cloud-connected systems, and distributed acoustic sensors (DAS) as key technologies. It stresses the importance of testing in real-world conditions, developing methods for specific vehicle identification, and exploring night vision cameras to improve low-light performance. The paper underlines the significance of automatic vehicle counting for urban traffic signal systems, the effectiveness of the YOLOv5 algorithm for vehicle recognition, and the potential of DAS technology for overground mobility recognition. It concludes that image processing is more affordable and widely used in real-time environments, offering better safety, precision, and speed than other sensor-based methods.
* Berwo et al. (2023) provided an in-depth overview of deep-learning techniques for vehicle detection and classification. They cover methods, datasets, loss and activation functions, optimization algorithms, and future research directions. The paper focuses specifically on deep learning methods, particularly DCNN-based strategies, for vehicle detection and classification. It categorizes deep learning approaches for object detection and classification and highlights challenges such as weather conditions, handling large datasets, viewpoint variations, size, color, localization, and occlusion. The paper discusses various deep learning techniques, including DCNNs, RCNNs, and DNNs, and suggests future research directions, such as multi-task joint optimization, multi-model information combination, handling scale and size variations, spatial correlations, and contextual modeling. It also points out the need for developing end-to-end optimized cascade architectures, leveraging weakly supervised and unsupervised learning, model optimization, and improving video detection and classification. The survey offers insights and guidelines for advancing deep learning frameworks for vehicle detection and classification, emphasizing the importance of balancing lightweight model speed and accuracy.
* Alghamdi et al. (2023) conducted a comprehensive study on a Vehicle Classification System for Intelligent Transport in a Constrained Environment, utilizing deep learning techniques, particularly CNN. The system involves data collection, preprocessing, training/testing phases using CNN, and synthetic image generation to improve model diversity. Challenges addressed include image noise, limited data quality, intra-class variability, computational resource constraints, and ensuring model generalization. Future directions include enhanced data collection, hardware optimization, model refinement, adaptation to new technologies, deployment in real-world scenarios, and interdisciplinary collaboration. Integration of sensors such as LiDAR, infrared, ultrasonic, and acceleration detectors is recommended to enhance system performance. The major findings underscore the system's validation accuracy of 90.85%, the superior performance of deep learning compared to other algorithms, efficiency, accuracy, and future research directions. Conclusions emphasize data ownership protection, the significance of intelligent transport systems, performance evaluation, and future improvements. The study positions the system as a promising tool for advancing vehicle classification in constrained environments, thus improving transportation efficiency and security.
* Khalil et al. (2024) conducted an in-depth survey of the use of DL techniques in ITS. The study involves a detailed review of DL applications in ITS, including traffic flow prediction, vehicle detection and classification, road condition monitoring, traffic sign recognition, and autonomous vehicles. The researchers also explored the potential of large language models (LLMs) in the context of ITS. The study identified several key challenges, such as data quality and availability, the high demand for labeled data, interpretability of DL models, real-time performance and computational efficiency, data privacy and security, and financial considerations for ITS infrastructure. Looking forward, the researchers emphasized the need to address data scarcity, improve interpretability, enhance real-time performance, ensure privacy, develop hybrid models, advance Explainable AI, improve adaptability and scalability, enhance resilience to adverse weather, and integrate multi-modal transportation systems. The study's main findings highlighted that DL-based ITS systems can improve transportation efficiency, safety, and mobility by leveraging AI technologies to learn from diverse datasets and make precise predictions. The researchers concluded that while DL has transformed ITS, it faces obstacles like the need for robustness, dependability, interpretability, and resistance to adversarial attacks. They noted that emerging AI technologies like LLMs hold the potential for further revolutionizing ITS. The technologies mentioned include DL, CNNs, RNNs, Federated Learning, Capsule Networks, and LLMs, with sensors in ITS comprising wireless sensor networks, GPS, and IoT for real-time data acquisition.

Table 4 summarizes the progress, challenges, and future perspectives for vehicle classification in ITS based on previous literature reviews. Significant advancements include techniques such as feature extraction, global representation generation, and classifiers to identify vehicle types, makes, and models.

**Table 4.** Progress, challenges, and future perspectives in vehicle classification within ITS.

|  |  |  |  |
| --- | --- | --- | --- |
| **Source** | **Advancements** | **Challenges** | **Future Perspectives** |
| Boukerche et al. (2017) | Feature extractor, global representation generator, and classifier | The diversity of vehicle types, the ambiguity between classes, varying conditions, and occlusions | Robust VTR systems, camera calibration-free systems, 3D AVC approaches, real-time systems, VMMGR |
| Won (2020) | MEMS, machine learning, wireless communication, and V2X technology. | High costs, sensor placement, privacy concerns, and the complexity of overlapping vehicles are all significant issues to consider | Universally accepted standards, closed-loop self-learning systems, and hybrid sensor systems |
| Shokravi et al.  (2020) | Vehicular Ad-Hoc Networks (VANETs), intelligent vehicles, On-Board Units (OBUs), Roadside Units (RSUs), Vehicle-to-Vehicle (V2V), and Vehicle-to-Infrastructure (V2I) communication | Local terrain, limited physical data, and unreliable GPS | Collaborative systems utilize vehicle sensors and VANET technology |
| Gholamhosseinian et al. (2021) | Intrusive sensors (loop detectors, magnetometers), non-intrusive sensors (LiDAR, accelerometers), off-road sensors (satellite, UAVs), and hybrid methods (WIM, VANETs) | Lack of a common dataset, broader performance metrics, environmental sensitivity, and occlusion | Hybrid solutions utilize VANET technology for real-time global classification and secure communication |
| Tippannavar et al. (2023) | Image processing, machine learning, IoT, cloud systems, and DAS | Redundancy in low-light conditions, error rates between different vehicle sizes, and signal mixing in ultrasonic sensors | Testing in real-world conditions involves specific vehicle identification methods and night vision cameras |
| Berwo et al. (2023) | Deep learning methods: DCNNs, RCNNs, DNNs | Weather conditions, large datasets, viewpoint variations, occlusion | Multi-task optimization, handling scale/size variations, end-to-end architectures, unsupervised learning |
| Alghamdi et al. (2023) | Deep learning (CNNs), sensors (LiDAR, infrared, ultrasonic, acceleration detectors) | Image noise, limited data quality, intra-class variability, and resource constraints | Enhanced data collection, hardware optimization, real-world deployment, and interdisciplinary collaboration |
| Khalil et al. (2024) | CNNs, RNNs, Federated Learning, Capsule Networks, LLMs, sensors (wireless sensor networks, GPS, IoT) | Data quality, demand for labeled data, interpretability, real-time performance, privacy, and financial | Addressing data scarcity, explainable AI, hybrid models, resilience to weather, and multi-modal integration |

Emerging technologies like MEMS, machine learning, wireless communication, VANETs, and V2X technology have also played an important role. Challenges involve diverse vehicle types, class ambiguities, varying environmental conditions, occlusions, modified appearances, high costs, and sensor placement complexity. Looking ahead, there is a need for robust vehicle tracking systems, mobile real-time solutions, and closed-loop self-learning systems. Various technologies are being used, including sensors, control systems, communications, electronic devices, digital image sensors, and computer vision techniques. Deep learning models like CNNs, RNNs, federated learning, and LLMs are also gaining attraction. Sensors encompass technologies such as LiDAR, infrared, ultrasonic, and hybrid methods combining multiple sensor types. In essence, the integration of advanced technologies such as machine learning, wireless communication, and VANETs offers a promising pathway to address the challenges in automatic vehicle classification systems.

4.2 Recent Research Papers

Recent research in the field of Intelligent ITS has made significant advancements in vehicle detection and classification using deep learning algorithms. Several notable papers have been published, each proposing novel approaches to address the challenges of accuracy, real-time processing, and applicability in diverse environmental conditions. These papers provide insights using CNN, YOLOv3, YOLOv4\_AF, and hybrid CNN models for vehicle classification, license plate detection, and traffic monitoring. The advancements in this research contribute to improving intelligent transportation systems and open up possibilities for broader applications in object detection, tracking, and traffic statistics.

The following paragraphs provide a detailed analysis of recently reported papers in the literature:

* Alghamdi et al. (2023) introduced a vehicle classification system based on CNN. This system is designed to work effectively in environments with limited image quality. The algorithm demonstrated a high accuracy of 90% by utilizing both appearance features and 3D parameters of vehicles for classification. The authors also highlighted the importance of protecting data ownership through watermarking. For future work, they suggested improving the model's accuracy by training it on higher-resolution datasets, collecting more samples, and addressing hardware and software limitations.
* Rajput et al. (2022) presented an automatic vehicle identification and classification model using the YOLOv3 algorithm for toll management systems. The YOLOv3 algorithm achieved a 94.1% accuracy and demonstrated good precision and recall for vehicle identification and classification at toll plazas. The paper also discusses future work, such as identifying and classifying additional vehicle classes and developing vehicle counting capabilities. The implementation involves using AI-based techniques, including deep learning, examining various sensors, and using a custom dataset.
* Zha et al. (2022) introduced a new model called YOLOv4\_AF. This model is an optimized version of the YOLOv4 model, designed to improve performance in object detection and classification, particularly for vision-based vehicle detection and classification. The proposed model achieved an mAP of 83.45% on the BIT-Vehicle dataset and 77.08% on the UA-DETRAC dataset, with F1 scores of 0.816 and 0.808, respectively. Critical improvements in YOLOv4\_AF include the integration of a Convolutional Block Attention Module (CBAM) to enhance attention mechanisms and modifications to the Feature Pyramid Network (FPN) to enhance multi-scale feature extraction. The paper suggests potential applications for the proposed model beyond vehicle detection, including object tracking, traffic statistics, and testing on other objects. However, it's important to note that the main limitation is the increased computational complexity and time due to the CBAM module. The future perspective includes tracking moving objects, conducting traffic statistics, and studying the detection and classification capabilities of the YOLOv4\_AF model on objects beyond vehicles.
* Srividhya et al. (2022) discussed an intelligent transportation system that uses video surveillance to classify vehicles and detect license plates. The system relies on critical algorithms such as the Inner-Outer Outline Profile (IOOPL) for shadow elimination and vehicle detection, as well as the delta learning rule for vehicle classification and log generation. The paper aims to enhance traffic monitoring, reduce congestion, predict traffic, and enhance traffic security. Future perspectives include focusing on night surveillance, occlusion handling, 3D modeling, and vehicle tracking. The key features discussed in the paper are video surveillance for intelligent transportation system applications, machine learning algorithms for vehicle classification, and the use of real-time videos from video cameras as data sources.
* Tas et al. (2022) have developed a CNN model to classify vehicles in low-resolution surveillance images. The model achieved an accuracy of 92.9% and demonstrated the potential of classifying vehicles using low-resolution images from standard security cameras. The study compared the proposed CNN model with VGG16 pre-trained models and concluded that despite slightly lower accuracy, the CNN model offers advantages in simplicity, lightweight architecture, and faster training time. The research opens up opportunities for further exploration of using standard security cameras for ITS. The dataset used in the study consists of 4,800 low-resolution vehicle images captured by a standard surveillance camera in Konya, Turkey, classified into six classes: bike, car, juggernaut, minibus, pickup, and truck. The future goal is to extend the use of standard security cameras in intelligent transportation systems applications.
* Shokri et al. (2023) evaluated the performance of YOLO, RCNN, and SSD deep learning algorithms for vehicle detection and classification in highway camera images. They found that the YOLO versions, particularly YOLOv7, exhibited the highest performance. YOLOv7 achieved a vehicle detection accuracy of 98.77% and a vehicle classification accuracy of 97.37%. The YOLO versions were noted for their high accuracy and near real-time capabilities on a CPU processor, making them well-suited for real-time traffic flow monitoring in Intelligent Transportation Systems. The researchers suggested that future work should involve evaluating deep learning architectures for vehicle detection and classification using UAV videos to improve accuracy and explore the potential for precise localization and tracking of vehicles. The study used data from highway cameras in Quebec, Canada, and additional image datasets from YouTube and Kaggle.
* Hayee et al. (2023) proposed a novel hybrid CNN model that utilizes Fisher Discriminative Least Squares Regression (FDLSR) for view-independent car make and model classification. The model achieves an impressive accuracy of 94.62. The paper outlines the process of fine-tuning deep CNN models, extracting features, applying FDLSR to enhance feature quality, and training classifiers on the reduced features. Notably, the research is focused on datasets such as Stanford Cars and BoxCars21k and introduces a new dataset of 129,000 images representing 94 different vehicle classes on Pakistani roads. The paper also sets forth plans for conducting experiments on the Pakistani cars dataset and implementing incremental learning for feature extraction. This innovative approach holds promising implications for the field of vehicle classification.
* Kamencay et al. (2023) introduced a new hybrid convolutional neural network architecture. This architecture combines data from CCTV and fiber Bragg grating sensor platforms to achieve a significantly improved vehicle classification accuracy of 90% to 97%. The system combines a unique hybrid CNN architecture with separate sensor and image data branches for final vehicle classification. The study also explores potential smart city applications of the system, such as automatic vehicle counting, dynamic road usage optimization, and vehicle speed monitoring. The features extracted by the CNN include low-level image features, such as edges and colors, and higher-level features, like shapes and objects. The system also uses data from a fiber Bragg grating sensor array and a CCTV camera system to achieve classification accuracy. It provides a backup verification by using the two independent data sources.
* Rafique et al. (2023) presented a framework for ITS using aerial imagery. The framework incorporates semantic segmentation, vehicle detection, classification, and tracking using advanced deep learning and filtering techniques. The algorithms utilized in this research include CNN, customized pyramid pooling, Kalman filter, and kernelized filter-based tracking. The reported accuracy of the framework is 95.78% on VAID, 95.18% on VEDAI, and 93.13% on DLR3K datasets. The paper details the use of CNN-based semantic segmentation, customized pyramid pooling module (CPPM) for vehicle detection, and Kalman filter-based and kernelized correlation filter-based techniques for vehicle tracking. Additionally, the paper suggests future work on improving vehicle tracking using an end-to-end deep learning method for overall traffic monitoring and surveillance.
* Maiga et al. (2023) developed a CNN-based model for vehicle classification using low-quality images from a standard security camera in poor lighting and weather conditions. The model achieved an impressive 95.8% accuracy and is suitable for IoT-based ITS applications with limited computational resources. It can classify vehicles such as bikes, cars, juggernauts, minibusses, pickups, and trucks. The study also outlines plans to develop a vehicle detection algorithm that can extract vehicle images from low-resolution video frames recorded by affordable surveillance cameras. The dataset used in the study consisted of 4,800 low-quality vehicle images captured under various low-lighting and weather conditions. The simplicity of the proposed CNN-based model's architecture and its computational efficiency make it a practical choice for real-world applications such as traffic flow monitoring.
* Chen et al. (2021) have presented a vehicle detection and classification method that utilizes static appearance and motion features. The algorithm is a multi-detector framework that combines static appearance and motion features, resulting in an accuracy of 0.9892. The process involves training detectors using small sets of RGB and binary images, manually labeling ground truth bounding boxes and vehicle classes, removing false detections, and integrating the detections into a matrix of overlapping detections to identify the final set of detections. The vehicle categories used in the research are complete small vehicle, incomplete small vehicle, complete large vehicle, and incomplete large vehicle. The proposed method demonstrates high performance in terms of accuracy, recall, precision, F1-score, and Kappa. The authors plan to optimize the method further by considering vehicle relationships across frames and expanding the training data to include smaller vehicles and rear views.
* Wu et al. (2021) implemented a vehicle classification and counting system that utilizes YOLO object detection technology to analyze surveillance camera footage of different road types. The system uses the YOLOv3 model and assesses accuracy through precision rate, recall rate, and F-measure. It categorizes vehicles into motorcycles, small cars, and heavy vehicles, aiming for future application in ITS. The paper also delves into the use of acoustic sensors, magnetometers, accelerometers, and other technologies, as well as the dataset comprising video footage from surveillance cameras and training images of vehicles.
* Butt et al. (2021) proposed a vehicle classification system based on CNN. The system was developed using a self-constructed dataset and then fine-tuned on the VeRi dataset to ensure its applicability across different regions. The system utilizes a pre-trained ResNet-152 model and fine-tunes it to enhance vehicle classification performance. It achieved an accuracy of 99.68% on the self-constructed dataset and 97.66% on the VeRi dataset. The paper aims to extend its work by developing a more detailed vehicle classification system to enhance its effectiveness in ITS. This will involve incorporating both manually crafted features and deep features learned automatically by CNN.
* Kim (2024) has presented a method for detecting vehicles, classifying their types and colors to facilitate safe autonomous driving. The deep learning-based approach achieved an accuracy of 93.2% in classifying vehicle type and color, utilizing a two-step approach involving YOLOv4 for vehicle detection and ResNet-50 CNN for classification. Limitations in low light conditions are recognized, suggesting future research with infrared and thermal imaging sensors. The study emphasizes the importance of accurately determining vehicle type and color for safe autonomous driving and proposes further exploration of advanced sensor technologies for road safety.
* Hashima et al. (2023) introduced an innovative deep-learning method for vehicle classification. The approach involves using seismic data, Fractional Wavelet Transform (FWT) for feature extraction, and Long Short-Term Memory (LSTM) for classification. This approach outperformed existing techniques. The researchers used an extensive dataset from Kyushu University, which included buses, cars, motorcycles, and seismic noise recordings. The classification accuracy achieved was 98%, illustrating the effectiveness of the proposed method. The study shows potential for improving Intelligent Transportation Systems (ITS) and has implications for road infrastructure planning and traffic management.
* Moallemi et al. (2023) introduced a new method for classifying vehicles as light, heavy, or super-heavy using vibration data from MEMS accelerometers. The algorithm involves preprocessing raw data, extracting features, labeling the features using WiM data, and applying unsupervised machine learning algorithms to cluster the vehicles. The Mean Shift algorithm achieved the highest classification accuracy of 96.87%. The study utilized five days of data, with four days for training and one for validation, focusing on low traffic volume during nighttime. The features used in the study include Maximum Amplitude, Standard Deviation, Mean, and Line Length. This unsupervised classification of vehicles passing over a bridge achieved a classification accuracy of 96.87%.
* Sarcevic et al. (2022) developed a real-time vehicle classification system that utilizes a single magnetometer. The system can classify vehicles into nine different classes with up to 74.67% accuracy on validation data. It employs an algorithm that involves vehicle detection, feature extraction, and classification using a multilayer perceptron neural network. The system uses a dataset of over 30,000 samples collected from a magnetometer sensor and corresponding camera images in a real-world environment over several months. Several features are utilized for vehicle classification, including detection length, highest and lowest values, locations of highest and lowest values, number of range changes, number of local maxima and minima, mean absolute value, mean value, number of direction changes, number of zero crossings, average waveform length, root mean square, and Willison amplitude. The classification is achieved through a multilayer perceptron (MLP) neural network. The paper also outlines future perspectives, such as improving recognition efficiency, adding more features to differentiate between types of trucks and buses, using feature selection algorithms to identify influential features, and collecting data from additional locations to address diversity across locations.
* Chen et al. (2019) introduced a method for detecting and classifying road vehicles using a roadside magnetic sensor. The method involves extracting features from magnetic signals using Mel Frequency Cepstral Coefficients (MFCC) and categorizing vehicles into four types (sedan, van, truck, bus) using a 3D Vector Quantization (VQ) algorithm. The paper does not provide specific accuracy results, but it outlines the features used and the classification approach and discusses future perspectives, including using multiple sensors to monitor multiple lanes and studying the impact of varying the distance between the sensor and passing vehicles.
* Alghamdi et al. (2023) developed a hybrid model that combines deep learning and genetic algorithms to classify eight vehicle categories. The algorithm achieved a high accuracy of 99.7% by utilizing a pre-trained CNN (VGG16) for feature extraction, a Genetic Algorithm for feature optimization, and various SVM kernels for classification. The researchers used the Stanford car dataset, which includes 8000 images of eight vehicle classes. They suggest that future work should expand the dataset and explore new pathways within the proposed framework.

Table 5 summarizes key information from each paper, including details about the proposed algorithms, the type of data used for training and testing, accuracy achieved, features used for classification, vehicle classes, and future perspectives on the proposed methods. Each paper discusses different vehicle detection and classification approaches, using technologies such as YOLO object detection, CNN, and specific algorithms designed for surveillance purposes. These researches collectively highlight the progress in vehicle detection and classification through deep learning models, emphasizing high accuracy, potential applications beyond vehicle detection, and future improvements and research considerations.

**Table 5.** A summary of recent developments in vehicle classification within ITS.

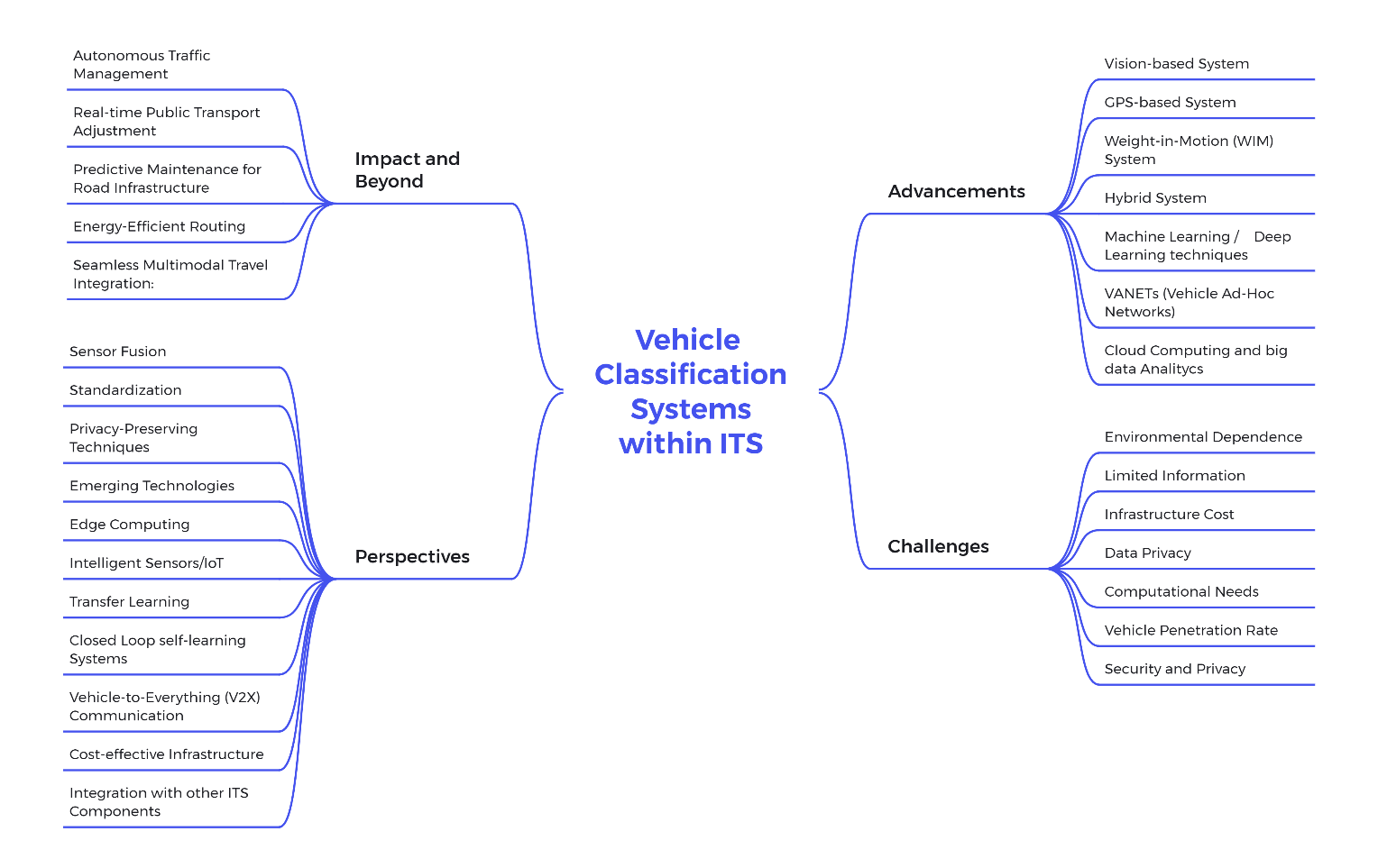
|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Source** | **Algorithm** | **Data** | **Accuracy** | **Classification** | **Perspectives** |
| Chen et al.  (2021) | Multi-detector | Various video datasets | 0.9892 | Small/large vehicles | Improve algorithms, add varied vehicles |
| Wu et al.(2021) | YOLOv3 | Surveillance footage | PR, RR, F-measure | Motorcycles, cars, large vehicles | Enhance stability accuracy for smart transport systems |
| Butt et al. (2021) | CNN | Self-constructed, VeRi datasets | 99.68% 97.66% (VeRi) | Car, Bus, Van, Truck, Motorbike | Develop fine-grained classification |
| Rajput et al. (2022) | YOLOv3 | Custom vehicle images | 94.1% | Various vehicle types | Identify more classes, develop vehicle counting |
| Zha et al. (2022) | YOLOv4\_AF | BIT-Vehicle, UA-DETRAC datasets | mAP: 83.45% (BIT), 77.08% (UA) | Various vehicle types | Track moving objects, study other objects |
| Srividhya et al. ( 2022) | IOOPL, Delta | Real-time videos | 92% | Various vehicle tasks | Enhance night surveillance, 3D modeling |
| Tas et al. (2022) | CNN | Low-res images from Konya, Turkey | 92.9% | Bike, Car, Truck, etc. | Research standard security cameras for ITS |
| Alghamdi et al. (2023) | CNN | Google vehicle images | 90% | Various types | Address low-res limitations, improve model |
| Shokri et al. (2023) | YOLO, RCNN, SSD | Highway, YouTube, Kaggle images | 98.77% (YOLOv7) | Car, Truck, Bus | Evaluate on UAV videos, improve heavy vehicle accuracy |
| Alghamdi et al. (2023) | Hybrid CNN, FDLSR | Stanford, BoxCars21k, Pakistani cars | 94.62% | Car make and model | Incremental learning, feature extraction |
| Kamenc et al. (2023) | Hybrid-CNN | CCTV, FBG sensor data | 90% - 97% | Tire width, construction type | Combine image/sensor features for classification |
| Rafique et al. (2023) | CNN, pooling | Aerial imagery datasets | 95.78% | Various vehicle types | End-to-end learning for traffic monitoring |
| Maiga et al. (2023) | CNN | Low-quality images | 95.8% | Bike, Car, Truck, etc. | Develop low-res video frame detection, expand dataset |
| Vikram et al. (2024) | Deep learning | Remote sensing images | 99.44% | Car, Bus, Truck | Generate vehicle density maps, license plate recognition |
| Kim (2024) | Deep learning | Road images | 93.2% | Sedan, Bus, Truck, SUV | YOLO for low-light, infrared/thermal imaging research |
| Hashima et al. (2023) | FWT, LSTM | Kyushu University data | 98% | Buses, Cars, Motorcycles | Utilize geophones |
| Moallemi et al. (2023) | Unsupervised ML | Sensor nodes, Weight-In-Motion | 96.87% | Light, Heavy, Super-heavy | Expand to other vehicle types |
| Sarcevic et al. (2022) | MLP | Magnetometer and camera images | 74.67% | 9 vehicle classes | Improve recognition, add features |
| Chen et al. (2019) | MFCC, VQ | Roadside magnetic sensor data | Not mentioned | Sedan, Van, Truck, Bus | Monitor multiple lanes, study sensor distance effects |
| Alghamdi et al. (2023) | VGG16, GA | Stanford car dataset | 99.78% | 8 vehicle categories | Increase dataset, explore new pathways |

6. Advances, Limitations, and Future Perspectives in Vehicle Classification

Based on the literature reviews presented in the previous sections, Figure 4 provides details on advancements, challenges, and perspectives related to vehicle detection and classification systems. Advancements include vision-based, GPS-based, WIM, hybrid systems, machine learning, VANETs, and cloud computing. Challenges rotate around environmental dependence, limited information, infrastructure cost, data privacy, computational needs, and vehicle penetration rate. Perspectives highlight the potential of machine learning, sensor fusion, standardization of data formats, privacy-preserving techniques, and emerging technologies like V2X communication, edge computing, and intelligent sensors/IoT.

Advancements:

* **Vision-based:** Utilizes computer vision algorithms and high-resolution cameras to classify vehicles based on their visual features, such as shape, size, and color. It provides high accuracy and can handle complex traffic scenarios. However, it is constrained by the need for adequate lighting and favorable weather conditions, which limits its effectiveness. Additionally, the cost of installation and maintenance is a significant disadvantage.
* **GPS-based:** This technology offers accurate information on a vehicle's location and can be integrated with other systems. However, it has limited data beyond location, making it challenging to differentiate between diverse vehicle types. Furthermore, there is a need to address privacy concerns related to GPS data collection.
* **Weight-in-Motion (WIM)**: WIM provides accurate measurements of vehicle weight, is useful for classifying heavy-duty vehicles, and is valuable for specific applications like toll collection and weight enforcement. However, its high installation and maintenance costs limit its widespread use.
* **Machine learning and artificial intelligence**: Integration of machine learning techniques, such as neural networks, for automated vehicle classification. These methods can learn from data patterns and improve classification accuracy over time.
* **Deep learning techniques:** The advent of deep learning, particularly CNNs, has revolutionized vehicle classification. CNNs excel at extracting features from images and videos, leading to highly accurate classification of vehicles by type (car, truck, motorcycle, etc.).
* **Vehicular Ad-hoc Networks (VANETs)**: Leveraging communication networks between vehicles and infrastructure to exchange real-time data for vehicle classification. VANETs enable collaborative classification and can enhance the accuracy of classification results.
* **Cloud computing and big data analytics**: Utilizing cloud-based platforms and big data analytics to efficiently process large volumes of vehicle data. These technologies enable real-time analysis and decision-making for vehicle classification in dynamic traffic environments.



**Fig 4.** Vehicle Classification in ITS: Challenges, Limitations, and Perspectives.

Challenges:

* **Environmental dependence**:Vision-based systems struggle with poor lighting or adverse weather conditions.
* **Limited information**: GPS offers limited vehicle details beyond location.
* **Infrastructure cost**: Intrusive systems are expensive to install and maintain.
* **Data privacy**: GPS and camera data raise privacy concerns.
* **Computational needs:** Machine learning approaches require large training datasets and substantial processing power.
* **Vehicle penetration rate:** VANETs rely on widespread vehicle adoption.
* **Security and privacy:** VANETs need robust security measures to protect data.

Perspectives:

* **Sensor fusion**: Combining data from multiple sensors, such as cameras, radar, LiDAR, and GPS, to improve the accuracy and reliability of vehicle classification. Sensor fusion techniques enhance the robustness of classification systems in diverse environmental conditions.
* **Edge computing**: Implementing edge computing solutions to perform data processing and classification tasks closer to the source of data, reducing latency and improving system responsiveness in real-time applications.
* **Privacy-preserving techniques**: Developing methods to ensure the privacy and security of vehicle data during classification processes, addressing concerns related to data sharing and storage.
* **Closed loop self-learning systems**: Develop self-learning systems that autonomously improve classification models, reducing manual data labeling and training efforts.
* **Standardization efforts**: Establishes common performance metrics (accuracy, cost-effectiveness, sustainability) for fair evaluation and comparison of classification systems.
* **Vehicle-to-Everything (V2X) Communication:** V2X technology allows vehicles to communicate with each other and roadside infrastructure. By incorporating onboard vehicle data (e.g., class, speed) into the classification process, V2X has the potential to further enhance accuracy and real-time traffic management.
* **Leveraging machine learning:** Machine learning algorithms can potentially improve classification accuracy by learning from large datasets and adapting to changing conditions even with limited sensor data (e.g., handling poor visibility or weather conditions).
* **Transfer learning:** Training robust classification models requires vast amounts of labeled data. Transfer learning techniques can address data scarcity issues by applying knowledge gained from one dataset to another.
* **Privacy-preserving techniques:** Methods such as anonymization and differential privacy can be developed to address privacy concerns associated with data collected from cameras and GPS systems.
* **Cost-effective infrastructure:** Innovative solutions are necessary to lower the infrastructure costs associated with vision-based systems, making them more accessible for broader deployment.
* **Intelligent sensors and IoT devices**: Establishes common performance metrics (accuracy, cost-effectiveness, sustainability) for fair evaluation and comparison of classification systems.
* **Integration with other ITS components**: Vehicle classification can be integrated with other ITS components, such as traffic signal control and route guidance systems, to optimize traffic flow and improve overall transportation efficiency.

Impact and Beyond:

* **Autonomous Traffic Management**:Vehicle classification systems can contribute to autonomous traffic management, optimizing traffic flow efficiency and improving road safety.
* **Real-time Public Transport Adjustment:** Vehicle classification systems can assist in real-time adjustments and optimization of public transportation, enabling quicker and more efficient responses to user demand.
* **Predictive Maintenance for Road Infrastructure:** Vehicle classification systems can be used to predict and perform preventive maintenance on road infrastructure, enhancing road safety and reducing downtime.
* **Energy-Efficient Routing:** Vehicle classification systems can help plan energy-efficient routes, minimize fuel consumption, and reduce greenhouse gas emissions.
* **Seamless Multimodal Travel Integration:** Vehicle classification systems can facilitate seamless integration of different modes of transportation, such as personal vehicles, public transportation, and shared mobility options, providing users with a more convenient and comfortable travel experience.

Conclusions

Vehicle classification is a crucial element of ITS that enables efficient traffic management, enhances safety, and improves overall transportation efficiency. Recognizing and understanding different types of vehicles on the road enables the system to customize specific functions for each vehicle type. This includes applying different traffic rules, counting axles in heavy trucks for weigh-in-motion applications, estimating emissions impact, and enhancing road safety by understanding unique driving behaviors. Through the integration of advanced technologies such as machine learning, computer vision, and sensor-based systems, researchers have made significant progress in developing sophisticated methods for accurately detecting and classifying vehicles on the road.

Diverse sensor technologies are used to classify vehicles, including inductive loops, magnetic sensors, and weigh-in-motion (WIM) sensors. These sensors capture specific details like the number of axles, vehicle size, axle spacing, weight, speed, and length. Inductive loops and magnetic sensors detect a vehicle's presence and size by measuring changes in magnetic fields, while WIM sensors measure the weight of the vehicle as it moves over a sensor-equipped roadway. By analyzing patterns such as axle configurations, vehicle dimensions, and load distributions, classification algorithms use these collected details to accurately determine vehicle types.

After analyzing several papers on vehicle classification systems based on deep learning algorithms, it is evident that significant advancements have been made in this field. The use of CNN and deep learning algorithms such as YOLOv3, YOLOv4\_AF, and various versions of YOLO have demonstrated high accuracy in vehicle detection and classification. These studies have highlighted the potential for real-world applications in ITS, toll management systems, and traffic flow monitoring. AI-based techniques, including deep learning, have shown promise in addressing challenges such as limited image quality, low-resolution surveillance images, and real-time processing requirements. A common theme across these papers is the emphasis on future work, including improving model accuracy through higher-resolution datasets, addressing hardware and software limitations, classifying additional vehicle classes, and exploring applications beyond vehicle detection. Overall, the research in this area showcases the potential for deep learning algorithms to significantly enhance vehicle classification systems, with implications for traffic monitoring, congestion reduction, traffic security, and further integration of standard security cameras in ITS.

Reviews emphasize the need for cost-effective, reliable, and privacy-conscious vehicle classification systems. Challenges include high computational needs for machine learning, privacy issues, and the need for widespread adoption of Vehicle Ad-Hoc Networks (VANETs). Future perspectives focus on machine learning advancements, sensor fusion, standardization, and privacy-preserving techniques to enhance system robustness and public acceptance. The future of ITS lies in integrating different approaches for comprehensive and adaptable traffic management solutions.

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