Afropolitan Journals

ISSN: 3027-2882 www.afropolitanjournals.com

A Comprehensive Systematic Scoping Review of Self-Driving Vehicle Models: An In-depth Analysis of Specifications, Emerging Trends, Challenges, and Future Directions

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DOI: *https://doi.org/10.62154/ajastr.2024.017.010458*

Abstract

Self-driving vehicles (SDVs), also known as autonomous vehicles (AVs), are anticipated to revolutionize transportation by operating independently through the integration of machine learning algorithms, advanced processing units, and sensor networks. Numerous organizations globally are actively developing SDV models, prompting this paper's objective to identify emerging trends and patterns in SDV development through a comprehensive systematic scoping review (SSR). This research involved selecting 85 relevant studies from an initial set of 551 records across multiple academic databases, utilizing well-defined inclusion and exclusion criteria along with snowballing techniques to ensure a thorough analysis. The findings emphasize critical technical specifications required for both full-scale and miniature SDV models, focusing on key software and hardware architectures, essential sensors, and primary suppliers. Additionally, the analysis explores publication trends, including publisher and venue distribution, authors' affiliations, and the most active countries in SDV research. This work aims to guide researchers in designing their SDV models by identifying key challenges and exploring opportunities likely to shape future research and development in autonomous vehicle technology.

Keywords: Self-Driving Vehicles, Autonomous Vehicles, Electric Vehicles, Autonomous Driving, Artificial Intelligence, Systematic Scoping Review, Mapping.

Introduction

Self-driving vehicles (SDVs) are anticipated to be a major innovation in the coming years as they rapidly approach reality (Daily, Medasani, Behringer, & Trivedi, 2017). Numerous automakers and research groups worldwide are actively developing this technology, showcasing their advancements in competitions and scholarly publications. As we entered 2020, we found ourselves in a transitional period where both SDVs and traditional vehicles coexisted. By 2040, SDVs may replace traditional vehicles on the roads (Behere & Törngren, 2015; Kato et al., 2015; Broggi, Debattisti, Grisleri, & Panciroli, 2015). The adoption of SDVs is steadily increasing. In 2018, Baidu's Apollo began mass production of autonomous minibuses for geo-fenced areas in China. Additionally, Pony.ai initiated a self-driving taxi service in Irvine, California, while Waymo offers free rides in its autonomous taxis in Phoenix's East Valley. In various countries, PerceptIn provides affordable, low-speed SDVs for short distances. During the COVID-19 pandemic, General Motors' Cruise division conducted over fifty thousand contactless meal deliveries in San Francisco using its autonomous fleet (Kato, Tokunaga, Maruyama, & Others, 2018). The Society of Automotive Engineers has established levels of vehicle automation, with the goal being level five—fully automated vehicles capable of navigating any environment without human input. We expect this advancement to revolutionize transportation by reducing traffic congestion, accidents, and the need for parking space, while also enhancing vehicle-sharing opportunities (Liu, Peng, & Gaudiot, 2017).

SDV technology integrates multiple complex systems, including hardware, sensors, software, computing units, and network protocols. Given the rapid evolution of technology, some current research may quickly become outdated. Therefore, understanding effective models developed by manufacturers and researchers is essential (Apollo, 2018). Despite the rise of advanced simulation tools like digital twins, physical models remain crucial (Pony.ai, 2020). However, due to competitive pressures, detailed information about these models is often proprietary. Companies like Google, Uber, and Tesla closely guard their developments, while others, such as Nvidia and Baidu's Apollo, provide more accessible resources, including open-source code on platforms like GitHub (Waymo, 2020; PerceptIn, 2023). Examining the development of these models is vital for identifying effective platforms for testing and developing autonomous driving systems. Key decisions include whether to use full-scale or miniature models, each with a unique sensor, hardware, and software configuration (Cruise, 2020; International, 2021). Finding common patterns in these configurations can streamline research efforts and overcome development challenges (Lin et al., 2018).

This paper maps recent, relevant publications on SDV models, detailing their hardware, software, and sensor components. We employ a SSR to structure this research area, providing a comprehensive overview. While our aim is to identify trends in SDV development by analyzing available models, with a focus on those that achieve levels 4 and 5 automations, our goal is to uncover common choices in SDV hardware, software, and sensors, thereby accelerating further research and development. This work does not address aspects like vehicle networking, security, and simulation that do not involve physical models. Instead, it focuses on the ego vehicle's development as a foundational step for researchers. Our main contributions include a systematic scoping review of recent papers on modern SDV model development, highlighting trends, technologies, and research opportunities. The structure of this paper is as follows: a review of related work; an outline of the research framework; a presentation and analysis of the results; an identification of ongoing research concerns; a discussion of research and publication issues;

an exploration of future research directions; an examination of the paper's limitations; and, finally, the conclusion.

Problem Statement: The development of SDV technology faces numerous technical challenges, including the integration of complex software and hardware architectures, as well as essential sensor configurations for effective performance. Despite increasing research efforts, a consolidated understanding of these critical technical requirements across full-scale and miniature SDV models remains limited. Additionally, there is a lack of clarity on global research trends and contributions, hindering coordinated advancements and shared progress in autonomous vehicle innovation.

Impact Statement: This paper provides a comprehensive review that significantly advances the field of SDV technology by synthesizing 85 key studies out of 551 entries, offering an in-depth analysis of essential software, hardware architectures, and sensors. By identifying emerging trends and highlighting the most active countries and research groups, this work guides researchers and developers in navigating current challenges and leveraging new opportunities in SDV development. This study not only bridges knowledge gaps but also establishes a foundational framework for ongoing innovations in autonomous vehicle technology, ultimately shaping the future of self-driving vehicles.

Research Review

A systematic scoping review (SSR) plays a crucial role in providing a detailed overview of a specific field or area of interest (Daily, Medasani, Behringer, & Trivedi, 2017; Silva, Soares, Souza, & Freitas, 2024). It allows researchers to assess the scope and depth of research within a particular domain, uncover patterns, trends, and gaps in the literature, and determine the concentration of studies across various categories, such as methodology, research focus, and results. Our study discovered papers that discuss the evolution of SDV research over the years, as well as one paper that systematically reviews the existing situation of research publications and results regarding SDVs (Fausten, Huck, Rühle, Baysal, & Kornhaas, 2015; Traub, Maier, & Barbehön, 2017; Liu, Peng, & Gaudiot, 2017; Munir, Azam, Hussain, Sheri, & Jeon, 2018; Jo, Kim, Kim, & Others, 2014; Ziegler, Bender, Schreiber, & Others, 2014; Tropea, De Rango, Nevigato, & Others, 2021).
This review includes other papers discussing regulations, localization, and mapping but does not focus on the hardware and software aspects most used in the development and testing of SDVs (Yu, Chen, Tang, Liu, & Gaudiot, 2022; Nvidia, 2020; Kitchenham & Charters, 2007). We found a number of papers that map, review, or survey different aspects of SDVs, such as software techniques, machine learning applications, external factors, vehicle-to-everything (V2X) networking, and cybersecurity (Bresson, Alsayed, Yu, & Glaser, 2017; Paden, Čáp, Yong, Yershov, & Frazzoli, 2016). These papers add to the extensive

survey by Hussain and Zeadally (Hussain & Zeadally, 2019). However, these topics differ from those covered in our study.

Evolution and Projections

Two review papers explore the history of SDV development (Silva, Soares, Souza, & Freitas, 2024; Barnett, Gizinski, Mondragon-Parra, & Others, 2020). Bimbraw traces the timeline from the first attempts to create an SDV in 1926 to the developments up to 2015 and future trends, dividing the discussion into historical antecedents, current progress, and future predictions. While the paper details the sensors used over time, it does not address the software and hardware evolution of SDVs. Bartl and Rosenzweig provide a historical perspective on automotive advancements over the past 65 years, highlighting significant milestones and analyzing 399 academic publications from 1989 to 2015 (Daily, Medasani, Behringer, & Trivedi, 2017). Research on SDVs is still heavily focused on developing the technology. Key areas include AI and machine learning for the vehicle's vision and decision-making, creating detailed maps, determining the vehicle's exact location, communication between vehicles and infrastructure, and ensuring safety (Barnett, Gizinski, Mondragon-Parra, & Others, 2020; El Khatib, Ou, & Karray, 2020; Brito, Loureiro, Todt, & Pereira, 2017; Hakak, Gadekallu, Maddikunta, & Others, 2023; Ahangar, Ahmed, Khan, & Hafeez, 2021). This focus is necessary because making fully autonomous vehicles is very complex, and there are many safety, reliability, legal, and ethical issues to address. Even though some thought technology development would become less important over time, it remains critical to solve ongoing challenges and successfully roll out SDVs (Wu, Cai, He, & Lu, 2024; Pham & Xiong, 2021; Kim, Kim, Jeong, Park, & Kim, 2021; Limbasiya, Teng, Chattopadhyay, & Zhou, 2022; Sun, Yu, & Zhang, 2022). Silva et al. systematically reviewed the scientific literature on the environmental impacts of SDVs, revealing benefits due to improved techniques, new design possibilities, and better traffic flow (Silva, Cordera, González-González, & Nogués, 2022). Finally, Li et al. conducted a systematic review of 80 studies on future SDVs in urban mobility and logistics, focusing on urban areas and highlighting possibilities for future integration (Li, Rombaut, & Vanhaverbeke, 2021).

Technologies

S. Liu et al. provided a comprehensive review of computing systems for SDVs, identifying and addressing technology development bottlenecks (Liu, Peng, & Gaudiot, 2017). Their book compiles information to guide researchers in building their own models, emphasizing cost-effective development (Liu, Li, Tang, Wu, & Gaudiot, 2020). Hussain and Zeadally provide an extensive review of SDVs, focusing on communication aspects and discussing state-of-the-art research results as well as technological and non-technological challenges, but they lack detailed information on the software and hardware used in SDV models (Hussain & Zeadally, 2019; ZMP, 2020). S. Liu et al. reviewed technologies applied in SDVs, covering sensors, computing units, runtime systems, middleware, algorithms, and V2X networks. They presented innovations in vehicle subsystems, architecture, and networks, highlighting security concerns but not mapping the most applied technologies (Liu et al., 2019). Lopes et al. reviewed 69 primary studies to examine the technological limits and effects of SDVs, focusing on aspects like feasibility, adaptation, traffic laws, perceived benefits, interactions between people and vehicles, and effects on urban mobility (Lopes, Siqueira, Araújo, Santos, & Santos, 2021). Khan et al. discussed organizational issues for achieving the highest level of automation in SDVs, including sensors, communication, mobile edge computing, machine learning, data analytics, and distributed learning (Khan et al., 2022).

Perception and Sensor Systems

Several reviews have focused specifically on the sensing and perception systems of SDVs (Khatab, Onsy, Varley, & Abouelfarag, 2021; Van Brummelen, O'Brien, Gruyer, & Najjaran, 2018; Rosique, Navarro, Fernández, & Padilla, 2019). Khatab et al. discussed the operations and challenges of autonomous driving, reviewing state-of-the-art sensory systems and algorithms (Khatab, Onsy, Varley, & Abouelfarag, 2021). Van Brummelen et al. expanded this focus to include the entire SDV perception system, including mapping and planning, historical problems, and recent advances in perception technology for SDVs (Van Brummelen, O'Brien, Gruyer, & Najjaran, 2018). Similarly, Rosique et al. conducted a systematic review of the SDV perception system, including an evaluation of various simulators for self-driving systems by comparing their performance with real-life hardware (Rosique, Navarro, Fernández, & Padilla, 2019).

Network System and Security

Implementing robust vehicle communication technologies is a critical component of SDVs. Key studies have examined the development and implications of these technologies. Ahangar et al. focused on enabling communication technologies ranging from traditional short-range systems like Bluetooth to more advanced networks such as cellular V2X (C-V2X) and 5G, emphasizing their crucial role in the safety and functionality of SDVs (Ahangar, Ahmed, Khan, & Hafeez, 2021). Hakak et al. examined major challenges and prospects of V2X communications, discussing interoperability issues and the importance of resilient infrastructure, especially in deploying 5G networks (Hakak, Gadekallu, Maddikunta, & Others, 2023). Wu et al. investigated the specific effects of V2X technologies in intelligent transportation systems (ITS), highlighting their significance for optimizing SDVs and the necessity of standardized safety measures (Wu, Cai, He, & Lu, 2024). The integration of communication networks in self-driving vehicles, transitioning them from standalone to connected SDVs, has introduced numerous security challenges, making it a prominent research topic. Sun et al. conducted a comprehensive study, categorizing cybersecurity risks into in-vehicle network attacks and external communication vulnerabilities, and proposed methods to protect SDVs from potential cyberattacks (Sun, Yu, & Zhang, 2022). Limbasiya et al. explored the challenges associated with implementing 6G technologies in SDVs, emphasizing the need for robust frameworks for malware detection and advanced defense strategies compatible with 6G infrastructure (Limbasiya, Teng, Chattopadhyay, & Zhou, 2022). Moubayed et al. discussed how AI can enhance SDV cybersecurity, focusing on AI-driven predictive analytics and anomaly detection systems to preemptively identify and mitigate cyber threats (Moubayed, Shami, & Al-Dulaimi, 2022). Alazab et al. emphasized the importance of a comprehensive cybersecurity framework that incorporates both technical solutions and regulatory standards, advocating for continuous advancement in cyber-defense technologies and the development of stringent cybersecurity protocols and standards (Alazab et al., 2023).

Outline

Table 1 presents a comparative analysis of existing research alongside our proposed study in the domain of SDVs. Our research offers a comprehensive review and mapping of re- cent publications on contemporary SDV model advancements, emphasizing cutting-edge technologies, emerging trends, and future research avenues. It delivers in-depth technical insights into the hardware, software, and sensor systems integral to SDVs. The study structure emphasizes the critical aspects of scholarly contributions in this area. In terms of publishers and publication venues, only two journals featured multiple papers centered on systematic reviews, as detailed in Table 2.

Table 1: Previous Research Overview

YEAR	WORKS	DESCRIPTION
2015	(Daily, Medasani, Behringer, & Trivedi, 2017)	Progression and historical trends in SDV research.
2016	(Paden, Čáp, Yong, Yershov, & Frazzoli, 2016), (Bevly, Cao, Gordon, & others, 2016)	Focus on specific SDV elements like software methodologies.
2017	(Bresson, Alsayed, Yu, & Glaser, 2017)	In-depth examination of software techniques in SDVs.
2017	(Brito, Loureiro, Todt, & Pereira, 2017)	Analysis of external factors influencing SDVs.
2017	(Liu, Peng, & Gaudiot, Computer, drive my car!, 2017)	Required computing architectures for SDVs.
2018	(Van Brummelen, O'Brien, Gruyer, & Najjaran, 2018)	Survey of vehicle perception technologies.
2019	(Hussain & Zeadally, 2019), (Liu, et al., 2019)	Comprehensive analysis of various SDV research topics and findings.
2019	(Rosique, Navarro, Fernández, & Padilla, 2019)	Survey of perception systems and simulation tools for vehicles.
2020	(Liu, Li, Tang, Wu, & Gaudiot, 2020)	Holistic review of SDV development processes.
2020	(Mozaffari, Al-Jarrah, Dianati, Jennings, & Mouzakitis, 2020), (Aradi, 2020)	Applications of machine learning in SDV technologies.
2020	(Barnett, Gizinski, Mondragon-Parra, & others, 2020), (El Khatib, Ou, & Karray, 2020)	Examination of external influences on SDVs.
2021	(Li, Rombaut, & Vanhaverbeke, 2021)	Prospects of autonomous vehicles in urban transportation and logistics through agent-based modeling.
2021	(Lopes, Siqueira, Araújo, Santos, & Santos, 2021), (Khatab, Onsy, Varley, & Abouelfarag, 2021)	Technological constraints, operational impacts, and challenges in autonomous driving.
2021	(Ahangar, Ahmed, Khan, & Hafeez, 2021)	V2X communication and sensor integration.
2021	(Pham & Xiong, 2021), (Kim, Kim, Jeong, Park, & Kim, 2021)	Cybersecurity threats and mitigation strategies in SDVs.
2022	(Limbasiya, Teng, Chattopadhyay, & Zhou, 2022), (Sun, Yu, & Zhang, 2022)	Overview of cybersecurity challenges in SDVs.
2022	(Khan, et al., 2022)	Key challenges in achieving full automation in SDVs.
2022	(Silva, Cordera, González-González, & Nogués, 2022)	Environmental implications of AVs.
2023	(Hakak, Gadekallu, Maddikunta, & others, 2023)	Application of 5G technology in SDVs.
2024	(Wu, Cai, He, & Lu, 2024)	Collective vehicle intelligence in V2X networks.
2024	**OUR PROPOSED WORK**	Development of SDV models, identifying challenges, research gaps, and emerging trends.

Table 2: Publishers with a Higher Number of Related Works

PUBLISHER	TOTAL	PAPERS
IEEE (TIS)	4	(Bresson, Alsayed, Yu, & Glaser, 2017), (Paden, Čáp, Yong, Yershov, & Frazzoli, 2016), (Bevly, Cao, Gordon, & others, 2016), (Barnett, Gizinski, Mondragon-Parra, & others, 2020)
IEEE (ITS)	3	(Mozaffari, Al-Jarrah, Dianati, Jennings, & Mouzakitis, 2020), (Aradi, 2020), (El Khatib, Ou, & Karray, 2020)

Research Framework

In conducting this SSR, we adhered to the methodologies outlined by Petersen et al. (Petersen, Feldt, Mujtaba, & Mattsson, 2008), which were subsequently utilized by Silva et al. (Silva, Soares, Souza, & Freitas, 2024), along with the comprehensive guidelines provided by Keele et al. (Kitchenham & Charters, 2007). This section presents the core components and specific aspects of our research approach.

Inquiry Objectives

This paper aims to deliver a thorough synthesis of SDV frame- works. The emphasis is on systematically categorizing and organizing findings around the core architectural elements, namely the hardware, software, and sensor technologies employed in SDVs. Furthermore, we are able to discern prevalent trends in SDV innovation, as well as the global distribution, frequency, and publication channels of research endeavors. The following inquiry objectives guide our examination and synthesis of the selected literature:

Technical Research Objectives (TRO):

1. TRO1: Which vehicle platforms are optimal for the development of SDV models?
2. TRO2: What are the prospective hardware architectures and specifications for future SDVs?
3. TRO3: What are the prospective software architectures and features for future SDVs?
4. TRO4: Which sensor configurations are essential for achieving full functionality in an SDV?

Publication Analysis Objectives (PAO):

1. PAO1: How are research outputs distributed across various publication platforms?
2. PAO2: How has the distribution of publications evolved over time?
3. PAO3: What are the institutional affiliations of the researchers?
4. PAO4: Which nations are the most prolific in contributing to SDV research?
5. PAO5: What are the most cited references in the field?
6. PAO6: What are the predominant research themes?

Research Technique

To initiate our SSR on SDV models, we implemented a thorough search strategy utilizing the Google Scholar database. The objective was to identify the primary terminologies used in publications concerning SDVs. Prior to finalizing the search string (SS), we meticulously examined several foundational papers to discern the most pertinent search terms (Hussain & Zeadally, 2019; Burgio, Bertogna, Capodieci, & Others, 2017; Kato, Tokunaga, Maruyama, & Others, 2018; Wang, Liang, Yao, & Others, 2017). Using these initial analyses and the references cited in these papers, we constructed the SS into three distinct segments. The first segment covered the term "autonomous", and its synonyms commonly used in literature. The second segment concentrated on terms related to the subject of study, specifically "vehicle." The third segment targeted terms associated with architecture, hardware, and models. We observed that the inclusion of the term "software" in the SS led to an overabundance of irrelevant results. Consequently, although not included in the SS, this term was considered in the search results. Furthermore, we deliberately excluded terms related to aerial and underwater vehicles, as they fell outside the scope of this review.

Selection Criteria

The journey toward SDVs has a long history, dating back to early 20th-century attempts (Silva, Soares, Souza, & Freitas, 2024). The 2007 DARPA Urban Challenge and its winning model, Boss, are two key milestones frequently cited in recent literature (Urmson, Anhalt, Bagnell, & Others, 2008). This was the first DARPA competition held in an urban environment, setting a precedent for SDV technology. Despite some Boss technologies and sensors still being used, they are considered outdated due to advancements in computer processing power and artificial intelligence, particularly in image detection and recognition. A significant shift in object recognition came with the ILSVRC-2012 competition winner, which utilized convolutional neural networks (CNNs) (Krizhevsky, Sutskever, & Hinton, 2017). By 2015, there was a notable increase in the use of hardware and software solutions designed specifically for vehicle applications rather than general-purpose computers. The release of the Nvidia Drive Computing Platform and the TensorFlow machine learning library, both crucial for modern SDV models, supported this shift (Oh & Yoon, 2019). We limited our search to publications from 2015 to December 2023, focusing on contemporary approaches to SDV development, considering these developments (NVIDIA, 2020; Google, 2020). The following criteria were applied:

Inclusion Criteria:

1. Research articles focusing on the development of SDV models, regardless of size.
2. Articles written in English.
3. Articles published from 2015 to the present.
4. Articles originating from the fields of engineering or computer science.

Exclusion Criteria:

1. Review articles
2. Articles concentrating on non-urban vehicles such as military, aerial, and underwater vehicles.
3. Articles focused on simulations.
4. Grey literature, including books or poster sessions.
5. Duplicate articles (only the most recent version was included).
6. Articles not available in full text.

Assessment and Selections

In December 2023, we carried out an extensive search across several databases to identify pertinent and high-quality articles for a SSR on SDVs. This initial search yielded a collection of successful secondary studies (Belmonte, Morales, & Fernández-Caballero, 2019; Barros-Justo, Pinciroli, Matalonga, & Martínez-Araujo, 2018; Tiwari & Rathore, 2018; Heradio, Chacon, Vargas, & Others, 2018; Lara Soares, Neri Nobre, & Cota de Freitas, 2019), forming the basis for our screening strategy. This strategy included searching for the first three components in the paper title, the final part in the title, the abstract, and keywords. Using this method, we identified key publications based on the defined search criteria, as summarized in Table 3.

Table 3: Publication Count by Database

PUBLISHER	PAPERS
Association for Computing Machinery (ACM)	10
Institute of Electrical and Electronics Engineers (IEEE)	90
Web of Science	142
Scopus	220
ScienceDirect	89
Total	**551**

Although Heradio et al. (Heradio, Chacon, Vargas, & others, 2018) reported that Google Scholar (GS) aggregates many papers from the databases and has reliability issues, potentially listing non- scientific results, we did not include it in this stage of the search. We removed duplicate papers identified across different databases. We then applied the inclusion and exclusion criteria to the remaining papers from the automated search, selecting 75 for full reading. We used the snowballing technique to include an additional ten papers by examining their relevant references. As a result, there were 85 final papers selected for this SSR. It was challenging to find papers that fully disclosed the details of SDV models, especially commercial ones. Despite this, we identified several companies involved in SDV development, such as Nvidia, Tesla, Intel, Google, Bosch, Argo AI, NXP, Baidu, Uber, Amazon, Mercedes, Audi, ZMP, and Percept In. However, most did not disclose detailed information about their developments in any publicly available document or report. Nevertheless, we found enough quality papers to provide meaningful results for this SSR.

Results and Discussions

The identified papers were categorized into two main groups: real-size models and mini-models. The first group, comprising 45 publications, details the development of SDVs using full- scale commercial vehicles. The second group includes 40 publications focusing on models based on small-scale vehicles, such as remote-control toys. Each category follows different research approaches and development levels, necessitating distinct answers to the research questions for real-size and mini-models. We will elaborate on these differences in the forthcoming discussions. As described in Subsection III-C, Inclusion, and Exclusion Criteria, our search included papers up to December 2023. While some publications were initially identified, several were excluded from the final analysis for not meeting the criteria. Consequently, the results presented in texts, figures, and tables do not reflect the data from these papers.

TRO1: Which vehicle platforms are optimal for the development of SDV models?

1) Real-Size Models:

The real-size model platforms were categorized into conventional gas, electric, and hybrid vehicles, as shown in Table 4. The differences in SDV development across these platform types are evident. The integration of autonomous driving systems varies significantly across these vehicle platforms. Conventional gas vehicles, typically controlled through mechanical means, pose unique challenges for model developers. The mechanical nature of steering, braking, and accelerating introduces delays that can critically affect the reaction time of an SDV, which needs to respond within 100 milliseconds. Moreover, additional mechanical components are often required to retrofit these vehicles for autonomous operation, as demonstrated by Belbachir and Gupta et al. (Gupta, Vijay, Korupolu, & Others, 2015; Belbachir, 2017). For models without pre-installed autonomous driving systems, implementing a drive-by-wire system is essential. This system replaces purely mechanical control commands with electrical or electromechanical alternatives (Kunz, Nuss, Wiest, & Others, 2015; Broggi, Cerri, Debattisti, & Others, 2015; Bojarski, Del Testa, Dworakowski, & Others, 2016; Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018; Buyval, Gabdullin, Gafurov, & Others, 2019).

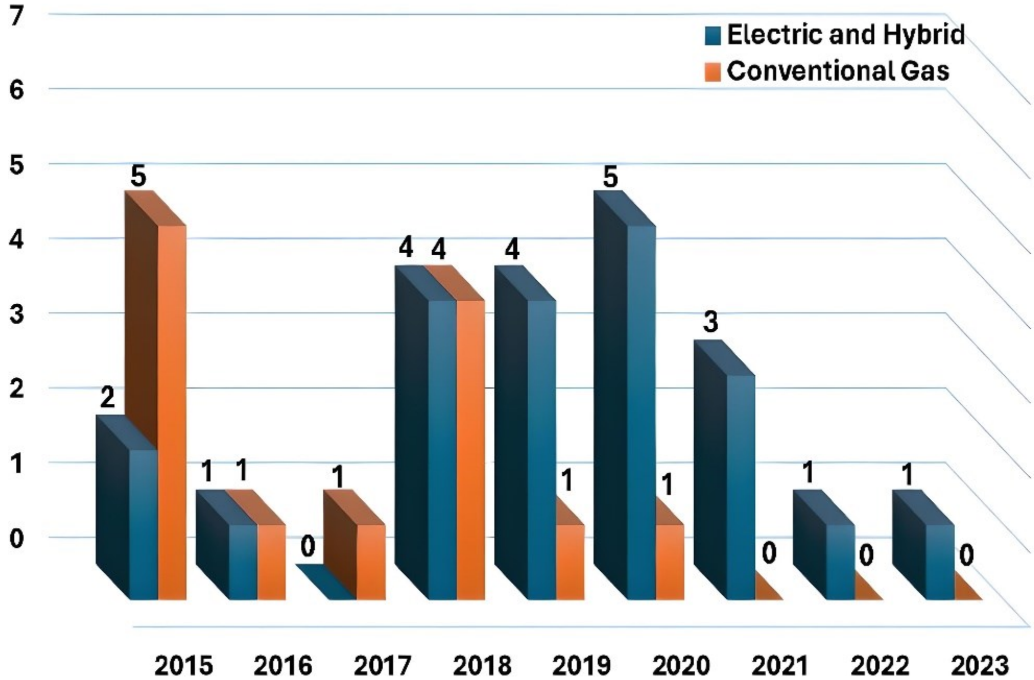

Figure 1: Vehicle Types Used for SDV Model Development (Conventional vs. Electric and Hybrid)

However, retrofitting traditional gas vehicles with drive-by-wire systems is complex and potentially hazardous, often requiring integration with the vehicle's Controller Area Network (CAN) and modifications to critical control and safety systems. Many modern conventional gas vehicles have some level of drive-by-wire capability, enabling electronic control over functions like throttle and braking. However, the extent of these capabilities varies and may not cover all vehicle controls. Conversely, electric and hybrid vehicles often come with comprehensive drive-by-wire systems, where electrical commands control most or all vehicle functions due to the nature of their engines. This feature simplifies the integration of autonomous control systems into models. Figure 1 illustrates the increasing use of electric vehicles for SDV prototyping in recent years, indicating a market shift from traditional gas vehicles to electric ones, as announced by several major manufacturers (NBCnews, 2020; Fortune, 2018; MotorBiscuit, 2019). This trend suggests that electric vehicles may become the standard platform for future SDVs.

Table 4: Types of Vehicles Utilized for SDV Model Development

TYPE	TOTAL	PAPERS
Conventional Gas	**20**	(Broggi, Debattisti, Grisleri, & Panciroli, 2015), (Jo K. , Kim, Kim, Jang, & Sunwoo, 2015), (Ziegler, Bender, Schreiber, & others, 2014), (Tropea, De Rango, Nevigato, & others, 2021), (Yu, Chen, Tang, Liu, & Gaudiot, 2022), (Nvidia, Self-driving cars, 2020), (Kitchenham & Charters, 2007), (Petersen, Vakkalanka, & Kuzniarz, Guidelines for conducting systematic mapping studies in software engineering: An update, 2015), (Hussain & Zeadally, 2019), (Bresson, Alsayed, Yu, & Glaser, 2017), (Gupta, Vijay, Korupolu, & others, 2015), (Kunz, Nuss, Wiest, & others, 2015), (Broggi, Cerri, Debattisti, & others, 2015), (Bojarski, Del Testa, Dworakowski, & others, 2016), (Belbachir, 2017), (Zong, Zhang, Wang, & others, 2018), (Taş, Salscheider, Poggenhans, & others, 2018), (Aramrattana, Detournay, Englund, & others, 2018), (Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018), (Buyval, Gabdullin, Gafurov, & others, 2019)
Electric	**20**	(Munir, Azam, Hussain, Sheri, & Jeon, 2018), (Paden, Čáp, Yong, Yershov, & Frazzoli, 2016), (Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018), (Buyval, Gabdullin, Gafurov, & others, 2019), (Buechel, Frtunikj, Becker, & others, 2015), (Martín, Marín, Hussein, & others, 2016), (Xu, Dherbomez, Hery, & others, 2018), (Buchegger, Lassnig, Loigge, & others, 2018), (Tang, Liu, Yu, & Shi, 2018), (Kessler, Bernhard, Buechel, & others, 2019), (Betz, Wischnewski, Heilmeier, & others, 2019), (Marin-Plaza, Hussein, Martin, & de la Escalera, 2019), (Valera, Huaman, Pasapera, & others, 2019), (de Miguel, Moreno, García, & others, 2020), (El-Tawab, Sprague, & Mufti, 2020), (Orjuela, Lauffenburger, Ledy, & others, 2020), (Lee & Wang, 2021), (Prasad, Huang, & Tang, 2020), (Tramacere, Luciani, Feraco, & others, 2021), (Chung & Yang, 2021)
Hybrid	**5**	(Kato, et al., 2015), (Bevly, Cao, Gordon, & others, 2016), (Reke, Peter, Schulte-Tigges, & others, 2020), (Grady, Nauman, & Miah, 2022), (NBCnews, 2020)

2) Mini Models:

Table 5 categorizes the platforms used for mini SDV models. Developers primarily opted for either do-it-yourself (DIY) vehicle kits or off-the-shelf remote control (RC) vehicles, with any remaining platforms classified as "others." DIY vehicle kits provide researchers with the flexibility to build vehicles from scratch (Azid, Kumar, Lal, & Sharma, 2017; Al Suwaidi, AlHammadi, Buhumaid, & Others, 2018; Sahu, Sahu, Choudhury, & Nag, 2019). Some advanced kits, such as the Elegoo Car Kit, include a processing unit, battery, and sensors (Wang, Liu, Zhang, & Shi, 2019). Several studies utilized these kits (Roestam & Hadisukmana, 2019; Febbo, Flood, Halloy, & Others, 2020; Fathy, Ashraf, Ismail, & Others, 2020; El-Hassan, 2020). Conversely, other research utilized more basic kits, which only include the vehicle chassis with wheels and steering system (Azid, Kumar, Lal, & Sharma, 2017; Sahu, Sahu, Choudhury, & Nag, 2019; Roestam & Hadisukmana, 2019; Fathy, Ashraf, Ismail, & Others, 2020). These basic kits require researchers to add components like batteries, electric motors, and control systems, offering greater freedom in mini-SDV development but necessitating additional effort to properly set up and control the vehicle (Studio, 2020). Most researchers chose professional 1:10 scale RC vehicles. These models, which come with pre-installed control systems, allow developers to focus on the autonomous features of the mini SDV model rather than building the vehicle controls from scratch (Pehlivan, Kahraman, Kurtel, Nakp, & Güzeliş, 2020). Notably, Gotlib et al. developed a model for the F1 Tenth competition, which promotes races between 1:10 SDV models and provides extensive guidance on building mini SDV models (Gotlib, Łukojć, & Szczygielski, 2019; F1tenth, 2020). Similarly, Perciński, Marcinkiewicz, and Blaga et al. developed their models for the Carolo-Cup, another competition for 1:10 scale SDVs (Perciński & Marcinkiewicz, 2018; Blaga, Deac, Al-doori, Negru, & Dănescu, 2018; Braunschweig, 2020).

Table 5: Types of Vehicles Used as Platforms for SDV Mini Model Development

TYPE	TOTAL	PAPERS
DIY vehicle Kit	**20**	(Fortune, 2018), (MotorBiscuit, 2019), (Azid, Kumar, Lal, & Sharma, 2017), (Al Suwaidi, AlHammadi, Buhumaid, & Others, 2018), (Sahu, Sahu, Choudhury, & Nag, 2019), (Wang, Liu, Zhang, & Shi, 2019), (Roestam & Hadisukmana, 2019), (Febbo, Flood, Halloy, & Others, 2020), (Fathy, Ashraf, Ismail, & Others, 2020), (El-Hassan, 2020), (Ullah, Asghar, Griffiths, & Others, 2022), (Ikhlayel, Iswara, Kurniawan, & Others, 2020), (Albin & Simske, 2021), (Mohammed, Abdullahi, & Ibrahim, 2021), (Hartono, Nizar, Robani, & Jatmiko, 2020), (Tabor, Dai, Sreenivasan, & Banerjee, 2022), (Sasamoto, Velázquez, Gutiérrez, & Others, 2021), (Hubert, Valdiero, Goergen, & Others, 2021), (Ponnan, Shelly, Hussain, & Others, 2022), (Ilié, Chaouche, & Pêcheux, 2020)
RC vehicles 1:10	**15**	(Karaman, Anders, Boulet, & Others, 2017), (Aguilar-Gonzalez, Lozoya, Orona, & Others, 2017), (Perciński & Marcinkiewicz, 2018), (Fayjie, Hossain, Oualid, & Lee, 2018), (Blaga, Deac, Al-doori, Negru, & Dănescu, 2018), (Do, Duong, Dang, & Le, 2018), (Kwon, Seo, Lee, & Kim, 2018), (Gotlib, Łukojć, & Szczygielski, 2019), (Walambe, Nikte, Joshi, & Others, 2019), (Zhou, Li, & Cao, 2019), (Valocky, Orgon, & Fujdiak, 2019), (Sajjad, Irfan, Muhammad, & Others, 2021), (Pannu, Ansari, & Gupta, 2015), (Bechtel, Mcellhiney, Kim, & Yun, 2018), (Jain, 2018)
Others	**5**	(Pannu, Ansari, & Gupta, 2015), (Bechtel, Mcellhiney, Kim, & Yun, 2018), (Jain, 2018), (Sun, Zheng, Qiao, Liu, Lin, & Bräunl, 2019), (Chaitra, Deepthi, Gautami, Suraj, & Kumar, 2020)

The prevalence of these competitions likely explains why many mini models are based on professionally scaled 1:10 RC vehicle models. The most frequently used model in the literature was from Traxxas (Traxxas, 2020). These 1:10 scale models, which are replicas of real-sized vehicles in many aspects, offer enough space to accommodate all necessary processing units and sensors, closely simulating real-sized vehicles' performance (Walambe, Nikte, Joshi, & Others, 2019; Sajjad, Irfan, Muhammad, & Others, 2021). However, modifications are needed, such as replacing the radio control system with an autonomous one, installing sensors, and distributing battery power to all electronic devices. Additionally, the plastic body often needs to be removed. Some mini SDV models did not fit into the main categories listed in Table 5. Two studies did not specify the platform details (Pannu, Ansari, & Gupta, 2015; Sun, Zheng, Qiao, Liu, Lin, & Bräunl, 2019). Sun et al. used a soccer bot for their model in a different Carolo Cup category (Sun, Zheng, Qiao, Liu, Lin, & Bräunl, 2019). Three other studies utilized smaller RC vehicles to reduce costs (Bechtel, Mcellhiney, Kim, & Yun, 2018; Jain, 2018; Pehlivan, Kahraman, Kurtel, Nakp, & Güzeliş, 2020).

TRO2: What are the prospective hardware architectures and specifications for future SDVs?

To understand each model's functioning and hardware configuration, it is critical to examine them closely to visualize a general architecture for the SDV. Since only a few papers provided diagrams of their architectures, a detailed review of the selected papers was crucial. This review led to the creation of a generic hardware architecture for the SDV, as illustrated in Figure 2. However, not all papers provided complete details, such as the network protocols used or specific computer con- figurations. Therefore, the results presented below are based on the available information from the reviewed papers.

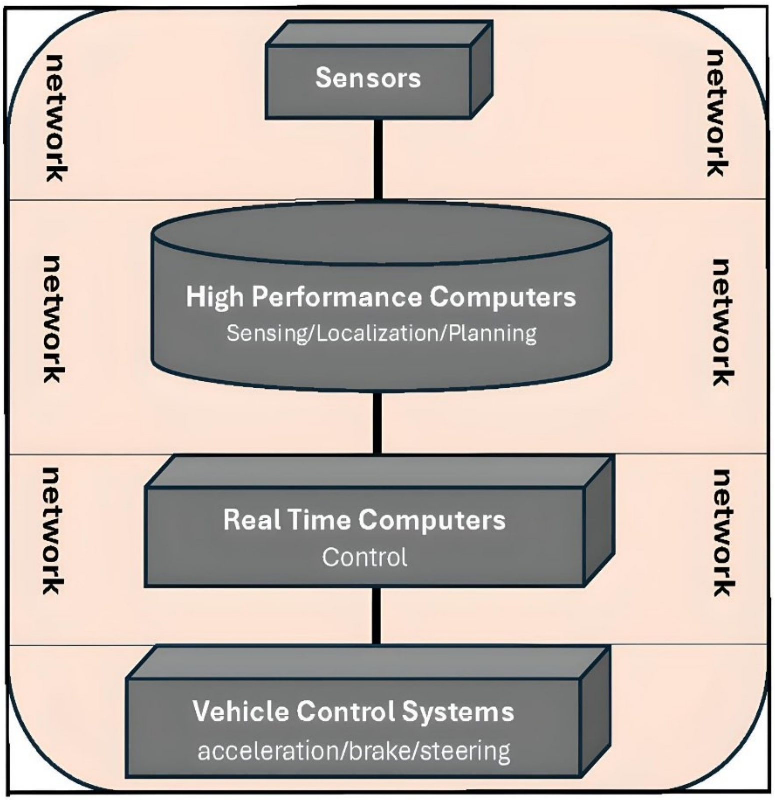

Figure 2: Generic Hardware Architecture for SDV

1) Network Architecture:

A network connects the sensors to one or more computers. In real-size models, Ethernet and CAN are the most used network protocols to link sensors (Kato, Takeuchi, Ishiguro, Ninomiya, Takeda, & Hamada, 2015; Broggi, Debattisti, Grisleri, & Panciroli, 2015; Munir, Azam, Hussain, Sheri, & Jeon, 2018; Jo, Kim, Kim, Jang, & Sunwoo, 2015; Kunz, Nuss, Wiest, & Others, 2015; Broggi, Cerri, Debattisti, & Others, 2015; Zong, Zhang, Wang, & Others, 2018; Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018; Buechel, Frtunikj, Becker, & Others, 2015; Martín, Marín, Hussein, & Others, 2016; Tang, Liu, Yu, & Shi, 2018; Kessler, Bernhard, Buechel, & Others, 2019; Betz, Wischnewski, Heilmeier, & Others, 2019; de Miguel, Moreno, García, & Others, 2020; Orjuela, Lauffenburger, Ledy, & Others, 2020; Chung & Yang, 2021; Lee, Wang, Ledy, & Others, 2020; Aeberhard, Kühbeck, Seidl, & Others, 2015). Typically, the CAN network connects sensors provided by the vehicle manufacturer, while Ethernet is used for adding new sensors. Additionally, some models use USB to connect cameras for image processing and LiDAR sensors (Broggi, Debattisti, Grisleri, & Panciroli, 2015; Munir, Azam, Hussain, Sheri, & Jeon, 2018; Kessler, Bernhard, Buechel, & Others, 2019). Typically, high-performance and real-time computers connect via Ethernet, with some models adopting high-speed Gigabit Ethernet (Tang, Liu, Yu, & Shi, 2018; Kessler, Bernhard, Buechel, & Others, 2019; Prasad, Huang, & Tang, 2020). One exception is the use of the automotive FlexRay network, an alternative to CAN, for interfacing an entire set of computers. Real-time computers and vehicle control systems all use the CAN network, which is standard in commercial vehicles. In contrast, mini models primarily use the USB protocol to connect their sensors, which is common for small-size sensors and computers in mini SDV prototyping. However, some models use Ethernet for high-performance LiDAR sensors, like their real-size counterparts (Wang, Liu, Zhang, & Shi, 2019).

Table 6: Count for Computers in Full-Scale SDV Models

TYPE	TOTAL	REFERENCES
One	7	(Kato, Takeuchi, Ishiguro, Ninomiya, Takeda, & Hamada, 2015), (Bojarski, Del Testa, Dworakowski, & Others, 2016), (Zong, Zhang, Wang, & Others, 2018), (Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018), (Valera, Huaman, Pasapera, & Others, 2019), (Orjuela, Lauffenburger, Ledy, & Others, 2020), (Chung & Yang, 2021)
Two to Four	18	(Munir, Azam, Hussain, Sheri, & Jeon, 2018), (Kunz, Nuss, Wiest, & Others, 2015), (Broggi, Cerri, Debattisti, & Others, 2015), (Belbachir, 2017), (Taş, Salscheider, Poggenhans, & Others, 2018), (Aramrattana, Detournay, Englund, & Others, 2018), (Buyval, Gabdullin, Gafurov, & Others, 2019), (Martín, Marín, Hussein, & Others, 2016), (Xu, Dherbomez, Hery, & Others, 2018), (Tang, Liu, Yu, & Shi, 2018), (Kessler, Bernhard, Buechel, & Others, 2019), (Betz, Wischnewski, Heilmeier, & Others, 2019), (Marin-Plaza, Hussein, Martin, & de la Escalera, 2019), (de Miguel, Moreno, García, & Others, 2020), (Prasad, Huang, & Tang, 2020), (Tramacere, Luciani, Feraco, & Others, 2021), (Reke, Peter, Schulte-Tigges, & Others, 2020), (El-Hassan, 2020)
Five or more	3	(Broggi, Debattisti, Grisleri, & Panciroli, 2015), (Jo, Kim, Kim, Jang, & Sunwoo, 2015), (Buechel, Frtunikj, Becker, & Others, 2015)
Not specified	4	(Gupta, Vijay, Korupolu, & Others, 2015), (Buchegger, Lassnig, Loigge, & Others, 2018), (Lee & Wang, 2021), (Grady, Nauman, & Miah, 2022)

2) Computing System for Real-Size Models:

Real-time computers and high-performance computers make up the two main components of the computing system in SDV models. High-performance computers handle computationally intensive tasks such as sensing, localization, and planning. These tasks involve challenges like point cloud processing and convolutional neural network (CNN) processing within the required time window for safe and accurate vehicle actions. Thus, as illustrated in Table 6, one or more computers were utilized for this purpose. Typically, these tasks utilize one or more high-performance computers. Real-time computers manage vehicle control functions such as acceleration, braking, and steering. As the name implies, these computers perform real-time actions that are crucial for responding to commands from high-performance computers. Every instance with multiple computers in the SDV models includes at least one dedicated to real-time applications.

Most SDV models use a combination of one real-time computer and one or more high-performance computers, creating a heterogeneous architecture based on CPUs and GPUs (Valera, Huaman, Pasapera, & Others, 2019). However, there are exceptions. For example, one model involved designing an autonomous go-kart using a BeagleBone Cyan as the primary computing unit for processing camera and LiDAR signals and controlling the vehicle (BeagleBoard, 2020). Despite the ambition of this project, the computing power was limited, comparable to a Raspberry Pi 3 or a Jetson Nano (Foundation, 2020; Nvidia, 2020b). Other models adopted Nvidia Drive Computers, designed specifically for autonomous driving applications (Nvidia, 2020a). One approach involved using the Nvidia Drive PX in an end-to-end manner, relying exclusively on camera inputs for vehicle control without other sensors (Bojarski, Del Testa, Dworakowski, & Others, 2016). This method was not widely adopted. Some models used the Nvidia Drive PX2, which incorporated cameras and additional sensors like LiDAR and GPS to control the vehicle.

Another approach involved combining Intel CPUs and Nvidia GPUs into a single computer, despite the need for GPU performance improvements for efficient autonomous driving. A different model was proposed as a future trend for SDVs using embedded computers, such as those from Nvidia. A few models employed a distributed computing architecture with five or more computing units. One example used fifteen computers, including industrial computers for sensor fusion and planning, as well as a separate real-time computer for vehicle control algorithms. Another model used twenty-one computers, each dedicated to processing data from one or two image sensors, as well as other application computers to handle the remaining tasks for autonomous operation. Some models opted for FPGAs, integrating multiple computing devices into a network. However, this approach has become less common, with a trend toward fewer, more powerful computing units to reduce complexity and cost in commercial vehicles. The Intel i7 CPU is the most frequently used processor in SDV models, with some instances of other processors like the discontinued Intel Core 2 Duo, Intel Xeon, and Intel i5 (Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018; Chung & Yang, 2021).

Nvidia GPU-based embedded computers are also popular for processing artificial intelligence and autonomous driving tasks, either alone or with other computing devices. Several SDV models commonly use the dSpace Micro Auto Box as a real-time computer. Designed for rapid vehicle prototyping, this system can connect to commercial vehicle CAN buses and override original system controls with custom strategies. Each study provides detailed hardware configurations for mini-SDV models (Kato, Takeuchi, Ishiguro, Ninomiya, Takeda, & Hamada, 2015; Taş, Salscheider, Poggenhans, & Others, 2018; Buyval, Gabdullin, Gafurov, & Others, 2019; de Miguel, Moreno, García, & Others, 2020). Common choices include the Raspberry Pi 3, the Nvidia Jetson series (TX1, TX2, and Nano) for high-performance tasks, and Arduino (Uno and Mega) for real-time control, typically using ARM-based CPUs with GPUs for enhanced processing capabilities (Wang, Liu, Zhang, & Shi, 2019; Febbo, Flood, Halloy, & Others, 2020; Karaman, Anders, Boulet, & Others, 2017; Fayjie, Hossain, Oualid, & Lee, 2018; Kwon, Seo, Lee, & Kim, 2018; Zhou, Li, & Cao, 2019).

3) Computing System for Mini Models:

The number of high-performance processing functions and the number of integrated sensors determine the architectural design of mini-SDV models. Models with only one computer combine both high-performance and real-time tasks. Those utilizing just a Raspberry Pi or Arduino as the main computing unit tend to have fewer functions compared to models equipped with more powerful Nvidia Jetson series computers (Azid, Kumar, Lal, & Sharma, 2017; Sahu, Sahu, Choudhury, & Nag, 2019; Roestam & Hadisukmana, 2019; El-Hassan, 2020; Blaga, Deac, Al-doori, Negru, & Dănescu, 2018; Sajjad, Irfan, Muhammad, & Others, 2021; Pannu, Ansari, & Gupta, 2015). However, the simpler setup is more cost-effective. Mini models with two computers separate vehicle control from high-performance tasks, ensuring real-time actions for commands issued by the high-performance computer. Real-time vehicles commonly use the Arduino microcontroller as the real-time computer, emulating an ECU, while a single-board computer manages other vehicle tasks. Table 7 and 8 details the specific number of computers and hardware selection for mini SDV Models.

TABLE 7: COUNTS FOR COMPUTERS IN THE MINI-SDV MODELS

TYPE	PAPERS	REFERENCES
One	17	(Azid, Kumar, Lal, & Sharma, 2017), (Sahu, Sahu, Choudhury, & Nag, 2019), (Roestam & Hadisukmana, 2019), (El-Hassan, 2020), (Ullah, Asghar, Griffiths, & Others, 2022), (Ikhlayel, Iswara, Kurniawan, & Others, 2020), (Albin & Simske, 2021), (Tabor, Dai, Sreenivasan, & Banerjee, 2022), (Sasamoto, Velázquez, Gutiérrez, & Others, 2021), (Hubert, Valdiero, Goergen, & Others, 2021), (Karaman, Anders, Boulet, & Others, 2017), (Fayjie, Hossain, Oualid, & Lee, 2018), (Blaga, Deac, Al-doori, Negru, & Dănescu, 2018), (Kwon, Seo, Lee, & Kim, 2018), (Zhou, Li, & Cao, 2019), (Sajjad, Irfan, Muhammad, & Others, 2021), (Pannu, Ansari, & Gupta, 2015)
Two	18	(Al Suwaidi, AlHammadi, Buhumaid, & Others, 2018), (Wang, Liu, Zhang, & Shi, 2019), (Febbo, Flood, Halloy, & Others, 2020), (Fathy, Ashraf, Ismail, & Others, 2020), (Mohammed, Abdullahi, & Ibrahim, 2021), (Hartono, Nizar, Robani, & Jatmiko, 2020), (Ilié, Chaouche, & Pêcheux, 2020), (Aguilar-Gonzalez, Lozoya, Orona, & Others, 2017), (Perciński & Marcinkiewicz, 2018), (Do, Duong, Dang, & Le, 2018), (Gotlib, Łukojć, & Szczygielski, 2019), (Walambe, Nikte, Joshi, & Others, 2019), (Valocky, Orgon, & Fujdiak, 2019), (Bechtel, Mcellhiney, Kim, & Yun, 2018), (Jain, 2018), (Sun, Zheng, Qiao, Liu, Lin, & Bräunl, 2019), (Chaitra, Deepthi, Gautami, Suraj, & Kumar, 2020), (Pehlivan, Kahraman, Kurtel, Nakp, & Güzeliş, 2020)
Not specified	1	(Ponnan, Shelly, Hussain, & others, 2022)

There are also unique approaches. Some models use the Odroid XU4 single-board computer for high-performance processing and the open-source AnyFCF7 for real-time motor control (Hardkernel, 2020; Keller, 2020). Others, like Pehlivan et al., employ the Robot Hat (Gotlib, Łukojć, & Szczygielski, 2019; Pehlivan, Kahraman, Kurtel, Nakp, & Güzeliş, 2020), a computer specifically designed for robot movement control, making it suitable for mini SDV applications. For the intensive task of training neural networks, three studies used an additional desktop or laptop computer (Hackster.io, 2019). These were not considered part of the primary computing system. This approach was necessary because the Raspberry Pi 3, which is commonly used in these models, was insufficient for efficiently training neural networks (Do, Duong, Dang, & Le, 2018; Bechtel, Mcellhiney, Kim, & Yun, 2018; Pehlivan, Kahraman, Kurtel, Nakp, & Güzeliş, 2020).

Table 8: Hardware Selection for Mini SDV Models

TYPE	PAPERS	REFERENCES
Raspberry Pi 3	**17**	(Al Suwaidi, AlHammadi, Buhumaid, & Others, 2018), (Sahu, Sahu, Choudhury, & Nag, 2019), (Fathy, Ashraf, Ismail, & Others, 2020), (El-Hassan, 2020), (Ilié, Chaouche, & Pêcheux, 2020), (Aguilar-Gonzalez, Lozoya, Orona, & Others, 2017), (Blaga, Deac, Al-doori, Negru, & Dănescu, 2018), (Do, Duong, Dang, & Le, 2018), (Walambe, Nikte, Joshi, & Others, 2019), (Sajjad, Irfan, Muhammad, & Others, 2021), (Pannu, Ansari, & Gupta, 2015), (Bechtel, Mcellhiney, Kim, & Yun, 2018), (Jain, 2018), (Sun, Zheng, Qiao, Liu, Lin, & Bräunl, 2019), (Chaitra, Deepthi, Gautami, Suraj, & Kumar, 2020), (Pehlivan, Kahraman, Kurtel, Nakp, & Güzeliş, 2020)
Nvidia Jetson Series	**9**	(Wang, Liu, Zhang, & Shi, 2019), (Febbo, Flood, Halloy, & Others, 2020), (Ullah, Asghar, Griffiths, & Others, 2022), (Ikhlayel, Iswara, Kurniawan, & Others, 2020), (Tabor, Dai, Sreenivasan, & Banerjee, 2022), (Karaman, Anders, Boulet, & Others, 2017), (Fayjie, Hossain, Oualid, & Lee, 2018), (Kwon, Seo, Lee, & Kim, 2018), (Zhou, Li, & Cao, 2019)
Arduino	**16**	(Azid, Kumar, Lal, & Sharma, 2017), (Al Suwaidi, AlHammadi, Buhumaid, & Others, 2018), (Wang, Liu, Zhang, & Shi, 2019), (Febbo, Flood, Halloy, & Others, 2020), (Fathy, Ashraf, Ismail, & Others, 2020), (El-Hassan, 2020), (Albin & Simske, 2021), (Mohammed, Abdullahi, & Ibrahim, 2021), (Hubert, Valdiero, Goergen, & Others, 2021), (Aguilar-Gonzalez, Lozoya, Orona, & Others, 2017), (Do, Duong, Dang, & Le, 2018), (Walambe, Nikte, Joshi, & Others, 2019), (Valocky, Orgon, & Fujdiak, 2019), (Jain, 2018), (Chaitra, Deepthi, Gautami, Suraj, & Kumar, 2020)
Others	**6**	(Sasamoto, Velázquez, Gutiérrez, & Others, 2021), (Ponnan, Shelly, Hussain, & Others, 2022), (Perciński & Marcinkiewicz, 2018), (Gotlib, Łukojć, & Szczygielski, 2019), (Sun, Zheng, Qiao, Liu, Lin, & Bräunl, 2019), (Pehlivan, Kahraman, Kurtel, Nakp, & Güzeliş, 2020)

TRO3: What are the prospective software architectures and features for future SDVs?

1) Software Architecture:

Figure 3 illustrates the development of a generic software architecture for SDVs after reviewing all selected papers. It's worth noting that not every SDV model included all the functions and sensors depicted in this generic architecture; however, each model incorporated at least one feature or sensor. Models built from commercial vehicles, which encompass nearly all full-size SDVs examined, typically had a comprehensive software architecture. In contrast, mini models often had a more streamlined architecture due to limited processing power. Despite this, some mini models, such as those from Wang et al. and Zhou et al. (Wang, Liu, Zhang, & Shi, 2019; Zhou, Li, & Cao, 2019), achieved a software architecture comparable to that of full-size models. The processing system in these SDV models consists of one or more computers with varying characteristics and configurations. While there is diversity in computer setups, the choice of operating system and middleware was nearly uniform across all the examined models.

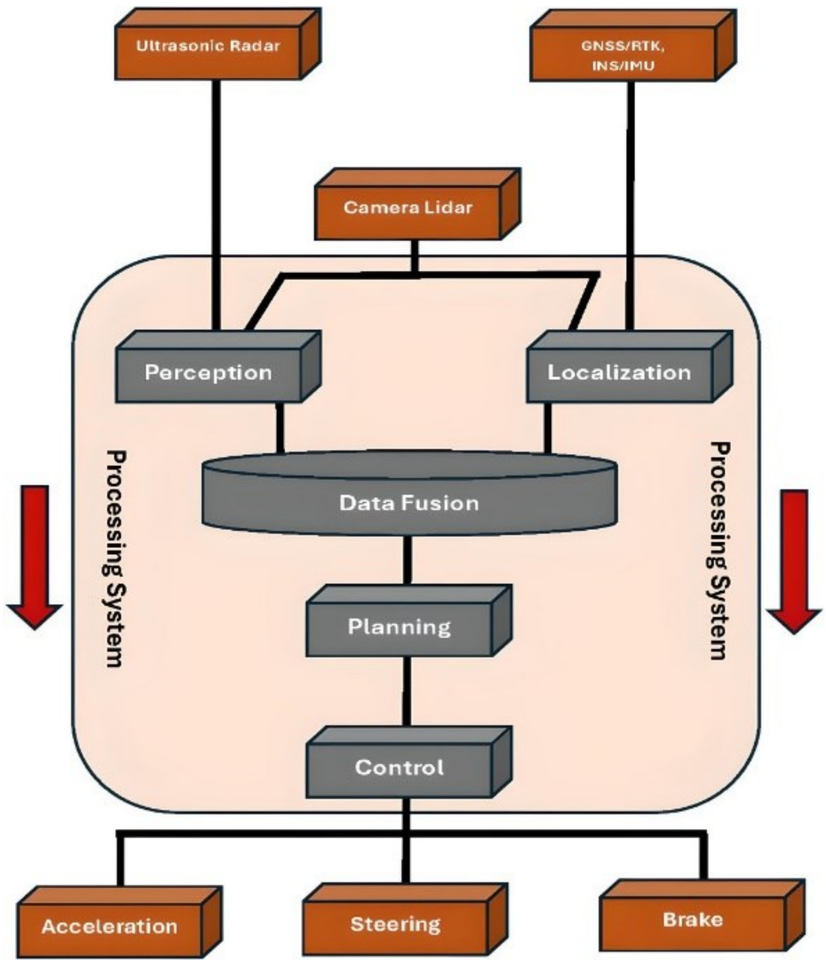

Figure 3: Software Architecture for SDVs

2) Middleware and Software Libraries:

The most widely used software for developing both mini and full-size SDVs is the Robot Operating System (ROS) (Munir, Azam, Hussain, Sheri, & Jeon, 2018; Gupta, Vijay, Korupolu, & Others, 2015; Taş, Salscheider, Poggenhans, & Others, 2018; Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018; Martín, Marín, Hussein, & Others, 2016; Betz, Wischnewski, Heilmeier, & Others, 2019; de Miguel, Moreno, García, & Others, 2020; Chung & Yang, 2021; Reke, Peter, Schulte-Tigges, & Others, 2020; Al Suwaidi, AlHammadi, Buhumaid, & Others, 2018; Wang, Liu, Zhang, & Shi, 2019; El-Hassan, 2020; Tabor, Dai, Sreenivasan, & Banerjee, 2022; Ilié, Chaouche, & Pêcheux, 2020; Karaman, Anders, Boulet, & Others, 2017; Gotlib, Łukojć, & Szczygielski, 2019; Zhou, Li, & Cao, 2019). This open-source middleware, or meta-operating system, is specifically designed for robotic applications, providing essential libraries and communication layers for autonomous driving tasks (de Miguel, Moreno, García, & Others, 2020; ROS.org, 2020). Modularizing the software into nodes, ROS allows independence between different SDV functions (Betz, Wischnewski, Heilmeier, & Others, 2019).

Developers typically recommend running ROS on Ubuntu Linux, despite it offering some operating system functions like hardware abstraction (ROS.org, 2020). In contrast, some researchers opt for the open-source Apollo framework (Buyval, Gabdullin, Gafurov, & Others, 2019; Kessler, Bernhard, Buechel, & Others, 2019), an extension of ROS with decentralized node control and enhanced communication capabilities. However, researchers have implemented modifications such as integrating a model predictive control module to address identified limitations in Apollo's planning and control modules (Kessler, Bernhard, Buechel, & Others, 2019). Autoware, a framework that builds on ROS, provides various modules for SDV tasks, including mapping and localization algorithms (Betz, Wischnewski, Heilmeier, & Others, 2019; Autoware.ai, 2020).

Alternative solutions have been developed to address specific shortcomings of ROS, such as its suitability for low-power edge computing systems. For instance, the π-OS middleware reduces communication overhead and library dependencies, achieving 50% lower latency than ROS (Tang, Liu, Yu, & Shi, 2018). Similarly, Project Cocktail, a data transmission module, manages system communications more efficiently by handling data flows as binary streams, thus enhancing real-time performance (Zhang, Wang, Zhang, & Others, 2018). Another middleware, PACPUS, focuses on optimizing software execution performance by allowing dynamic loading and network distribution of components during execution (Broggi, Cerri, Debattisti, & Others, 2015). Additionally, various SDV projects have utilized the C++-developed gold firmware, which offers similar characteristics to ROS (Broggi, Debattisti, Grisleri, & Panciroli, 2015; Broggi, Cerri, Debattisti, & Others, 2015). The evolution of ROS to ROS2 addresses some of the original version's limitations by maintaining modularity while improving real-time performance (Reke, Peter, Schulte-Tigges, & Others, 2020).

Two widely used software libraries in SDV development, particularly in mini models, are OpenCV and TensorFlow. OpenCV, an open-source computer vision library, is extensively used for image collection and processing, handling both images and videos (Kato, Takeuchi, Ishiguro, Ninomiya, Takeda, & Hamada, 2015; Jo, Kim, Kim, Jang, & Sunwoo, 2015; Valera, Huaman, Pasapera, & Others, 2019; Al Suwaidi, AlHammadi, Buhumaid, & Others, 2018; Wang, Liu, Zhang, & Shi, 2019; Febbo, Flood, Halloy, & Others, 2020; Blaga, Deac, Al-doori, Negru, & Dănescu, 2018; Fayjie, Hossain, Oualid, & Lee, 2018; Zhou, Li, & Cao, 2019; Sajjad, Irfan, Muhammad, & Others, 2021; Pannu, Ansari, & Gupta, 2015; Bechtel, Mcellhiney, Kim, & Yun, 2018; Jain, 2018). TensorFlow, a deep learning library, is primarily used for building and training models for image classification (Valera, Huaman, Pasapera, & Others, 2019; Wang, Liu, Zhang, & Shi, 2019; Febbo, Flood, Halloy, & Others, 2020; Do, Duong, Dang, & Le, 2018; Mohammed, Abdullahi, & Ibrahim, 2021; Chaitra, Deepthi, Gautami, Suraj, & Kumar, 2020; Pehlivan, Kahraman, Kurtel, Nakp, & Güzeliş, 2020). While OpenCV has machine learning functionalities, developers often prefer to build models in TensorFlow and then import them into OpenCV for application in SDVs.

TRO4: Which sensor configurations are essential for achieving full functionality in an SDV?

Figure 3 illustrates the six essential sensors required for constructing an SDV. While not all SDV models in the reviewed papers utilized every sensor, some full-size models incorporated the complete sensor suite (Taş, Salscheider, Poggenhans, & Others, 2018; Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018; Kessler, Bernhard, Buechel, & Others, 2019; Betz, Wischnewski, Heilmeier, & Others, 2019; Chung & Yang, 2021; Lee & Wang, 2021). There were also several complex mini models, but none of them included the entire set of sensors (Wang, Liu, Zhang, & Shi, 2019; Roestam & Hadisukmana, 2019; El-Hassan, 2020; Perciński & Marcinkiewicz, 2018; Blaga, Deac, Al-doori, Negru, & Dănescu, 2018; Zhou, Li, & Cao, 2019; Jain, 2018). Table 9 details the specific sensors used in each SDV model.

1) LiDAR:

LiDAR (light detection and ranging) is a crucial sensor for perception and localization in SDVs. It produces point cloud data that facilitates mapping the environment, determining the vehicle's position, detecting objects, and measuring distances (Kato, Takeuchi, Ishiguro, Ninomiya, Takeda, & Hamada, 2015). Popular libraries like OpenCV can process this data. However, the high cost of LiDAR, which can reach up to $75,000, poses a significant barrier to its widespread adoption (Doe, 2021). Consequently, developers often seek alternatives, such as using only cameras. Despite this, some researchers consider LiDAR indispensable for SDVs (Tang, Liu, Yu, & Shi, 2018; Kessler, Bernhard, Buechel, & Others, 2019). LiDAR sensors come in two types: 2D and 3D. While the 2D LiDAR serves for object detection and distance measurement, the 3D LiDAR enhances sensing capabilities by measuring an object's height, width, and depth, which is crucial for identifying its characteristics. A common application of 3D LiDAR is the simultaneous localization and mapping (SLAM) algorithm, which creates real-time maps of the environment with detailed object information. To mitigate costs, mini SDV models typically use 2D LiDAR, which starts at around $100. This sensor can be used for 2D mapping, object detection, and ranging. Additionally, its data can be combined with camera inputs to achieve functions like those of the more expensive 3D LiDAR (Blaga, Deac, Al-doori, Negru, & Dănescu, 2018). Notable manufacturers of LiDAR sensors include Velodyne, Hokuyo, Ibeo, Sick, and Slamtec.

Table 9: Sensor Utilization in SDV Models

TYPE	TOTAL	PAPERS
LiDAR	**31**	(Kato, Takeuchi, Ishiguro, Ninomiya, Takeda, & Hamada, 2015), (Broggi, Debattisti, Grisleri, & Panciroli, 2015), (Munir, Azam, Hussain, Sheri, & Jeon, 2018), (Gupta, Vijay, Korupolu, & Others, 2015), (Broggi, Cerri, Debattisti, & Others, 2015), (Belbachir, 2017), (Taş, Salscheider, Poggenhans, & Others, 2018), (Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018), (Buechel, Frtunikj, Becker, & Others, 2015), (Aramrattana, Detournay, Englund, & Others, 2018), (Martín, Marín, Hussein, & Others, 2016), (Buyval, Gabdullin, Gafurov, & Others, 2019), (Tang, Liu, Yu, & Shi, 2018), (Kessler, Bernhard, Buechel, & Others, 2019), (Betz, Wischnewski, Heilmeier, & Others, 2019), (de Miguel, Moreno, García, & Others, 2020), (Orjuela, Lauffenburger, Ledy, & Others, 2020), (Chung & Yang, 2021), (Prasad, Huang, & Tang, 2020), (Wang, Liu, Zhang, & Shi, 2019), (El-Hassan, 2020), (Tabor, Dai, Sreenivasan, & Banerjee, 2022), (Ilié, Chaouche, & Pêcheux, 2020), (Karaman, Anders, Boulet, & Others, 2017), (Fayjie, Hossain, Oualid, & Lee, 2018), (Blaga, Deac, Al-doori, Negru, & Dănescu, 2018), (Gotlib, Łukojć, & Szczygielski, 2019), (Zhou, Li, & Cao, 2019)
Camera	**48**	(Kato, Takeuchi, Ishiguro, Ninomiya, Takeda, & Hamada, 2015), (Broggi, Debattisti, Grisleri, & Panciroli, 2015), (Munir, Azam, Hussain, Sheri, & Jeon, 2018), (Jo, Kim, Kim, Jang, & Sunwoo, 2015), (Kunz, Nuss, Wiest, & Others, 2015), (Broggi, Cerri, Debattisti, & Others, 2015), (Zong, Zhang, Wang, & Others, 2018), (Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018), (Taş, Salscheider, Poggenhans, & Others, 2018), (Aramrattana, Detournay, Englund, & Others, 2018), (Martín, Marín, Hussein, & Others, 2016), (Tang, Liu, Yu, & Shi, 2018), (Kessler, Bernhard, Buechel, & Others, 2019), (Betz, Wischnewski, Heilmeier, & Others, 2019), (de Miguel, Moreno, García, & Others, 2020), (Chung & Yang, 2021), (Prasad, Huang, & Tang, 2020), (Wang, Liu, Zhang, & Shi, 2019), (El-Hassan, 2020), (Sahu, Sahu, Choudhury, & Nag, 2019), (Roestam & Hadisukmana, 2019), (Febbo, Flood, Halloy, & Others, 2020), (Fathy, Ashraf, Ismail, & Others, 2020), (Ullah, Asghar, Griffiths, & Others, 2022), (Ikhlayel, Iswara, Kurniawan, & Others, 2020), (Albin & Simske, 2021), (Hartono, Nizar, Robani, & Jatmiko, 2020), (Ilié, Chaouche, & Pêcheux, 2020), (Karaman, Anders, Boulet, & Others, 2017), (Perciński & Marcinkiewicz, 2018), (Do, Duong, Dang, & Le, 2018), (Blaga, Deac, Al-doori, Negru, & Dănescu, 2018), (Gotlib, Łukojć, & Szczygielski, 2019), (Zhou, Li, & Cao, 2019), (Sasamoto, Velázquez, Gutiérrez, & Others, 2021), (Ponnan, Shelly, Hussain, & Others, 2022), (Sun, Zheng, Qiao, Liu, Lin,

		& Bräunl, 2019), (Bechtel, Mcellhiney, Kim, & Yun, 2018), (Jain, 2018), (Chaitra, Deepthi, Gautami, Suraj, & Kumar, 2020), (Pehlivan, Kahraman, Kurtel, Nakp, & Güzeliş, 2020)
Radar	**14**	(Broggi, Debattisti, Grisleri, & Panciroli, 2015), (Kunz, Nuss, Wiest, & Others, 2015), (Broggi, Cerri, Debattisti, & Others, 2015), (Zong, Zhang, Wang, & Others, 2018), (Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018), (Taş, Salscheider, Poggenhans, & Others, 2018), (Aramrattana, Detournay, Englund, & Others, 2018), (Martín, Marín, Hussein, & Others, 2016), (Tang, Liu, Yu, & Shi, 2018), (Kessler, Bernhard, Buechel, & Others, 2019), (Betz, Wischnewski, Heilmeier, & Others, 2019), (Chung & Yang, 2021), (Prasad, Huang, & Tang, 2020)
Ultrasonic	**21**	(Kunz, Nuss, Wiest, & Others, 2015), (Taş, Salscheider, Poggenhans, & Others, 2018), (Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018), (Martín, Marín, Hussein, & Others, 2016), (Tang, Liu, Yu, & Shi, 2018), (Kessler, Bernhard, Buechel, & Others, 2019), (Betz, Wischnewski, Heilmeier, & Others, 2019), (Orjuela, Lauffenburger, Ledy, & Others, 2020), (Azid, Kumar, Lal, & Sharma, 2017), (Sahu, Sahu, Choudhury, & Nag, 2019), (Roestam & Hadisukmana, 2019), (Febbo, Flood, Halloy, & Others, 2020), (El-Hassan, 2020), (Mohammed, Abdullahi, & Ibrahim, 2021), (Hartono, Nizar, Robani, & Jatmiko, 2020), (Valocky, Orgon, & Fujdiak, 2019), (Pannu, Ansari, & Gupta, 2015), (Bechtel, Mcellhiney, Kim, & Yun, 2018), (Pehlivan, Kahraman, Kurtel, Nakp, & Güzeliş, 2020)
GNSS/RTK	**27**	(Kato, Takeuchi, Ishiguro, Ninomiya, Takeda, & Hamada, 2015), (Broggi, Debattisti, Grisleri, & Panciroli, 2015), (Munir, Azam, Hussain, Sheri, & Jeon, 2018), (Jo, Kim, Kim, Jang, & Sunwoo, 2015), (Gupta, Vijay, Korupolu, & Others, 2015), (Kunz, Nuss, Wiest, & Others, 2015), (Broggi, Cerri, Debattisti, & Others, 2015), (Zong, Zhang, Wang, & Others, 2018), (Taş, Salscheider, Poggenhans, & Others, 2018), (Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018), (Martín, Marín, Hussein, & Others, 2016), (Tang, Liu, Yu, & Shi, 2018), (Kessler, Bernhard, Buechel, & Others, 2019), (Betz, Wischnewski, Heilmeier, & Others, 2019), (Broggi, Cerri, Debattisti, & Others, 2015), (Buechel, Frtunikj, Becker, & Others, 2015), (Orjuela, Lauffenburger, Ledy, & Others, 2020), (Chung & Yang, 2021), (Prasad, Huang, & Tang, 2020), (Al Suwaidi, AlHammadi, Buhumaid, & Others, 2018), (Roestam & Hadisukmana, 2019), (El-Hassan, 2020), (Aguilar-Gonzalez, Lozoya, Orona, & Others, 2017), (Blaga, Deac, Al-doori, Negru, & Dănescu, 2018)
INS/IMU	**26**	(Broggi, Debattisti, Grisleri, & Panciroli, 2015), (Munir, Azam, Hussain, Sheri, & Jeon, 2018), (Jo, Kim, Kim, Jang, & Sunwoo, 2015), (Broggi, Cerri, Debattisti, & Others, 2015), (Kunz, Nuss, Wiest, & Others, 2015), (Zong, Zhang, Wang, & Others, 2018), (Taş, Salscheider, Poggenhans, & Others, 2018), (Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018), (Martín, Marín, Hussein, & Others, 2016), (Tang, Liu, Yu, & Shi, 2018), (Kessler, Bernhard, Buechel, & Others, 2019), (Betz, Wischnewski, Heilmeier, & Others, 2019), (Buechel, Frtunikj, Becker, & Others, 2015), (Orjuela, Lauffenburger, Ledy, & Others, 2020), (Chung & Yang, 2021), (El-Hassan, 2020), (Ilié, Chaouche, & Pêcheux, 2020), (Karaman, Anders, Boulet, & Others, 2017), (Perciński & Marcinkiewicz, 2018), (Blaga, Deac, Al-doori, Negru, & Dănescu, 2018), (Gotlib, Łukojć, & Szczygielski, 2019), (Zhou, Li, & Cao, 2019)

2) Camera:

SDVs also widely use cameras for localization and perception. Various types of cameras have been applied, including static and moving, monochrome and color, stereo, spherical, and smart cameras. These cameras range from low-resolution models at 640 x 480 pixels (Pannu, Ansari, & Gupta, 2015) to high-resolution models reaching up to 4416 x 1242 pixels (Karaman, Anders, Boulet, & Others, 2017), exceeding the Full HD resolution typically seen in television broadcasts. The most common application of cameras in SDV models is object detection and classification. Some models use cameras as the sole sensor for obstacle avoidance, utilizing an end-to-end approach that relies solely on camera input for driving. Often, full-size models use cameras exclusively for detection as part of a larger sensor suite, while mini models with limited computing resources use them for obstacle avoidance (Bojarski, Del Testa, Dworakowski, & Others, 2016; Blaga, Deac, Al-doori, Negru, & Dănescu, 2018; Do, Duong, Dang, & Le, 2018; Kwon, Seo, Lee, & Kim, 2018; Valocky, Orgon, & Fujdiak, 2019; Pannu, Ansari, & Gupta, 2015; Bechtel, Mcellhiney, Kim, & Yun, 2018). Additionally, cameras are used for mapping the environment in SLAM applications.

Monochrome and color cameras are employed to detect road lanes, traffic signals, pedestrians, and other road objects (Broggi, Debattisti, Grisleri, & Panciroli, 2015; Broggi, Cerri, Debattisti, & Others, 2015; Taş, Salscheider, Poggenhans, & Others, 2018; Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018; Marin-Plaza, Hussein, Martin, & de la Escalera, 2019; Roestam & Hadisukmana, 2019; Fathy, Ashraf, Ismail, & Others, 2020; El-Hassan, 2020; Karaman, Anders, Boulet, & Others, 2017; Blaga, Deac, Al-doori, Negru, & Dănescu, 2018). More complex camera setups, such as stereo cameras, are used to provide depth information through disparity maps by matching and comparing images from two lenses (Kato, Takeuchi, Ishiguro, Ninomiya, Takeda, & Hamada, 2015). This setup allows for precise distance measurement of obstacles, a capability not possible with monocular cameras. Some models feature advanced camera systems, such as those mounted on the vehicle roof, to provide a 360-degree spherical view (Reke, Peter, Schulte-Tigges, & Others, 2020). Other systems, like the Intel Mobileye, offer the advantage of on-camera image processing, which reduces the computational load on the vehicle's main computing system. Key manufacturers of cameras for SDV applications include Baumer, Flir, Point Grey, IDS, Sekonix, Zed, and Kurokesu. The PiCamera is the most popular choice for mini-SDV models.

3) Radar & Ultrasonic:

Radar is a key component in the perception system of SDVs, used for obstacle detection at short, medium, and long ranges. It provides precise range and velocity measurements, although it has less accurate classification capabilities compared to cameras. Consequently, other sensors like LiDAR, cameras, and GNSS systems often integrate with radar (Kunz, Nuss, Wiest, & Others, 2015; Taş, Salscheider, Poggenhans, & Others, 2018). Its most common application is as a long-range radar to detect obstacles in front of and behind the vehicle, making it particularly useful during cruise mode. Radars have a perception range of 0.25 to 250 meters, with the main suppliers including Continental, Smart Micro, and Bosch. Ultrasonic sensors, which detect objects up to 5 meters away, support the vision system in low-speed tasks such as parking. These sensors are popular in mini-SDV models, serving a similar function to radars in full-size vehicles.

Some full-size SDVs use multiple ultrasonic sensors around the vehicle for obstacle detection within approximately 2.5 meters (Zong, Zhang, Wang, & Others, 2018; Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018; de Miguel, Moreno, García, & Others, 2020; Chung & Yang, 2021). However, Fathy et al. (Fathy, Ashraf, Ismail, & Others, 2020) argued that the delay in ultrasonic waves returning from obstacles makes them less efficient at longer distances, preferring stereo cameras for better results. This approach eliminates the need to combine multiple sensors, as El-Hassan (El-Hassan, 2020) did with ultrasonic and LiDAR sensors and Sajjad with ultrasonic and monocular cameras (Sajjad, Irfan, Muhammad, & Others, 2021). Ultrasonic sensors are already present in many modern vehicles, and the vehicle's CAN bus provides access to their data. Only Buechel et al. provided detailed information about the specific sensor brand and version used (Buechel, Frtunikj, Becker, & Others, 2015). The low-cost HC-SR04 ultrasonic sensor, commonly used for mini SDV models, integrates easily into electronic circuit boards, making it suitable for budget-friendly SDV development (Azid, Kumar, Lal, & Sharma, 2017; Roestam & Hadisukmana, 2019; Valocky, Orgon, & Fujdiak, 2019; Sajjad, Irfan, Muhammad, & Others, 2021).

4) Navigation Sensor:

The global navigation satellite system (GNSS), which includes regional systems such as GPS, Galileo, Glonass, and Compass, provides global localization for SDVs with an update frequency of 10 Hz. Real-time applications find this frequency insufficient, necessitating a significant improvement in GNSS precision, typically around 6 meters, for SDV applications that demand centimeter-level accuracy. The real-time kinematic (RTK) system can enhance this precision by correcting GNSS information to achieve centimeter-level accuracy (Liu et al., 2019; Taş, Salscheider, Poggenhans, & Others, 2018). RTK involves multiple base stations spaced several kilometers apart, which obtain their positions from the GNSS and replicate this information to a rover station mounted on the SDV. An inertial navigation system (INS), which uses data from the inertial measurement unit (IMU), often combines GNSS signals to further improve the update rate.

Table 10: SDV Navigation Sensors

TYPE	TOTAL	PAPERS
GNSS-RTK-INS/IMU	**14**	(Broggi, Debattisti, Grisleri, & Panciroli, 2015), (Munir, Azam, Hussain, Sheri, & Jeon, 2018), (Jo, Kim, Kim, Jang, & Sunwoo, 2015), (Broggi, Cerri, Debattisti, & Others, 2015), (Kunz, Nuss, Wiest, & Others, 2015), (Zong, Zhang, Wang, & Others, 2018), (Taş, Salscheider, Poggenhans, & Others, 2018), (Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018), (Aramrattana, Detournay, Englund, & Others, 2018), (Martín, Marín, Hussein, & Others, 2016), (Buechel, Frtunikj, Becker, & Others, 2015), (Kessler, Bernhard, Buechel, & Others, 2019), (Orjuela, Lauffenburger, Ledy, & Others, 2020), (Aguilar-Gonzalez, Lozoya, Orona, & Others, 2017)
GNSS-INS/IMU	7	(Kunz, Nuss, Wiest, & Others, 2015), (Buechel, Frtunikj, Becker, & Others, 2015), (Broggi, Cerri, Debattisti, & Others, 2015), (Belcarz, Białek, Komorkiewicz, & Żołnierczyk, 2018), (Martín, Marín, Hussein, & Others, 2016), (Chung & Yang, 2021), (El-Hassan, 2020)
GNSS-RTK	2	(Kato, Takeuchi, Ishiguro, Ninomiya, Takeda, & Hamada, 2015), (Kunz, Nuss, Wiest, & Others, 2015)
GNSS	3	(Al Suwaidi, AlHammadi, Buhumaid, & Others, 2018), (Roestam & Hadisukmana, 2019), (El-Hassan, 2020)
INS/IMU	7	(Tang, Liu, Yu, & Shi, 2018), (Fathy, Ashraf, Ismail, & Others, 2020), (Ilié, Chaouche, & Pêcheux, 2020), (Perciński & Marcinkiewicz, 2018), (Blaga, Deac, Al-doori, Negru, & Dănescu, 2018), (Gotlib, Łukojć, & Szczygielski, 2019), (Zhou, Li, & Cao, 2019)

The INS provides an update rate of approximately 200 Hz, twenty times higher than the GNSS, making it suitable for real-time applications. However, the accuracy of INS diminishes over time, making it unsuitable for standalone use. Combining RTK, GNSS, and INS systems offers accurate, real-time vehicle localization. The INS is also effective in environments where GNSS-RTK signals are unavailable, such as underground parking lots, bridges, and tunnels. Employing other localization methods that utilize maps and known object characteristics captured by cameras or LiDAR can enhance system reliability in cases of extended GNSS signal loss (Taş et al., 2016). An economical approach involves combining GNSS with a camera-based localization system to enhance accuracy, which is more cost-effective than using a high-precision GNSS-RTK system with INS. Table 10 highlights the application of navigation sensors in various SDV models. The preferred combination of sensors for navigation is GNSS-RTK-INS/IMU, due to its superior performance. Mini SDV models typically use only GPS or IMU, focusing on proving specific concepts at a lower cost. The most used navigation sensor brands include Novatel, U-blox, and OXTS.

PAO1: How are research outputs distributed across various publication platforms?

Academic journals play a crucial role in disseminating scientific research and fostering discussion about new ideas. Data shows in Figure 4, a higher concentration of publications in conferences than journals, as illustrated in Table 11. Only three venues have published more than one paper. Additionally, we generated a co-citation map using citation analysis software (Smith & Johnson, 2022). This analysis helps identify core journals and conferences influential in a specific field, highlighting those significantly impacting research development and dissemination (Brown et al., 2021). Using a minimum of three citations per journal in the analyzed articles, the co-citation map revealed 55 publishers, as illustrated in Figure 5. It indicates that the IEEE Intelligent Vehicles Symposium, IEEE Transactions on Intelligent Transportation Systems, and the Journal of Field Robotics are the most influential venues, leading the red cluster and affecting smaller clusters around them. The Journal of Field Robotics, despite not featuring models analyzed in this study (Doe, 2019), has significantly influenced the field by publishing key articles.

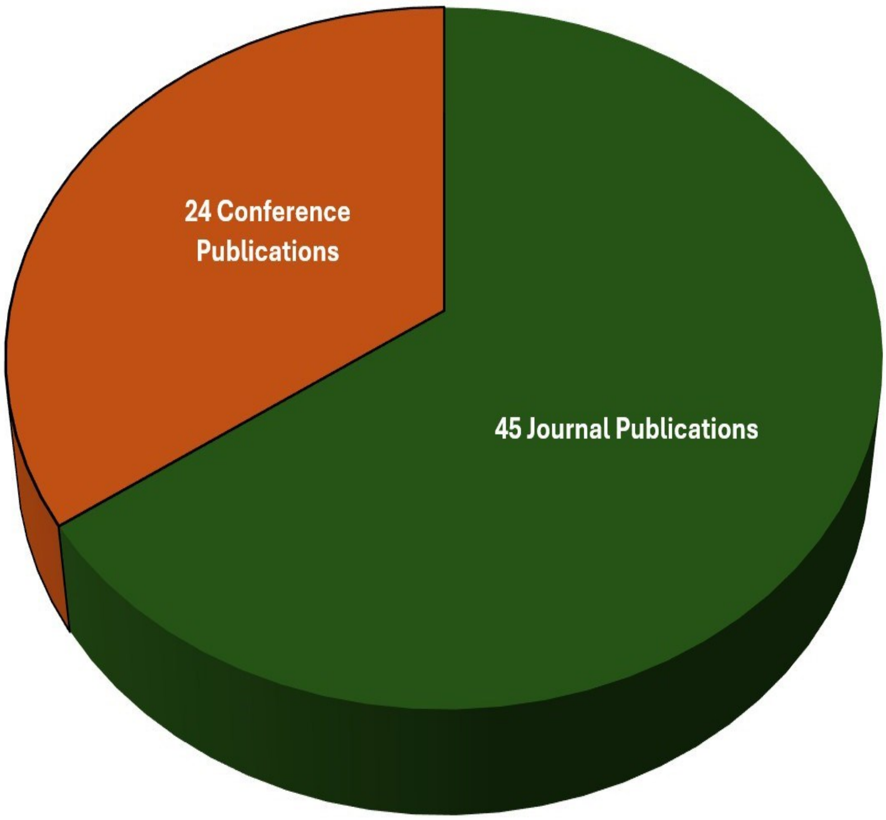

Figure 4: Publication Count by Publishing Type

Table 11: Number of Papers per Publisher Type

PUBLISHER	PAPERS	REFERENCES
IEEE	4	(Broggi, Cerri, Debattisti, & Others, 2015), (Taş, Salscheider, Poggenhans, & Others, 2018), (Aramrattana, Detournay, Englund, & Others, 2018), (Sajjad, Irfan, Muhammad, & Others, 2021)
IEEE	3	(Broggi, A., Debattisti, S., Grisleri, P., & Panciroli, M., 2015), (Kunz, F., Nuss, D., Wiest, J., & Others, 2015), (Kessler, T., Bernhard, J., Buechel, M., & Others, 2019)
IIPhDW	2	(Perciński & Marcinkiewicz, 2018), (Gotlib, Łukojć, & Szczygielski, 2019)

PAO2: How has the distribution of publications evolved over time?

Figure 6 illustrates the number of publications per year. We noted a decrease in publications in 2016 and 2017, possibly due to the time required to adopt changes in machine learning and processing power advancements up to 2015. A similar decrease occurred in 2021 and 2022, during which many papers focused on improving algorithms and technologies for SDVs, such as artificial intelligence, computer vision, path planning, and sensors. The shift in re- search focus towards technological improvements, following numerous model-related contributions from 2018 to 2020, accounts for the lower number of model publications in these years.

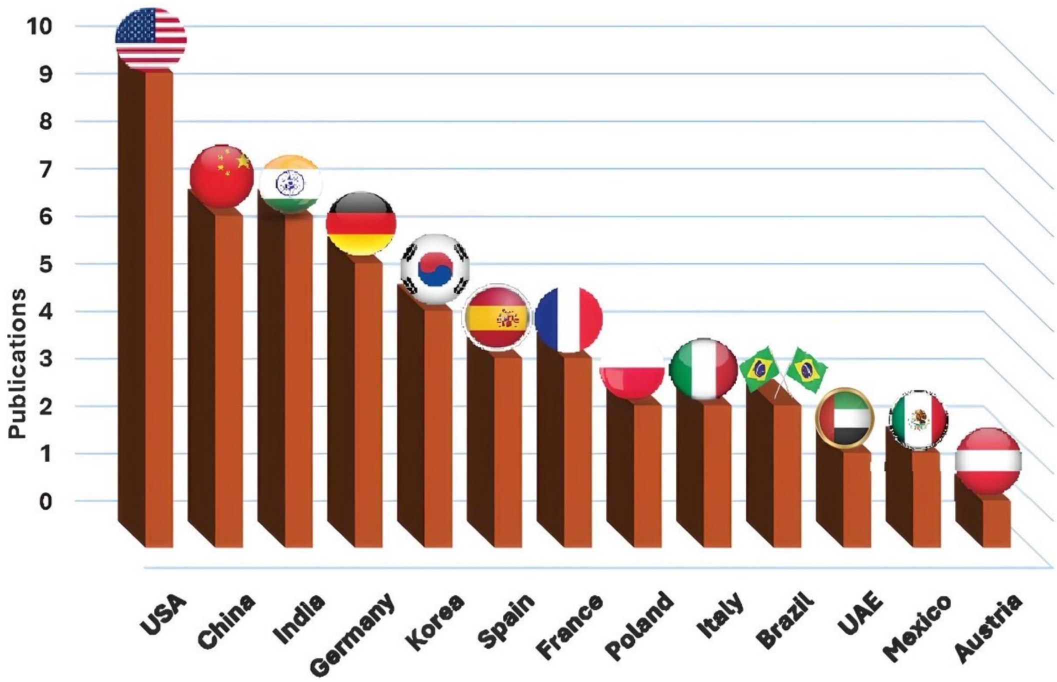

Figure 5: Leading Countries in SDV Research

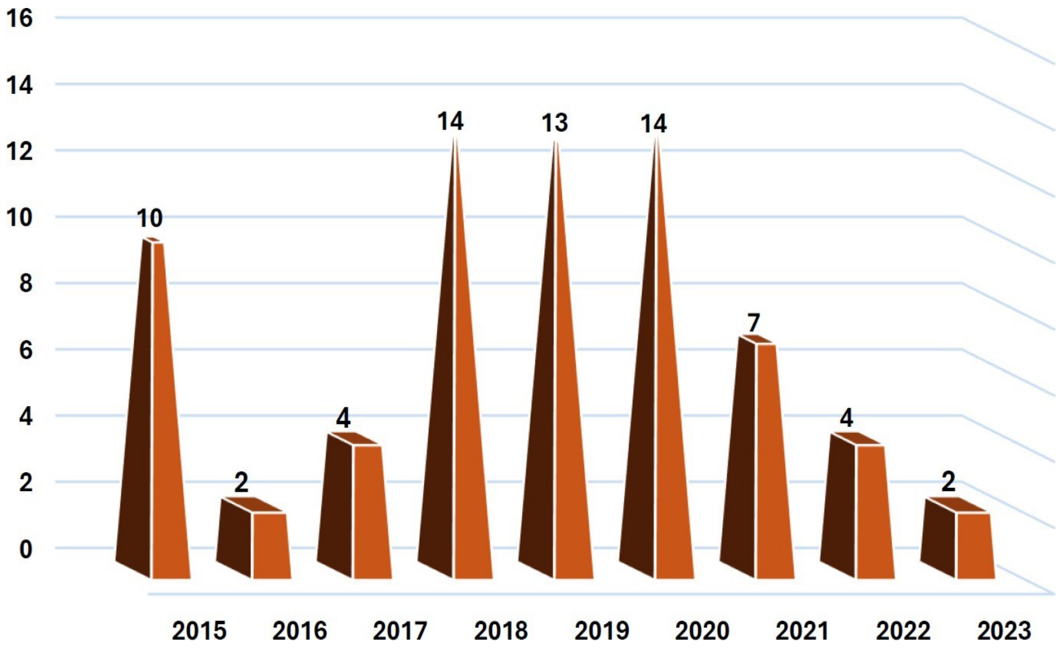

Figure 6: Yearly Distribution of Publications

PAO3: What are the institutional affiliations of the researchers?

The analysis aimed to determine whether SDV development was primarily concentrated in academia, industry, or research centers. The development of all selected papers from Mini Models took place within academia. Two papers on commercial vehicle models emerged from collaborations between academia and industry, while industry research teams published three, and a research center published one. This does not imply a lack of industry interest in SDV development, but it does suggest that competitive pressures may prevent the disclosure of detailed development information in academic papers (Buechel et al., 2015; Buchegger et al., 2018). Except for Apollo, companies often promote their SDV solutions, but rarely clarify the details (Taş et al., 2017).

PAO4: Which nations are the most prolific in contributing to SDV research?

Using SCOPUS data and analysis software, the study identified the most prolific countries, and their citation counts in SDV development. Researchers from 35 countries have contributed to SDV models, with the distribution shown in Figure 7, considering countries with more than one published paper. The United States and China lead in the number of publications but rank lower in citations, indicating less impact in the research community compared to Germany, Japan, and South Korea (Kato et al., 2015; ROS.org, 2020; Autoware.ai, 2020). Germany shows a strong influence, with the highest citation count. Japan, with only one significant publication, has greatly impacted the field by developing the widely adopted Autoware software stack for autonomous driving. Additionally, we created Table 12 to assess the extent of influence of publications from each country.

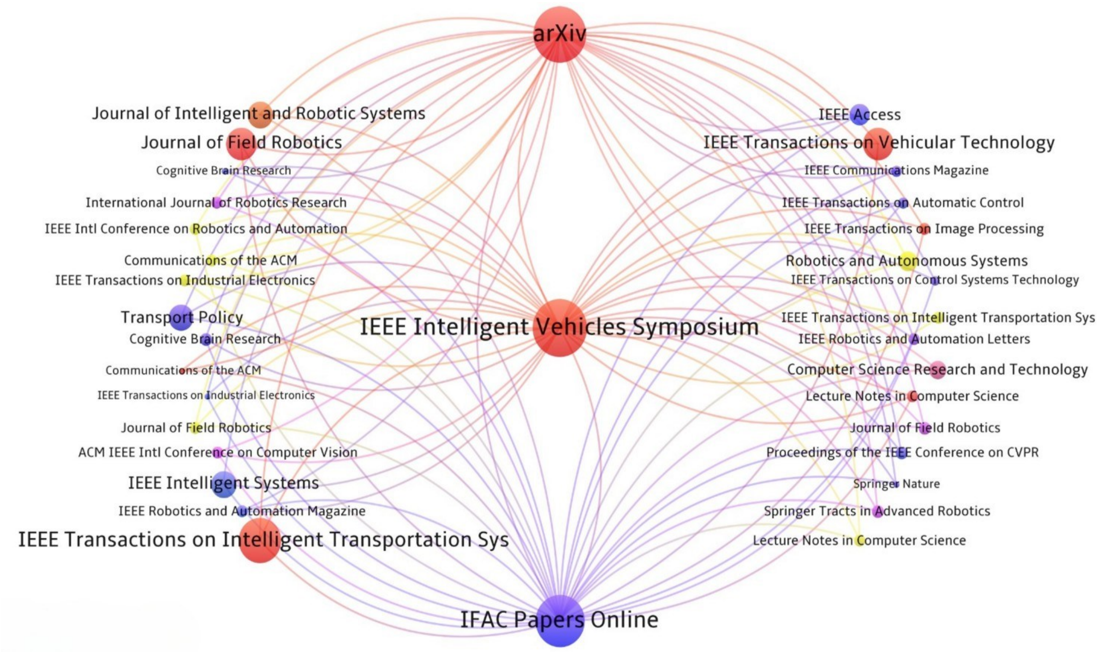

Figure 7: Co-Citation Journals from SDV Model Papers

Table 12: Quantity of Citations by Country

COUNTRY	QTY	COUNTRY	QTY	COUNTRY	QTY	COUNTRY	QTY
Germany	938	China	111	Italy	244	India	64
Japan	395	Vietnam	74	United States	189	France	40
South Korea	370	Brazil	72	Spain	30	Others	2

PAO5: What are the most cited references in the field?

Breakthrough publications can influence an entire research field. Co-citation mapping of references reveals trend-setting papers (Mingers & Leydesdorff, 2015). We applied co-citation analysis to the 85 SDV model papers, filtering out non-relevant entries using references cited at least twice. The resulting 43 references formed four distinct clusters (red, blue, yellow, and purple) in Figure 8. The analysis highlights the pivotal role of the DARPA Challenges and the Grand Cooperative Driving Challenge (GCDC) in advancing SDV technology (Thrun et al., 2006; Kammel et al., 2008; Ozguner et al., 2007). The Journal of Field Robotics significantly influenced the field by publishing research from many DARPA Challenge participants. Key references in the red cluster include milestone studies on supporting technologies like the release of ROS, advancements in image detection and classification, and the development of Autoware for autonomous driving (Geiger et al., 2012; Leonard et al., 2008; Montemerlo et al., 2008; Urmson et al., 2009).

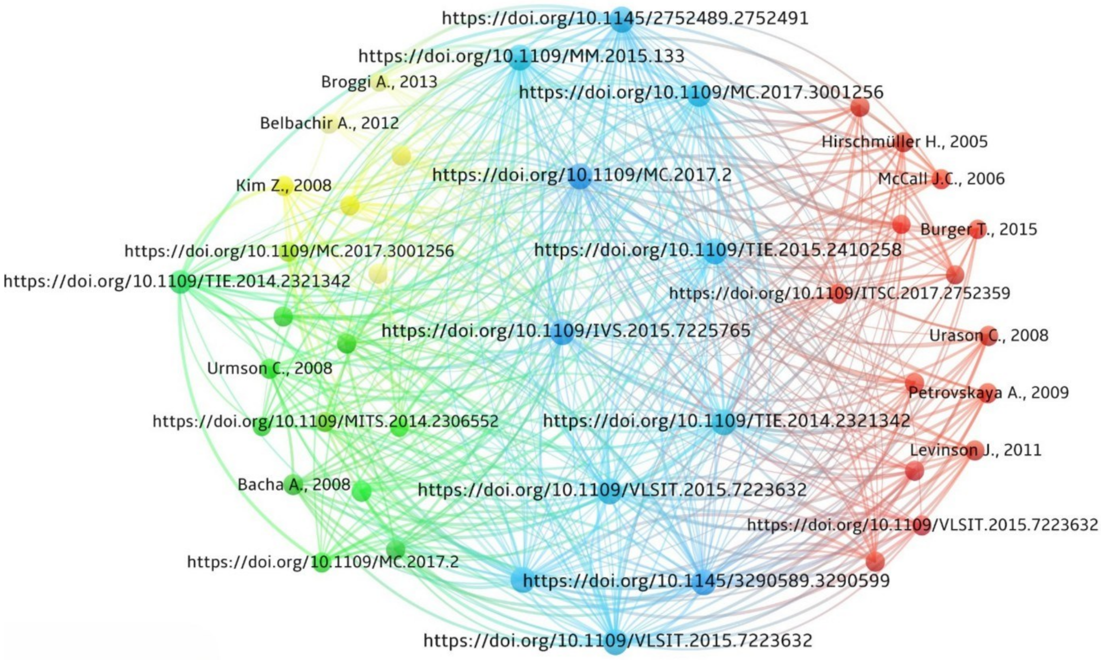

Figure 8: Co-Citation References from SDV Model Papers

PAO6: What are the predominant research themes?

The analysis of keyword co-occurrence reveals the most prevalent concepts within the SDV research field, indicating changes and stability in topics over time (Taş et al., 2016; Quigley et al., 2009; Broggi et al., 2013; Hirschmüller et al., 2005). This helps establish research priorities and academic planning. Excluding keywords that appeared only once, 51 keywords were identified, forming seven clusters, with four main clusters providing relevant insights (Figure 9). The main nodes describe SDVs and related terms. The blue cluster includes keywords related to perception systems, such as lane detection, localization, and tracking. The red cluster focuses on neural networks' application, emphasizing their importance in SDV development. The green cluster is associated with ROS and its role in developing software architectures for motion and path planning. The purple cluster focuses on mini-model development, with keywords like Arduino and ultrasonic sensors (Dickmanns et al., 1990; Levinson et al., 2011; Bertozzi et al., 2013; Chu et al., 2012). Image processing for computer vision, crucial for navigation, remains a popular topic, encompassing lane detection, object detection, localization, deep learning, and vehicle planning systems (Jo et al., 2014; Sedighi, 2016; Fukui et al., 2022).

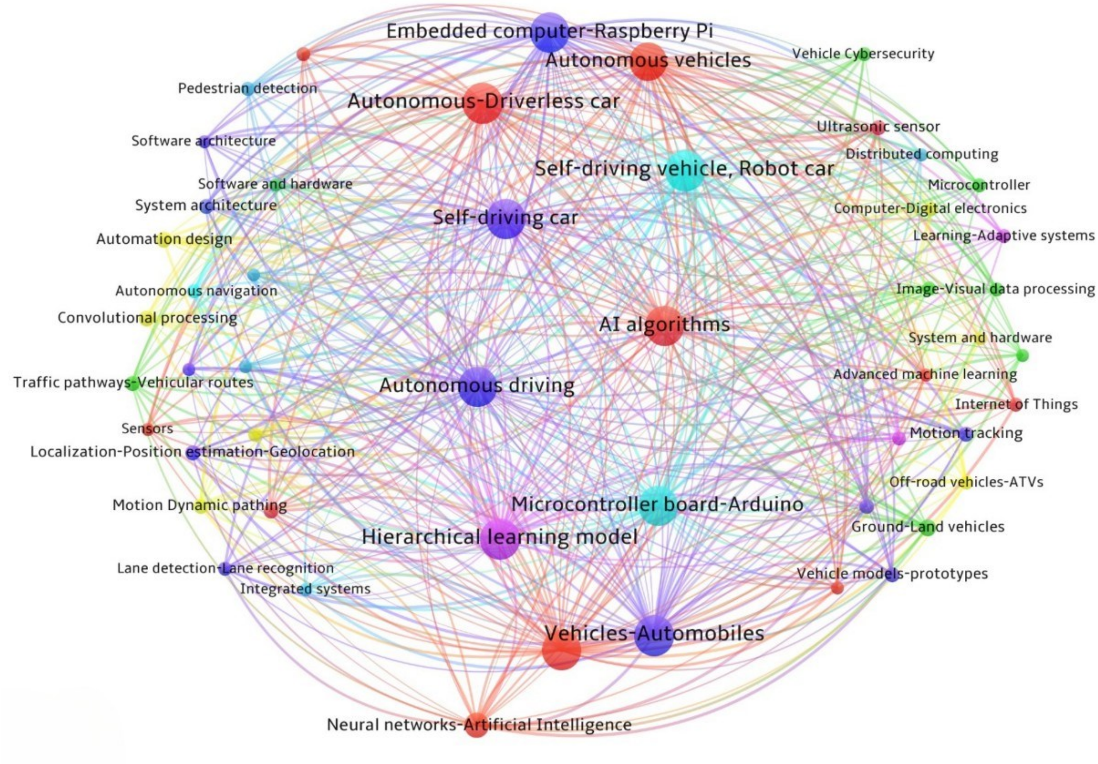

Figure 9: Co-Occurrence Keywords from SDV Model Papers

Unresolved Research Issues

Several SDV models reveal trends in the field, yet they also demonstrate diverse choices in hardware, software, and sensors, offering significant opportunities for further research and exploration. This section highlights some critical research areas in the development of SDV architectures.

5G Network

The advent of 5G networks presents new possibilities for SDV development, addressing issues related to speed and quality of data exchange among vehicles. The newly commercialized 5G network promises one-millisecond latency, 99.999% reliability, 99.999% availability, and a very high throughput of 10 Gbps (Khan et al., 2022). Despite being a new technology, SDVs expect its integration to play a crucial role in their future development. Assessing its impact and comparing it with other technologies is essential.

Robot Operating System 2 (ROS2)

Many studies have utilized the Robot Operating System (ROS) for developing SDV models. This open-source framework offers libraries and communication layers for robotic applications, including SDVs (Munir et al., 2018; Gupta et al., 2015; Taş et al., 2018; Xu et al., 2018; Betz et al., 2019; Ponnan et al., 2022; Ilié et al., 2020; Karaman et al., 2017; Gotlib et al., 2019; Zhou et al., 2019). Other frameworks, like Apollo and Autoware, extensions of

ROS, are also popular (Buyval et al., 2019; Kessler et al., 2019; Marin-Plaza et al., 2019). The evolution of ROS into ROS2 retains its modularity while enhancing real-time performance. ROS2 provides several quality-of-service policies that improve communication efficiency across different networks (ROS.org, 2020). Further research can leverage ROS2 to propose new SDV models and compare their impact with previous versions.

Simultaneous Localization & Mapping (SLAM):

SLAM is a technique that enables vehicles to navigate independently by building maps of their environment and locating themselves simultaneously. LiDAR (Light Detection and Ranging) is a commonly used sensor for this purpose, providing perception, localization, and mapping capabilities. Various research has used LiDAR to support SLAM (Kato et al., 2015; Broggi et al., 2015; Munir et al., 2018; Gupta et al., 2015; Ziegler et al., 2014; Aradi, 2020; Taş et al., 2018; Xu et al., 2018; Betz et al., 2019; Buyval et al., 2019; Ponnan et al., 2022; Ilié et al., 2020; Karaman et al., 2017). However, the high cost of LiDAR, up to $75,000, is a barrier to widespread SDV adoption (Lin et al., 2018). Researchers are exploring alternatives, such as using only cameras to perform SLAM tasks (Kato et al., 2015; Broggi et al., 2015; Munir et al., 2018; Behere & Törngren, 2015; Kunz et al., 2015; Aradi, 2020; Taş et al., 2018; Xu et al., 2018; El Khatib et al., 2020; Do et al., 2018; Walambe et al., 2019; Zhou et al., 2019). Developing alternative sensors or algorithms for image processing and machine learning to use camera data for SLAM is a crucial research area.

Multi-robots and Edge Computing

Multi-robot systems allow different SDVs to work together, such as ground vehicles collaborating with drones to cover larger areas. These systems must use SLAM techniques to perform localization and mapping in parallel across multiple vehicles. Due to SLAM's high processing demands, efficient cloud systems with high-performance edge servers near the vehicles are vital. Edge computing places servers close to vehicles to improve responsiveness and reduce delays and instability from network communication (Fukui et al., 2022; Bilal et al., 2018; Shang et al., 2022; Chattopadhyay et al., 2021). Research in this area is promising, focusing on multi-robot systems and their applications.

Cybersecurity Concerns

SDVs are vulnerable to various cyber threats due to their reliance on interconnected systems and components. Key concerns include the security of electronic control units, sensors (like LiDAR and cameras), and the software algorithms that process sensor data (Pham & Xiong, 2021). Cyberattacks can manipulate vehicle software, disrupt operations, or gain unauthorized control (Chattopadhyay et al., 2021). Robust cybersecurity measures, such as advanced intrusion detection systems and secure design of vehicle components and communication networks, are essential. Ensuring the security of SDVs involves both technological solutions and comprehensive regulatory frameworks.

Level 5 Fully Autonomous Driving

Achieving level 5 automation, where SDVs function reliably in all weather and road conditions, requires significant advancements in sensor technology and AI-based adaptive systems. Innovations in LiDAR technology, such as solid-state and frequency modulated continuous wave (FMCW) LiDAR, offer enhanced detection capabilities. New sensors, like stereo thermal and event cameras, aim to improve perception in challenging conditions. AI-based systems, including mediated perception and behavior reflex approaches, offer adaptability but face challenges in achieving the required reliability for safe autonomous driving. Continued research into AI methodologies is needed to navigate complex real-world scenarios (Kim et al., 2020; Bhadoriya et al., 2022; Li et al., 2018).

System Evaluation

Evaluating SDVs involves several open research challenges that are crucial for ensuring their safe and efficient deployment. High-fidelity simulation environments are essential for testing SDVs in various driving scenarios, including those too risky or complex for real-world tests. Simulators must evolve to use neural rendering for photorealistic reconstructions, enabling adjustments to vehicle trajectories and sensor configurations. Additionally, integrating vehicle-to-everything (V2X) technologies enhances SDV situational awareness but presents new evaluation challenges. Innovative approaches in simulation technology and evaluation frameworks are needed to address these challenges effectively (Hakak et al., 2023; Wu et al., 2024; Rosique et al., 2019).

Comprehensive Discussion

SDV development is a dynamic and multifaceted area within modern automotive technology. This paper systematically re- viewed key aspects of SDV development, including vehicle platform choices, hardware and software architectures, and sensor requirements. Our findings provide insights into the current state and challenges of SDV models, highlighting technological trends, economic considerations, and practical constraints. In this section, we synthesize these insights by addressing the research and publication questions, drawing conclusions from the systematic scoping, and suggesting implications for future research and development in SDV. Our goal is to provide a clear understanding of the current landscape and pave the way for further advancements in this rapidly evolving sector.

Research Question 1 (RQ1):

The analysis of vehicle platform choices for developing SDV models reveals significant insights into current trends and challenges. The shift from conventional gas vehicles to electric and hybrid vehicles marks a crucial development. The limitations of conventional gas vehicles, particularly the delay in vehicle actuation and the need for additional mechanical components, drive this transition, posing challenges in meeting the critical-time reaction limit required for SDVs. This highlights the necessity for more compatible and adaptable platforms. The adoption of electric and hybrid vehicles with drive-by-wire systems signifies a pivotal evolution in model development. These vehicles inherently support the integration of autonomous driving systems, offering a more seamless and efficient approach. This trend also reflects broader market movements, as indicated by the growing use of electric vehicles in recent years. The growing preference for these platforms suggests potential standardization in the future, in line with major manufacturers' announcements.

Furthermore, the choice of vehicle platforms for mini-SDV models highlights diverse approaches within the field. Using DIY vehicle kits and professional RC vehicles indicates a range of strategies researchers adopt, balancing flexibility and convenience. The preference for professional RC vehicles, particularly Traxxas models, underscores their suitability for replicating real-size vehicle performance in miniaturized models. Competitions like the F1 Tenth and Carolo-Cup, which demand high-performance standards, further influence this choice. However, each platform choice presents its own set of challenges and trade-offs. DIY vehicle kits offer greater customization but require more extensive setup and integration of various components. Professional RC vehicles, on the other hand, reduce the burden of implementing basic vehicle controls, but necessitate adaptations for autonomous functionalities. The evolution of vehicle platforms for SDV development reflects a dynamic and adaptive field that responds to technological advancements and practical implementation challenges. The trend towards electric and hybrid vehicles for full-size models and the varied approaches for mini-SDV models demonstrate the continuous search for an optimal balance between technological capability and practical applicability. Future research could further optimize these platforms, considering aspects like cost-effectiveness, ease of integrating autonomous systems, and scalability for real-world applications.

Research Question 2 (RQ2):

Exploring hardware architecture for SDV models highlights a diverse and evolving landscape. The findings illustrate a clear trend toward integrating advanced networking protocols and sophisticated computing systems to meet the demands of autonomous driving. The prevalence of Ethernet and CAN protocols in full-size models underscores the importance of robust and reliable communication systems for vehicle autonomy. The distinction between full-size and mini-SDV model architectures is particularly notable. Full-size models pre- dominantly use high-performance and real-time computing systems, reflecting the complex computational requirements of autonomous driving tasks such as sensing, localization, and planning. This dual-computer setup, where one computer handles real-time vehicle control and another manages high- performance tasks, demonstrates the critical need for both rapid response capabilities and intensive data processing in SDVs. Adopting specific hardware, such as Nvidia Drive Computers and the Intel i7 CPU, across

various models indicates a consensus on the effective balance of processing power and efficiency. However, pursuing less complex and cost-effective solutions is evident in using single-board computers like the Raspberry Pi and Arduino for mini models.
These selections highlight the ongoing challenge of balancing performance with practical constraints such as cost and size. Although less common, developing models with distributed computing architectures presents an interesting alternative to centralized systems. These architectures, capable of managing multiple tasks across multiple units, may offer greater flexibility and scalability for future SDVs.

Research Question 3 (RQ3):
The software architecture for SDV models is characterized by a blend of standardized and customized solutions that optimize performance, modularity, and adaptability. Investigating the software architecture of SDV models highlights several key trends and considerations in the field. The architectural diversity between full-size and mini models reflects the varying requirements and constraints of different vehicle sizes and purposes. Mini SDV models tend to focus on one specific aspect of SDV development, whereas full-size SDVs can implement the full set of software features. Using the Robot Operating System (ROS) as a primary software framework in mini and full-size models underscores its versatility and effectiveness in SDV development. Despite its need to run over an operating system, the adapt- ability of ROS has made it a preferred choice for developers due to its modular design and comprehensive libraries. This choice facilitates the development of complex autonomous driving tasks by promoting modularity and independence between different functions. However, the move towards ROS2, with its enhanced real-time performance capabilities, suggests a continuous evolution in software frameworks to meet the increasing demands of SDV systems.
The integration of other frameworks, such as Apollo and Autoware, and the development of custom solutions, such as π-OS middleware and Project Cocktail, indicate a response to specific limitations or requirements not fully addressed by ROS. This includes low-power edge computing compatibility, reducing communication overhead, and optimizing real-time performance. These developments reflect the field's push to- wards more efficient, scalable, and responsive software architectures. Moreover, the widespread use of software libraries such as OpenCV and TensorFlow, particularly in mini-SDV models, highlights the importance of robust image processing and deep learning capabilities in autonomous driving. The preference for TensorFlow in building and training deep learning models, supplemented by OpenCV for image processing, illustrates the need for advanced machine learning techniques in developing SDVs.

Research Question 4 (RQ4):
Exploring the sensor requirements for SDVs underscores the complexity and diversity of sensor technology needed for effective autonomous navigation. The range of sensors, from

LiDAR and cameras to radar, ultrasonic, and GNSS-RTK- INS/IMU systems, illustrates the multidimensional approach required to address the myriads of challenges in autonomous driving. Despite its high cost, LiDAR's pivotal role in perception and localization highlights the ongoing tension between technological capability and economic feasibility in SDV development.

The move towards more cost-effective solutions, such as integrating 2D LiDAR with cameras in mini models, reflects a pragmatic approach to overcoming budgetary constraints while maintaining functionality. The extensive use of cameras in various forms and configurations indicates their versatility and critical role in object detection, classification, and environmental mapping. The disparity between the capabilities of monochrome and stereo cameras and the innovative use of spherical cameras for 360-degree views points to the continuous evolution and specialization of camera technology in SDVs. Radar's specific application in detecting obstacles, particularly in cruise mode, and ultrasonic sensors' role in low-speed tasks like parking exemplify the need for various sensors to cover different operational scenarios. Integrating these sensors with more sophisticated systems, such as GNSS- RTK-INS and IMU for navigation, further emphasizes the complexity of sensor integration in SDVs. The array of sensors and varying applications across different models demonstrate the field's adaptability and responsiveness to diverse operational requirements and constraints. However, the challenge lies in balancing performance, cost, and complexity, particularly in mini models where processing power and space are limited.

Publication Questions:

The findings reveal a predominant preference for conferences as publication venues over journals. This trend might reflect the field's rapid evolution, where researchers favor faster dissemination platforms to share cutting-edge findings. However, the concentration in a few venues reveals the need for diverse dissemination channels to promote broader discussions. The co-citation analysis highlights influential venues, guiding researchers towards platforms with substantial impact and recognition. The variation in the number of publications correlates with significant technological changes and focuses within the field. Periods of reduced publication activity, such as 2016–2017 and 2021–2022, likely indicate consolidation phases in which the community absorbed and implemented new technological advances or concluded that this field has reached its saturation point.

The predominance of academic institutions in developing SDV models signals a strong foundation in theoretical re- search and innovation. However, the competition between the private sector and the public to lead the market in this field could prevent any industry collaboration. Public research funds, like the prizes offered in the DARPA and GCDC challenges, could provide incentives to overcome this issue. Furthermore, the influence of specific references and competitions emphasizes the importance of foundational studies and practical challenges in shaping the field. These milestones not only guide the research's focus, but also stimulate innovation and collaboration within the community. The wide geographical distribution of SDV research reflects global interest and investment in SDV technology. However, the concentration of publications from specific countries suggests regional hubs of expertise and funding. The analysis of the main research topics reveals a strong emphasis on perception systems, neural networks, and software architecture. The persistent focus on these areas suggests their critical role in advancing SDV technology. Future research should continue to innovate in these core areas while exploring new directions, such as the ethical implications of autonomous driving, integration with smart city infrastructure, and addressing societal impacts.

Future Research Directions

The evolution of SDVs necessitates ongoing innovation and exploration. In addition to the overall discussion and the open research issues, this section outlines future research directions to guide the development of robust SDV models.

Optimizing Diverse Computational Architectures for SDVs

1) ***Efficiency and Performance Enhancement:***

Future research should prioritize the optimization of task distribution across various processors within a multi-architecture system. This entails the creation of adaptive algorithms capable of dynamically responding to the vehicle's computational demands in real-time, ensuring peak performance and energy conservation.

2) ***Specialized Hardware Accelerators:***

Explore the design and implementation of specialized hard- ware accelerators tailored to specific SDV functionalities, such as image analysis or machine learning inference. These accelerators can markedly enhance the processing speed and overall efficiency of critical operations within an SDV frame- work.

3) ***Advanced Software Frameworks for Heterogeneous Computing:***

Innovate sophisticated software frameworks that facilitate the programming and management of diverse computing re- sources in SDVs. These frameworks should support the seam- less integration of CPUs, GPUs, FPGAs, and custom accelerators, enabling more efficient use of heterogeneous computing environments.

Strengthening Cybersecurity in Autonomous Vehicles

1) ***Adaptation to Emerging Threats:***

Research efforts should be directed towards developing SDV systems that can withstand a broad spectrum of cybersecurity threats. This includes the advancement of robust encryption techniques, secure communication protocols, and sophisticated anomaly detection mechanisms.

2) Securing V2X Communications:

As V2X communications are integral to SDV operations, their security must be assured. Future investigations should focus on secure communication protocols and authentication systems to defend against attacks and ensure the integrity of transmitted data.

3) Cybersecurity Testing and Evaluation Frameworks:

Develop comprehensive testing and evaluation frameworks capable of simulating cyber-attacks on SDV systems. This will facilitate the identification of vulnerabilities and the assessment of the effectiveness of cybersecurity strategies.

Enhancing Vehicle-to-Everything (V2X) Communications

1) 5G and Next-Generation Networks for V2X:

Investigate the potential of 5G and emerging communication technologies to enhance V2X communication capabilities. This includes examining the low-latency and high-reliability characteristics of 5G to enable real-time communication between vehicles and infrastructure.

2) Universal Interoperability Standards:

The development of universal interoperability standards for V2X communications is crucial for the widespread adoption of SDV technologies. Research should focus on establishing protocols that facilitate seamless communication across vehicles and infrastructure from different manufacturers.

3) Edge Computing Integration for V2X:

Investigate the integration of edge computing into the processing of V2X communications. Analyzing how data processing can be conducted closer to the source can minimize latency and enhance the responsiveness of SDV systems.

Research Limitations

As in any empirical research, this manuscript faces threats to validity. This section discusses and addresses the main risks associated with this study. This research aims to identify studies that have contributed to SDV models on both a real and reduced scale, discussing important development details, architectures, hardware, and software. The searches returned by the search string and accepted under the defined inclusion and exclusion criteria must necessarily focus on architecture, hardware, or models as the primary goal of the studies. For instance, despite testing on a real model, this paper did not accept approaches that aim to enhance artificial intelligence techniques applied in an SDV context. This mapping, on the other hand, looked at approaches that present SDV models using artificial intelligence techniques. The search string re- turned certain studies that met the inclusion and exclusion criteria, presenting very simple models with minimal contributions compared to other works. This phenomenon was demonstrated in some studies involving mini models of SDVs. However, because our study was a systematic scoping re- view with strict inclusion and exclusion criteria, we included these simple contributions. Therefore, while it is important to acknowledge this information, it does not threaten the study's validity. We included papers with minimal contributions but excluded unsubstantiated information. Finally, it is also important to emphasize that we excluded papers focused on simulations because they would result in many papers, most of which would not present contributions related to real models. However, it is important to acknowledge that some of these excluded studies may significantly contribute to the future of SDV models.

Conclusion

This paper presents a comprehensive systematic scoping review (SSR) of the current technical characteristics of self-driving vehicles (SDVs) in terms of platform, hardware, software, and sensors. Relevant information is also provided regarding the publication venues, countries, author affiliations, and publication years of the selected studies. Although some related works have mapped SDVs through different lenses, such as machine learning applications and employed algorithms, none have specifically focused on mapping the characteristics of SDV models developed in recent years. To address this, a set of research and publication questions was formulated. Out of 551 papers identified through the research string, 85 were selected, with every available detail of the models identified and analyzed. This analysis enabled the construction of a generic overview of the overall SDV architecture, highlighting key differences and unique features to identify innovation possibilities within the field. Major companies have notably withheld some advancements by not making proprietary information publicly available, which limits academic insight. The global search for studies indicates strong academic interest in SDV development, with a clear trend toward electric vehicles as the preferred platform choice. Despite the emergence of generic software and hardware architecture, significant research remains necessary to refine each component. Additionally, a trend to reduce the number of computers in vehicles has emerged. While the SDV sensor set is well-defined, sensors like LiDAR must become more affordable to increase SDV accessibility, despite numerous attempts to minimize their use. This paper serves as a guide for researchers, enabling the design of SDV models at various scales based on the study's findings. Furthermore, the information provided offers a foundation for focusing research efforts on specific fields to facilitate the construction of fully functional SDVs. Future mapping studies could concentrate on various other aspects of the SDV model, including algorithms for specific tasks (e.g., machine learning), model performance aspects, simulation tools, hardware and software testing, security, networking, and edge computing, such as vehicle-to-everything (V2X).

Acknowledgements: We extend our gratitude to Georgia Southern University and the University of Lagos for their library and software support.

Declarations: The authors have no conflicts of interest to declare that are relevant to the content of this article.

Data Availability Statement: All data analyzed during this study is included within the article.

Author Contributions

Qasim Ajao: Conceptualization (equal); Formal analysis (equal); Methodology (equal); Software (equal); Visualization (equal); Writing– original draft (lead). Nicholas Hamilton: Conceptualization (equal); Methodology (equal); Project administration (equal); Resources (equal); Supervision (equal); Writing – review & editing (equal).

Oluwatobi Sodiq: Conceptualization (equal); Methodology (equal); Project administration (equal); Supervision (equal); Writing – review & editing (equal). Patrick Moriarty: Funding acquisition (lead); Project administration (equal); Resources (equal); Supervision (equal); Writing – review & editing (equal).

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