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TOPICAL REVIEW

Quantum Computing for Advanced Driver Assistance Systems and Autonomous Vehicles: A Review

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ABSTRACT Advanced Driver Assistance System (ADAS) has become an essential feature in vehicles, and it is leading to the evolution of autonomous vehicles. But the technologies to implement ADAS suffer from certain inherent limitations, such as latency rate, computational speed, accuracy of the algorithm, security, and privacy, which are also the important factors for realizing full autonomous vehicles. With respect to these hindrances, an in-depth analysis of the existing research has shown that quantum machine learning (QML) can hold a powerful and alternate solution for the development of autonomous vehicles. The perks of quantum computation (QC) over classical systems are apparent with respect to security, privacy, and an exponentially high computation rate. The current review study underlines the benefits of quantum computation and asks for more QML research to improve real-time decision-making in autonomous vehicles, ultimately improving their safety and efficiency. The promise of quantum computing to handle the massive data and computational complexity that classical methods struggle with necessitates new studies in quantum machine learning (QML) for autonomous vehicles.

INDEX TERMS Quantum machine learning (QML), autonomous vehicles (AVs), quantum computation (QC), advanced driving assistance system (ADAS), connected vehicles.

I. INTRODUCTION

Over the past few years, the automotive industry has been concentrating extensively on the development and implementation of various Advanced Driver Assistance Systems (ADAS) with an ultimate aim to realize autonomous vehicles. ADAS is a combination of technologies that assist drivers to prevent accidents, reduce human error, and help with eclectic driving tasks. These systems employ sensors like radar, LiDAR, cameras, and ultrasonic sensors to monitor the vehicle's surroundings, delivering real-time feedback and, in some situations, taking control of the vehicle to avoid accidents. The main goal for implementing these technologies is to increase both driving comfort and safety through regular monitoring of surrounding environmental conditions.

Similarly, the evolution of Vehicle-to-Everything (V2X) communication plays a salient role in the development of autonomous driving. Vehicle-to-Everything (V2X) is a communication system that enables cars to communicate real-time data with one another, surrounding infrastructure, pedestrians, networks, and other entities. Its goal is to increase road safety, traffic efficiency, and driving convenience by allowing cars to adapt proactively to changing driving circumstances. V2X serves as the foundation for many intelligent transportation systems (ITS) and is necessary for the development of self-driving cars. Different types of V2X include vehicle-to-vehicle (V2V), vehicle-to-pedestrian (V2P), vehicle-to-infrastructure (V2I), and vehicle-to-network (V2N), with enabling technologies like dedicated short-range communication (DSRC) and cellular V2X (C-V2X).

Currently, vehicles are equipped with sensors like radar, lidar, ultrasonic sensors, and cameras, where data collected by them is processed to implement driver assistance systems and autonomous navigation. In this regard, machine learning (ML) has become an integral part in the development of

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autonomous vehicles with techniques such as face recognition systems [1], motion recognition [2], object detection [3], [4], object classification [5], etc.

Many ADAS systems and autonomous vehicles depend on vision-based techniques like image classification for perceiving the surrounding environment, like the detection of lanes, pedestrians, obstacles, road signs, traffic signals, etc. Various ML models have been utilized for image classification and recognition. The automobile manufacturers have endeavored to improve the safety of all, including the passengers, vehicles, neighboring vehicles, and pedestrians, through the development of diverse safety systems.

A. ACTIVE AND PASSIVE SAFETY SYSTEMS

The safety-based ADAS systems are broadly categorized into two types: active (or proactive) and passive (or reactive). Passive safety systems are designed to protect the vehicle occupants from injuries that may occur after a collision through proper activation and usage of airbags, seatbelts, and padded dashboards. In the case of active safety systems such as automatic braking systems, lane-keeping assistance, adaptive cruise systems, etc., the decision-making and subsequent control of the vehicle will be automated during a critical driving situation without human intervention.

The substantial growth in automated driving technology offers opportunities for smarter urban mobility but poses some challenges for urban stakeholders. Faisal et al. [6] in his work assessed the status, impacts, and policy strategies for autonomous vehicles in various smart cities, using a systematic review of existing evidence. The review showed the far-reaching impacts of these developments and also pointed out potential research gaps in the field of autonomous vehicles. Kukkala et al. [7] summarized the challenges such as optimized energy usage, adaptation to dynamic weather conditions, mitigation of response delays, and ensuring robust security measures, which need to be addressed in the realm of ADAS. Raouf et al. [8] in their paper explored sensor-based prognostic health management (PHM) of ADAS and emphasized the fault identification and isolation (FDI) techniques while also addressing the existing gaps and challenges that lie in the development of autonomous vehicles (AV).

B. COMPUTATIONAL CHALLENGES AND NEED FOR V2X COMMUNICATION

The next generation of ADAS has started implementing Vehicle-to-Everything (V2X) communication technologies for the expansion of the operational design domain (ODD) of the systems, which offers automated driving solutions that are safe, secure, as well as efficient. Ibrahim et al. [9] use advanced computational models to address power control and spectrum allocation issues in V2X communications. To improve system performance and dependability, the author makes use of optimization techniques including continuous convex approximation and multi-access spectrum allocation. The methods have been validated by simulations, and they demonstrated enhanced vehicular network performance. This highlights the necessity of robust computational strategies for the development of successful V2X systems. Incorporating MATLAB and CarMaker into future research on quantum machine learning for advanced driving assistance systems (ADAS) offers significant benefits. These methods can create large, realistic datasets that simulate a wide range of driving circumstances, which is necessary for training robust quantum models such as Quantum Support Vector Machines. They provide a controlled environment for rigorous benchmarking versus classical algorithms, allowing for exact evaluation of quantum improvements in computational performance and decision-making accuracy. Furthermore, the tools' dynamic simulation capabilities put quantum models' flexibility and robustness to the test under a variety of climatic and vehicular situations. This approach not only improves the practical application of quantum computing in ADAS, but it also fosters interdisciplinary collaboration, which is critical for addressing the complex issues of integrating modern computational technologies into automotive systems. Such strategic integration speed ups the transition from theoretical models to scalable, real-world applications, ensuring that ADAS technologies are both effective and reliable.

Phatnani et al. [10] in their work covered the utilization of computational techniques needed for the improvement of ADAS and V2X systems for Indian roads. Adapting to traffic and dynamic infrastructure changes presents challenges and calls for a large amount of processing capacity for instantaneous data processing and decision-making. In order to successfully handle these complex and dynamic factors, which are necessary for the development of ADAS and V2X systems, the study recommends adopting advanced computational methodologies. Atakishiyev et al. [11] emphasize the computational power requirements that are essential for implementing explainable AI in autonomous driving. The author highlights the need for robust computational resources for handling complex algorithms, real-time data processing, and the generation of interpretable decisions that are crucial for ensuring trust and transparency in autonomous vehicle systems. Liu et al. [12] in their study spoke about the advancements and difficulties in computing systems for autonomous vehicles. The author emphasizes how crucial sensors and machine learning are for improving perception and decision-making. The author lists various significant difficulties, such as enhancing sensor integration and cybersecurity, and provides details on seven critical performance indicators for those systems, including accuracy and power efficiency. From the above discussion, it can be inferred that computing power plays an important role in the successful implementation of technologies like ADAS, V2X, autonomous vehicles, and other associated technologies.

Table 1 reveals several noticeable impediments to progress in the advancement of ADAS, V2X connected vehicle

TABLE 1. Limitations of conventional computing for V2X communication and autonomous vehicles.

Research paper	Objectives	Findings
Kawser [13]	The paper examines V2X communication through PC5 in ADAS, basically focusing on its integrations with LTE, ITS, and essential hardware.	Enhancing V2X privacy and security to overcome cyber threats and address integration and spectrum obstacles.
Grigorescu et al., [14]	The paper defines AI-driven architectures for self-driving cars, concentrating on scene perception, motion control, and path planning.	Need to improve perception systems for real-time object recognition and 3D perception. DL integration in safety-critical systems is challenging due to insufficient ML safety standards, particularly robustness.
Ben Abdessalem et al. [15]	Developing search optimization and neural networks for automated ADAS testing in simulations.	Neural networks and multi-objective search enhance ADAS testing by identifying critical flaws and behaviors missed manually.
Dey et al.,[16]	This paper examines Het-Net's V2I and V2V communications performance using DSRC, Wi-Fi technologies, and LTE.	Address slow data rates, minimum coverage radius, and switching of devices between networks.
Zhang et al.,[17]	The paper introduces a DRL-based decentralized algorithm for optimizing V2I user capacity and ensuring latency and reliability for V2V pairs within ADAS systems.	Training large datasets, sample efficiency, and high computational power requirements are challenging issues.
Parekh et al. [18]	The paper evaluates ADAS research and development in motion control, path planning, cybersecurity, pedestrian detection, and the environment.	Insufficient real-world testing of AI for pedestrian and trajectory planning. Limited research on AV transparency and user psychological impact.
Bharilya et al. [19]	The paper examines ML methods for AV trajectory prediction and compares their accuracy.	The need for better sensor fusion algorithms and improved methods for predicting pedestrian and cyclist behaviors to enhance the accuracy and safety of autonomous vehicle trajectory predictions.
Garikapati [20]	The paper focuses on how AI and learning algorithms in AV can assist in improving security and software quality.	Addressing various security and ethical concerns. Lack of comprehensive frameworks to address algorithmic bias and data bias.
Wippelhauser et al. [21]	Introduction of a method for ADAS prototyping and large-scale V2X testing in complex traffic scenarios using declarative programming in Artery/OMNet++.	Effectively showcased ADAS utility-enhancing design and evaluation in dynamic situations.
Nadezda et al. [22]	The paper develops IoT- and V2X-based ADAS for enhancing the safety of vehicles using various modern protocols and cloud computing.	V2I and V2V implementation enhances ADAS by performance updates and streamlined architecture.
Guo et al. [23]	The author introduces a multi-task learning approach that enables AVs to cooperatively and efficiently identify drivable zones, lane lines, and traffic objects.	Demonstrating the model's efficacy on the BDD100K dataset and emphasizing the importance of comprehensive road scene awareness for AV safety.
Hasenjäger et al. [24]	The authors survey on personalized ADAS, focusing on improving driver acceptance, usability, and continuous interaction.	ADAS maturation includes personalized features and HMI design challenges for continuous driver-vehicle interaction.

technology, and autonomous vehicles. These obstacles include latency issues, the need for extensive training of datasets, limited Wi-Fi technology access, energy packet constraints in communication, and the reliance on reinforcement or deep learning algorithms, which demand substantial data storage and computational power—a limitation of conventional systems. Considering these constraints, introducing the concept of quantum computation as an alternative to conventional computing becomes highly necessary. Quantum computation is renowned for its exceptional ability to tackle problems that are computationally intense thanks to its unique properties such as entanglement [25], [26] and superposition [27]. These properties enable it to perform calculations at a exponential rate, which holds promise for overcoming the aforementioned limitations in the realm of autonomous vehicle development.

C. QUANTUM COMPUTING: A SOLUTION FOR AUTONOMOUS VEHICLE DEVELOPMENT

Quantum systems produce unusual patterns that classical systems are incapable of doing, so it implies that quantum computers may outperform classical computers on machine learning tasks. This field of quantum machine learning explores how to concoct and implement quantum software that could enable machine learning that is faster than classical computers. Recently introduced quantum algorithms like Quantum Support Vector Machine (QSVM), Quanvolutional Neural Network, Quantum-like Bayesian (QLB), etc., which have outperformed some conventional algorithms in certain applications in terms of accuracy and computational speed.

Quantum computation [28], [29] is a combination of quantum physics, computer science, and information theory. This field of computing harnesses the very principle of quantum mechanics in performing certain types of calculations more efficiently than the currently used classical computers. Unlike classical computers, quantum computers use quantum bits, or qubits. Qubits can be entangled, which means that the state of one qubit is dependent on the state of another even if they are physically apart. These computers leverage entanglement and superposition to process and store information in a fundamentally different way than classical computers. This assists them in tackling complex problems, such as cryptography [30], artificial intelligence [31], [32], and material science [33], [34], by solving problems that were formerly intractable for classical computers due to their sheer computational complexity. Practically, quantum computers are still in the early stages of development, and various researchers are working on the technical aspects of these computers so that they can be utilized for solving real-world problems.

Gill et al. [35] give a thorough introduction to quantum computing. The author talks about the theoretical foundations of quantum mechanics and how it can greatly improve computational power compared to classical computing. The author underscores the advancements in quantum hardware and software development and examines the numerous uses of quantum computing in domains such as finance, data science, and drug design. A significant aim is on the obstacles of quantum decoherence and qubit interconnectivity that are important for achieving quantum advantage in the current era of noisy intermediate-scale quantum (NISQ) devices.

Olorunsogo et al. [36] discuss a novel approach in utilizing quantum computing to enhance the development of artificial intelligence (AI). The author talks about the obstacles being faced in the existing AI systems, like algorithmic biases and computational constraints, and suggests that quantum computing, with its more powerful processing power, can solve these problems.

Cao et al. [37] present a quantum neural model for use in quantum neural networks. The author states that by utilizing superposition and entanglement, this model circumvents the linear limitations of quantum mechanics and applies classical neural network functionalities such as nonlinear activation to the quantum domain. The author explains how quantum neurons can process information in superposition and potentially provide computational advantages over classical methods by building both feedforward and Hopfield networks using their applications. The work shows how, using the principles of quantum mechanics, quantum neurons could significantly improve machine learning capabilities.

Dong et al. [38] discuss a novel method of quantum reinforcement learning (QRL). The author amalgamates principles of quantum theory, such as quantum parallelism and state superposition, into classical reinforcement learning frameworks. The key concept of the paper involves representing states and actions as quantum states, allowing for simultaneous exploration of numerous possibilities, therefore exponentially speeding up the learning process compared to classical methods.

Stavdas et al. [39] investigate how software-defined networking combined with quantum key distribution (QKD) might improve security in vehicle-to-infrastructure communications. The author discusses the security flaws in quantum computing and offers a way to protect communications by preventing key interception through the application of quantum mechanics. By combining QKD with software-defined networking and free-space optical (FSO) technologies, network resources can be managed more effectively, guaranteeing a communications infrastructure that is both secure and future-proof for the automobile industry.

Mujoo et al. [40] investigate how to enhance autonomous cars' ability to detect pedestrians by using quantum computing. The author presents a quantum version of the k-nearest neighbors' algorithm that achieves 95% accuracy as opposed to 50%, a major improvement over its classical equivalent. The study shows that massive datasets may be processed more quickly using quantum computing, which raises the possibility of significant advancements in self-driving car safety features. The author also highlights the potential for incorporating quantum computing into automobile technology in the future by stating the theoretical speedup and suggesting a wireless networking framework for real-time data processing.

Mishra et al. [41] discuss a new quantum-secure key agreement protocol tailored for autonomous vehicles. This protocol improves security for communication between users and automobiles as well as between cloud servers and vehicles by utilizing a three-factor authentication mechanism based on the Ring Learning With Errors (RLWE) technique. With its efficient and quantum-resistant design, this protocol is a step forward from conventional approaches and tackles the new risks brought about by quantum computing technology.

Ohzeki et al. [42] explore the method of amalgamating quantum technologies in practical applications, specifically in the control and automation of industrial vehicles. The author discusses the use of quantum annealing (QA) and digital devices for managing the movement of automated guided vehicles (AGVs) in factories without any collisions. The study aims to employ the D-Wave 2000Q quantum annealer to solve optimization problems related to AGV control, formulated as Quadratic Unconstrained Binary Optimization (QUBO) problems.

In the context of the significant advancements in quantum computation, as mentioned above, it can play a crucial role in shaping and propelling the development of autonomous vehicles while addressing the challenges faced in classical computing. Below is an outline of some key benefits of quantum computation that can be harnessed for the development of autonomous vehicles.

- Faster Processing Speed
- Enhancement in fusion of sensors
- Improve Machine learning efficiency
- Increase in Security

Table 2 below demonstrates the evolution of quantum computing research in vehicular technologies, moving from theoretical advancements to practical implications. Fig. 1 shows the graphical representation for the given table.

TABLE 2. Evolution of quantum computing applications in vehicular technology.

Year	Paper	Application	Category
2017	Biamonte et al. [43]	Perception and classify cation	Quantum Machine Learning (QML)
2020	Wauters et al. [44]	Trajectory Optimization	Reinforcement Learning
2021	Noori et al. [45]	Real-time data classification	Hybrid QML models
2023	Khalid et al. [46]	Dynamic control and trajectory tasks.	Reinforcement learning
2024	Zhao et al. [47]	V2X Security	Quantum Cryptography

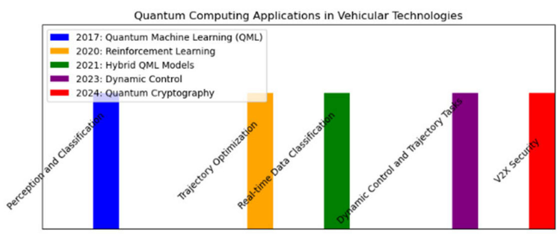

FIGURE 1. Representation of quantum computing applications in vehicular technology.

We propose a strategy for implementing autonomous vehicles through the integration of quantum computation with machine learning, resulting in the evolution of quantum machine learning. Quantum machine learning is a rapidly evolving interdisciplinary field that combines the principles from quantum computing and machine learning.

Wittek [48] investigated how the substantial computational benefits and efficiency gains that quantum computing promises could transform machine learning. The goal of the research is to evaluate if quantum techniques may provide improved generalization performance and how machine learning could benefit from an exponential speedup from quantum computing. Their work provided a comprehensive review of the adaptation of several machine learning methods, including clustering, pattern recognition, regression analysis, and classification, to quantum computing. Ramezani et al. [49] highlighted the theoretical benefits and practical uses of supervised, unsupervised, and semi-supervised quantum machine learning methods. The author concludes that quantum computing has the potential to significantly reduce the computational complexity and improve the efficiency of machine learning algorithms through quantum parallelism, entanglement, and superposition. Various research has been done in the fields of quantum computation and machine learning; some of the research is discussed below.

Song et al., [50] explored how classical cognitive theory assumes human traffic behavior and they examined the pedestrian crossing using a Quantum like Bayesian (QLB)-like model, and they showed that the algorithm's efficiency is better compared to classical, or data-driven models in the case of capturing human unpredictability. In their research, various problems related to autonomous vehicles are discussed, like problems associated with various fragmented scenarios, extreme situations, and unpredictable human behavior. Essentially, the suggestion is that when addressing human behavior in situations involving autonomous vehicles and pedestrians, the classical probability approach might not be adequate due to the innate irrationality and unpredictability of human actions. This leads to the adoption of Quantum Lattice Boltzmann (QLB), which integrates quantum-like behaviour to improve the interplay simulations.

Majumder et al., [51] explore the employment of a hybrid deep-learning model that integrates both quantum and classical layers, offering resilience against various adversarial attacks faced during image classification for autonomous vehicles, in particular traffic sign recognition. By exploiting a classical CNN (convolutional neural network) for feature extraction and incorporating a quantum layer, which utilizes quantum gates, this approach aims at harnessing the quantum mechanical features such as superposition and entanglement. The paper discusses some kinds of attack models, which include the gradient attack, fast gradient sign method (FGSM), project gradient descent attack (PGD), sparse L1 descent attack, and SPSA (Simultaneous Perturbation Stochastic Approximation).

Senokosov et al. [52] have studied the integration of quantum effects and classical models using the approach of hybrid quantum-classical models, which can significantly assist in enhancing the image recognition and classification tasks. This approach was implemented using the two models, firstly, one with parallel quantum layers, and secondly, with a "quanvolutional" layer, showcasing the high accuracy, with one achieving as high as 99% accuracy on the Modified National Institute of Standards and Technology (MNIST) dataset. The postulate suggests that exploiting quantum effects within the neural network holds promise of improving image-related tasks and can have a wide range of applications in various sectors.

Lilja, [53], have highlighted the development of an algorithm that aims at solving trajectory planning problems using quantum computing in the realm of autonomous vehicles. Trajectory planning assists in navigating unfamiliar environments without pre-established routes. An attempt was made to create an algorithm for handling the complex trajectory efficiently.

In addition, the ongoing advancements in the field of quantum computation stand poised to make a significant impact in the realm of autonomous vehicles. The literature survey shows the need for research works to make concentrated efforts aimed at amalgamating the two fields of quantum computation and machine learning to address the multifarious challenges faced by the autonomous vehicles. These challenges entail latency issues, limited access to advanced Wi-Fi technology, the arduous task of training extensive datasets, constraints in communication energy, and heavy reliance on deep learning or reinforcement algorithms, all of which have impeded the pace in the development of the autonomous vehicles. Considering these challenges, the integration of quantum computation, particularly through aspects of quantum machine learning, emerges as a potential solution. This integration holds a promising future in the field of autonomous vehicles by overcoming all those above-mentioned hindrances by enhancing the time complexity and efficiency of the programs, thereby commencing the faster development in the autonomous vehicle domain.

In this regard, our review article seeks to provide a comprehensive examination of quantum computing, emphasizing both its advantages and disadvantages for developing autonomous car technology. It examines how the unparalleled processing power and efficiency of quantum computing could transform driverless cars and the Advanced Driver-Assistance System (ADAS). Thus, our review will provide a wholesome understanding to the readers to explore the possibilities of implementing quantum computing in ADAS and autonomous vehicles.

II. RISE OF QUANTUM MACHINES

A. THE QUBIT

A qubit or quantum bit is the basic unit of information or a two-level quantum mechanical system in quantum computing. This is similar to classical computing. However, classical bits can be only represented as 0 and 1, a qubit can exist in a superposition state that is a mix of both 0 and 1. In quantum mechanics, there is a widely accepted norm to represent an element ψ belonging to an abstract complex vector space as a "Ket" which is denoted by $|\psi\rangle$. The present notation employs the angular brackets and vertical bars, which refers to the mathematical entities as Kets instead of vectors. The notation used helps in emphasizing the unique aspects of quantum states and their abstract mathematical representation within the framework of quantum mechanics. Here, Fig. 2 represents the general representation of the qubit.

$$|\mathbf{1}\rangle = [\mathbf{0}\ \mathbf{1}]' \ |\mathbf{0}\rangle = [\mathbf{1}\ \mathbf{0}]' \quad \text{`}'\text{'} = \text{Transpose} \tag{1}$$

$|1\rangle$ and $|0\rangle$ are the column vectors. These states form the basis of quantum binary systems, which are analogous to bits in classical computing.

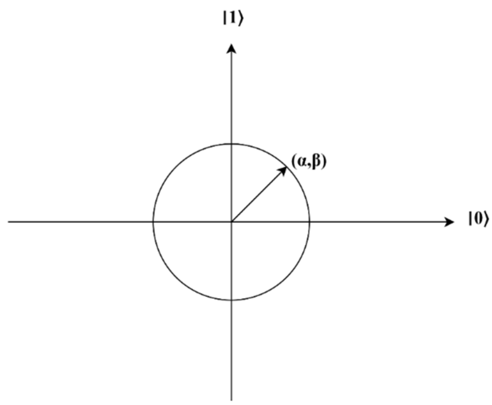

FIGURE 2. Representation of qubit.

B. THE QUBIT STATE

The state of the classical bit is represented by a binary value (11 or 00), while the state of a qubit is described by a vector within a two-dimensional vector space, which is commonly referred to as the state space. This state space is also known as Hilbert space. The quantum system's state is defined using a time-dependent vector $|\psi(t)\rangle$, which encompasses all conceivable information about the system at any given moment. The vector $|\psi(t)\rangle$ belongs to the Hilbert space, and it can vary with time. In quantum mechanics, it is typical to normalize the states.

C. SUPERPOSITION STATE

The principle of superposition stands as a foundational concept in quantum physics. This principle affirms that the states of a quantum system have the capacity to be superimposed or combined, which is analogous to the way classical waves merge to form a coherent quantum state distinct from its individual components. While a qubit can exist in a discrete state as $|1\rangle$ or $|0\rangle$, it also has the capability to exist in a superposition state—a linear combination of these basis states. If the qubit's state is denoted as $|\psi\rangle$, its superposition state can be expressed as,

$$|\boldsymbol{\psi}\rangle = \boldsymbol{\alpha}\ |\mathbf{0}\rangle + \boldsymbol{\beta}\ |\mathbf{1}\rangle \tag{2}$$

In this notation, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are complex coefficients that describe the probability amplitudes of the quantum system being in each respective state. Probability for $|\mathbf{0}\rangle$ and $\mathbf{1}\rangle$ is given by $|\alpha|^{\mathbf{2}}$ and $|\ \beta|^{\mathbf{2}}$.

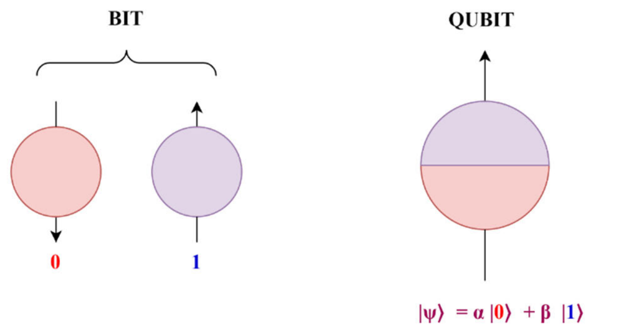

FIGURE 3. Superposition state of qubits.

Here, Fig. 3 represents the superposition state of the qubit, where α and β are complex numbers called the amplitudes of the state of the qubit.

The best way of envisaging the principles of superposition is to consider an atomic qubit that is based on an electron exhibiting its DOWN or UP spin and affected by a magnetic field. The word spin here describes the angular momentum, which can be quantized to mean DOWN or UP (0 or 1). Prior to its measurement, the qubit exists in a superposition state, which implies that it can be in a fraction of 1 or 0, in other words, weighted combinations like 1-63% and 0-37% (the α and β parameters).

The states $|0\rangle$ and $|1\rangle$ can be represented in column vector forms as follows.

$$|0\rangle = [1\ 0]' \text{ and } |1\rangle = [0\ 1]' \tag{3}$$

Basically, the superposition is described by taking the linear combination of the state vectors for the 0 and 1 paths, so the path state is described by a vector, which is analogous to the equation.

$$|\psi\rangle = \alpha[1\ 0]' + \beta[0\ 1]' \tag{4}$$

Zhang et al. [54] explain the idea of superposition as a key idea in quantum computing, focusing on how it allows for quantum parallelism. The fundamental idea behind quantum algorithms' possible speed advantage over classical algorithms is their ability to work on several states at once. The significance of superposition in the larger context of quantum computing research is illustrated by the author's explanation of how it drives the design and efficiency of quantum algorithms.

D. ENTANGLEMENT

Entanglement is a representation of a distinctive form of correlation among the multiple quantum systems, a phenomenon that is absent in the classical realm. In the case of two entangled particles, such as electrons or photons, performing a measurement on one particle instantaneously influences the behavior of the corresponding measurement on the other particle, regardless of their physical separation. These distinctive or peculiar and counterintuitive characteristics led Albert Einstein to call it "spooky action at a distance," since there is no existing known explanation yet as to why it occurs. Therefore, when one qubit is measured, this act of measurement not only collapses its state but also simultaneously collapses the state of the other entangled qubit(s). Fig. 4 clearly illustrates the entanglement process, highlighting the intricate interactions between quantum states. This visual representation enhances our understanding of the theoretical framework discussed previously.

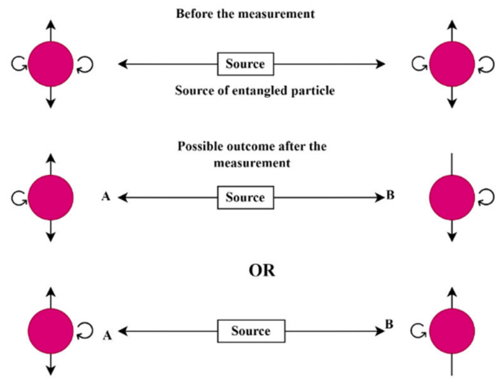

FIGURE 4. Schematic representation of the entanglement process.

E. QUANTUM OPERATORS AND GATES

A logic is a branch of mathematics that focuses on the validity of reasoning from axiom-basis assumptions and the application of legitimate rules of inference to determine the truthfulness of statements. Logic does not establish the absolute truths about the real world; rather, it provides the mathematical foundation where reasonable conclusions are inferred from presumptions. Attempts to codify the laws of mind gave rise to the idea of the logic gate.

Quantum gates are akin to their classical reversible counterparts, which exhibit logical reversibility, yet they markedly differ in terms of universality. In contrast to the minimum three bits required for the smallest universal classical reversible gates, quantum gates achieve universality with just two bits. Certain universal classical logic gates, like the Toffoli gate, which provides reversibility, can be directly mapped onto quantum logic gates. These quantum gates are mathematically represented by unitary matrices. In the context of a qubit or a two-dimensional quantum system, any unitary operator is termed a one-qubit quantum gate. In the quantum circuit model, logical qubits traverse wires, with quantum gates manipulating these qubits. A quantum gate operating on n-qubits has input qubits conveyed through n wires, while another set of n wires carries away the output qubits from the gate. Therefore, quantum gates are represented by 2n x 2n matrices with orthonormal rows. It is noted that single qubit gates, such as Hadamard gates, are depicted by 2×2 matrices.

In mathematical terms, an operator P^ is defined as a set of instructions that, when applied to a quantum state represented by a ket, such as $|\psi\rangle$, results in the transformation of the state into another ket, like $|\psi'\rangle$, within the same vector space. Similarly, when this operator is applied to a bra, it yields another bra.

$$\mathbf{P}^\wedge \mid \boldsymbol{\psi}\rangle = \mid \boldsymbol{\psi}'\rangle \text{ and } \langle \boldsymbol{\Phi} | \mathbf{P}^\wedge = \langle \boldsymbol{\Phi}' \mid \tag{5}$$

DiVincenzo et al. [55] focus on the quantum XOR or controlled NOT gate and offer a thorough analysis of the creation and relevance of quantum logic gates. The historical background of reversible computing is presented, along with the evolution of classical to quantum logic gates and the significance of the quantum XOR gate for quantum entanglement, quantum error correction, and the realization of universal quantum gate architectures. Kauffman et al. [56] explain how some Yang Baxter equation solutions can be paired with local unitary operators to create a universal set of quantum gates. The author illustrates how topological entanglement, quantum entanglement, and quantum computation are significantly related to one another and how these components interact within the context of quantum computing.

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \textbf{ Pauli X} \qquad \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \textbf{ Pauli Z}$$

$$\begin{bmatrix} 0 & -i \\ i & 0 \end{bmatrix} \textbf{ Pauli Y} \qquad 1/2^{0.5} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \textbf{ Hadamard gate}$$

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \textbf{ CNOT}$$

FIGURE 5. Representation of various quantum gates.

From Fig. 5, one can illustrate various fundamental quantum gates like Pauli X, Y, Z, and the Hadamard gate that manipulate qubit states through flips and phase shifts, and the CNOT gate, salient for entangling qubits and the creation of superpositions.

F. QML ALGORITHM

Quantum computers were first developed several years ago, and presently, quantum computing (QC) technology offers a range of platforms, each excelling in a specific domain. The potential applications of quantum computing are diverse and hold promise for various fields. The notion of enhancing classical machine learning through quantum computing has been under consideration for quite some time and is not as novel or groundbreaking as some might perceive. Demonstrations of machine learning using D-Wave quantum annealers, for instance, can be traced back to as early as 2009 [57].

Quantum computers assist in harnessing the power of quantum parallelism by processing all the quantum information, which is encoded in a superposition of all the potential inputs, which enables simultaneous computation of all output values for all the inputs. The emergence of quantum computation and association with algorithms treads its way back to David Deutsch's work on universal quantum computation in 1985 [58], which was built upon earlier concepts introduced by Feynman [59].

The quantum machine learning discipline is applied in several fields concentrating on various facets of quantum computation and communication; these include

- Formulation of quantum algorithms for both communication and computing.
- Advancement in the development of hardware tailored for quantum communication and computing.
- Enhancement in the scalability of quantum computing systems.
- Exploring various solutions for robust fault tolerances in quantum systems.
- Seeking meticulous proofs of the universality of quantum computation
- Designing various quantum algorithms specifically for the applications in machine learning.

These multifaceted undertakings have collectively contributed to the understanding and evolution of quantum computing, which contributes many innovative algorithms, advanced hardware, various fault-tolerant strategies, scalability improvements, assorted machine learning applications, and the endeavor of universal computational capabilities.

In 1994, the introduction of quantum algorithms by Peter Shor aimed at efficient factorization of prime numbers [60]. This pioneering algorithm gave the demonstration of a significantly faster computational capability as compared to classical methods. Therefore, the emergence of quantum computing posed a freshly discovered security challenge. Codes such as Rivest-Shanir-Adleman (RSA), which were considered secure based primarily on unproven mathematical complexity assumptions have abruptly become vulnerable. This threat arose not from the lack of mathematical proof but from the emergence of the novel computing paradigm, which was governed by the laws of physics.

Paradoxically, the solution to the challenge of unconditional security has been offered by quantum theory in quantum key distribution (QKD). Even quantum computers cannot compromise the security provided by quantum cryptography.

Peral García et al. [61], in the paper review all of the research on quantum machine learning (QML). It uses systematic literature review approaches to categorize and analyze various quantum machine learning algorithms and their applications. The study shows that despite the present limits in quantum computing, QML has potential in a number of sectors, such as finance and chemistry. It highlights the quantum versions of conventional machine learning algorithms like k-nearest neighbors and support vector machines. Tychola et al. [62] give a thorough analysis of QML, or quantum machine learning, and how it relates to traditional machine learning. The author investigates how QML can be able to handle complicated datasets more effectively than traditional techniques, especially by contrasting the algorithms of Quantum Support Vector Machine (QSVM) and Support Vector Machine (SVM). Notwithstanding the present constraints of quantum technology, the results show that QSVM can perform better than SVM in complicated settings, pointing to a bright future for QML in fields like generative models and unsupervised learning.

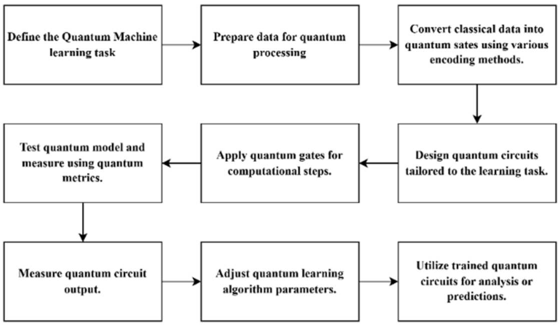

FIGURE 6. **Schematic representation of the working of QML algorithms.**

Biamonte et al. [43], explore how quantum computing speeds up certain activities, like data classification and sampling, which may improve machine learning through the use of quantum algorithms. Despite the present hardware restrictions, the author highlights the theoretical underpinnings of quantum machine learning (QML) and looks at real-world applications. It also provides insights into the future of QML by highlighting quantum algorithms that may perform better in machine learning applications than their conventional counterparts. Fig. 6 outlines the sequential process of representing a quantum machine learning model, defining the steps from task definition to the culminating deployment of the model.

G. QUANTUM COMPLEXITY

The complexity of a problem is related to various factors, including computing time, algorithms, and other elements. Evaluation of the overall computational cost requires analyzing resources through the execution of various necessary algorithms to solve the problem. The time taken by a computer to run an algorithm is the runtime of that algorithm on that explicit computational platform. Computational complexity measures how the algorithm's requisites for space, time, and other resources grow as the size of the dataset or complexity of the problem increases. The algorithm is typically used on the new datasets or functions to discover specific properties, like factoring numbers, finding patterns, organizing data, and determining minimum values.

As an algorithm's problem size increases, so does the running time. This phenomenon is called time complexity. The varieties of time complexities include:

- Polynomial time complexity
- Constant-time complexity
- Non-polynomial time complexity

Pelayo et al. [63], introduce methods that are devoted to complexity problems, quantum algorithms, and the mathematics behind them. It seeks to bridge the gap between computer science, physics, and mathematics by concentrating on the benefits of intrinsic parallelism in computational tasks resulting from the superposition of quantum states.

H. INTRODUCTION TO QUANTUM FEATURES MAPS

Traditional machine learning approaches often require transforming their input data into an alternative space. This transformation is done either to make the data more convenient to work with or because the new space offers properties that are beneficial for the model analysis. An illustration of this is the Support Vector Machine (SVM). Classification of data by SVM uses a linear hyperplane. A linear hyperplane works effectively when data is inherently linearly separable in the original space; however, this is unlikely to be true for many datasets. To address this, a workaround involves the transformation of data into a new space, which achieves linearity through a feature map.

Let φ be the set of input data and ↿ be a feature space. Then a feature map Ω is defined as:

$$\boldsymbol{\Omega} : \boldsymbol{\varphi} \rightarrow ↿ \tag{6}$$

The output data points $\boldsymbol{\varphi}(\mathbf{x})$ on the output map are called feature vectors. Here, ↿ is a vector space. The relation of the transformation is shown in Fig. 7. When training data from two datasets in the original space are presented, a simple linear model is not enough to separate them. But when this data is mapped to a higher-dimensional feature space, even a complex linear model is inadequate for creating a separable hyperplane that acts as the decision boundary [64].

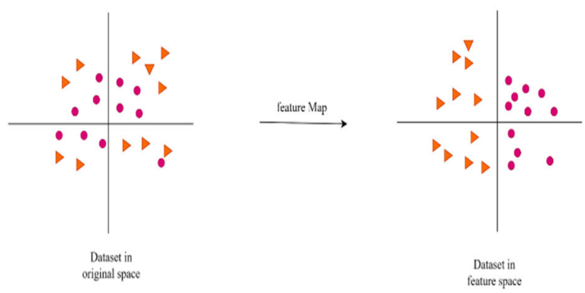

FIGURE 7. **Depicting the quantum feature space transform.**

Chen at al. [65] in their study covered the creation of quantum feature maps for quantum-enhanced support vector machines (QSVMs), which provide effective access to high-dimensional Hilbert space. A genetic algorithm and variational circuits with hardware-efficient ansatz and unitary decomposition are the two approaches that are being discussed. The research presents the use of these techniques in generating precise classifications with different gate costs and accuracies using datasets such as moon shapes and ad hoc datasets. Suzuki et al. [66], present the quantum circuit model for the conversion of input data into qubits nonlinearly. Without actually building a classifier, the work shows how to determine the minimal accuracy for training datasets with a given feature map and kernel. The author discusses how classification accuracy varies with different encoding functions by applying the quantum SVM algorithm to multiple nonlinear 2-dimensional datasets. Altares-López, et al. [67], discuss a multi-objective genetic method that may be used to automatically create and optimize quantum classifiers using QSVMs and quantum feature maps. The method entails experimenting with parameterized quantum circuit topologies to optimize accuracy while reducing circuit complexity. The algorithm evolves quantum circuits across generations using genetic operations like crossover, mutation, and selection. Schuld et al. [64] describe how a kernel and then a unique Reproducing Kernel Hilbert Space (RKHS) are generated from a feature map. The author shows how one can associate the Hilbert space of a quantum system with an RKHS in order to integrate quantum mechanics with kernel theory.

I. QUANTUM EMBEDDING

Generally, a quantum algorithm is fed input data to generate a result. The input data should be such that it can be manipulated on the quantum computer. Contemporary applications of quantum machine learning today use quantum feature maps for mapping classical data into quantum data in Hilbert space. This is a very salient aspect of designing various quantum algorithms, which has a direct impact on the computational cost. This process is referred to as quantum embedding, and it involves the conversion of classical x data into a set of gate parameters in the quantum circuit, creating a quantum state $|\psi_x\rangle$ [68], [69]. Gianani et al. [70], in their work, investigated the optimization of quantum state embeddings through manipulation of atomic internal states and superconducting platforms. Their focus was on the practical application of quantum embedding for machine learning. Using various experimental platforms, the study illustrates how classical information can be embedded into quantum states. It also emphasizes the fidelity and clustering of the resulting quantum states from the embedding process. Li et al. [71], address the cooperative development of high-level quantum solvers, quantum devices, and quantum embedding in order to solve strongly correlated chemical systems. It makes recommendations for ways to advance quantum solvers and embedding strategies in order to increase the precision and effectiveness of simulations for big molecular systems. The study highlights the possibilities of quantum computing in theoretical chemistry by imagining the applications of effective Variational Quantum Eigensolver (VQE) algorithms for complex chemical systems. In order to achieve quantum machine learning on near-term quantum devices, the research presented by Chen et al. [72] addresses a unique architecture that combines quantum embedding with transformers. It employs a vision transformer (ViT) in particular to improve the quantum embedding capabilities, presenting empirical proof of its relevance to contemporary quantum machine learning issues, such as raising the classification accuracy on high-dimensional datasets. Sun et al. [73], explored wavefunction treatments and the idea of quantum embedding in Density Functional Theory (DFT). The application of the wavefunction in density functional theory (DFT) embedding examines the excited state properties. Additionally, the various challenges associated with combining wavefunction methods with density functional approximations had been discussed. In order to provide a more thorough examination of embedding formalities based on richer quantum variables, the study also examines Green's function embedding, which is frequently employed in condensed matter problems and in quantum chemistry.

J. INFORMATION ENCODING

There are diverse methods that can be used for encoding the information into an n-qubit system, which are characterized by a state. The nature of encoding typically varies depending on the characteristics of the datasets and the specific problem at hand. In the domain of quantum machine learning and data mining, the significance of encoding is of the utmost salient. Quite few methods of encoding involve basis encoding, tensor product encoding, amplitude encoding, and Hamiltonian encoding. For the preparation of a quantum algorithm as a quantum state, a quantum circuit can be defined, which prepares the corresponding state. This circuit can be produced through various classical preprocessing steps, which are illustrated in Fig. 8.

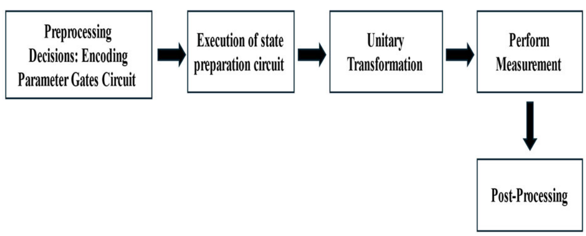

FIGURE 8. Preparing classical inputs for quantum algorithms [25].

III. QML VERSUS CLASSICAL ML

The process flow for quantum machine learning (QML) and classical machine learning algorithms share structural similarities but differ in the nature of their particular steps because of the underlying computational paradigms. In quantum machine learning (QML) the process begins with the definition of quantum-specific machine learning task, which highlights the need for problems that leverage quantum computation's advantages. Then, the input data is prepared in the format that is suitable for quantum processing, emphasizing the need to encode the classical data into the quantum states. This is followed by designing a quantum circuit for the particular machine learning task, which is an essential step only unique to quantum machine learning (QML). Applying quantum gates for performing operations and measurement of quantum circuits are the QML-specific steps, which involves quantum state manipulation and observation. In contrast, the classical machine learning (ML) flowchart begins with the definition of a problem without any computational paradigm constraints. Data preprocessing, splitting of dataset into training, testing, and validation sets, and model selection are the steps being shared conceptually with quantum machine learning (QML) but are grounded in classical computation. Training, evaluation, and deployment are analogous to quantum machine learning (QML), which is also carried out within the classical computing framework.

Quantum machine learning (QML) offers a set of theoretical advantages over classical machine learning (ML) that is largely derived from the unique properties of quantum mechanics. Quantum machine learning (QML) has the potential to outperform classical machine learning (ML) in several aspects. These include handling data more efficiently, managing high-dimensional data and complex computations, designing quantum circuits, performing quantum measurements, and utilizing quantum learning algorithms that offer speedups for specific tasks. Table 3, represents the comparison between the QML and classical ML. In essence, quantum machine learning (QML) holds a promise for the certain types of computational tasks, especially those that involve large-scale data and complex model patterns. It is currently more of a complement to classical ML than a replacement, with its effectiveness highly dependent on ongoing advances in quantum computing technology.

When comparing quantum machine learning (QML) to classical techniques, it is critical to understand the quantum routines that underpin QML algorithms and their applications. As shown in table 4, quantum procedures such as Grover's algorithm, variational quantum circuits (VQC), and HHL algorithm enable breakthroughs in support vector machines, neural networks, and reinforcement learning. Variational Quantum Circuits (VQC) allow for the development of Q decision trees, circuit-centric quantum classifiers, and deep reinforcement learning approaches, providing diverse solutions for classification and decision-making. The HHL algorithm enables quantum principal component analysis (QPCA), quantum linear regression, quantum support vector machines (QSVM), and quantum least squares, all of which are useful for high-dimensional data analysis and optimization. Q k-Means and Quantum Phase Estimation help in clustering and unsupervised learning. Grover's algorithm is used in sophisticated applications such as Q-K Median, Q Neural Networks, Q Perceptron Models, and QKNN to provide rapid data retrieval and predictive modeling. These routines emphasize QML's unique capabilities to address issues that are computationally intensive for classical approaches, particularly in high-dimensional and complicated data settings. For more information, refer to the papers being provided.

TABLE 3. Comparison between quantum machine learning (QML) and classical machine learning (ML).

Step	Quantum Machine Learning	Classical Machine Learning
Defining the problem	Defining the specific quantum learning task suitable for quantum computation.	Defining the problem that is addressed with the model.
Preparation of data	Preparation of the input data in a format that is suitable for quantum processing.	Gathering data from different sources.
Data Encoding	Encoding the classical data into quantum states.	No need for any conversion.
Model Design	Designing a quantum circuit specifically for the machine learning task.	Selection of the model based on the problem. Problems can be classification, regression, etc.
Model Operation	Applying quantum gates to do operations.	No gates are needed for this to function.
Model Measurement/ Testing	Quantum learning algorithm, adjustment of the parameters in the quantum circuit.	Tuning and optimizing the model
Adjustment/ Learning Alg orithm	Model evaluation and deployment (making predictions and analyzing)	Iterating the algorithm and tuning the parameters based on the testing and validation results.

A. PROSPECTS OF QML IN AUTONOMOUS VEHICLES

Quantum Machine Learning (QML) is emerging as a transformative technology with tremendous promise to improve the functionality and capacities of self-driving vehicles (AVs). By leveraging quantum mechanics concepts, QML provides solutions that have the potential to exceed classical machine learning systems in terms of speed. Accuracy, and efficiency. This QML integration in AV systems solves a wide range of complex challenges, including real-time data processing and decision-making, as well as security advancements and operational optimization. The table 5 below lists specific use cases for QML in autonomous vehicles, highlighting how these complex algorithms are being used to improve many areas of AV technology. Each entry in the table provides insights into diverse domains where QML has been effectively implemented or has significant potential, demonstrating the breadth of influence quantum computing could have.

These examples showcase the significant potential of QML in autonomous vehicles by reducing latency, increasing computational speed, and improving algorithm correctness. Autonomous vehicles can achieve safer and more efficient

TABLE 4. Overview of existing quantum machine learning algorithms.

Key Quantum Techniques	Applications of Quantum Machine Learning
Variational Quantum Circuit	Q decision tree [74] Circuit-centric quantum classifiers [75] Deep Reinforcement Learning [76]
HHL Algorithm	QPCA [77] Q Linear Regression [78] QSVM [79] Q Least Squares [80]
Quantum phase estimation	Q k-Means [81]
Grover's Algorithm	Q- K Median [82] Q K-means [81] QKNN [83] Q Neural Network [84] Q Perceptron Models [85]

TABLE 5. Quantum computing advances in autonomous vehicle technologies.

Key Applications	Research & Contribution	Reference
Optimization of Path planning	Quantum Reinforcement Learning (QRL) optimizes navigation paths, enhancing decision accuracy uncertainty	Team et al. [86]
Sensor Fusion and Data Processing	QSVM and QPCA enhance traffic pattern classification and data noise reduction, improving obstacle detection and sensor fusion.	Zhuang et al. [87] Zhao et al. [47]
Real-Time Decision-Making	QCNNs accelerates feature extraction and object recognition, significantly reducing latency and improving response times in complex environments.	Baek et al. [88]
Cryptographic Security	The paper proposes using QKD with FSO technology in V2I networks for secure, unbreakable key exchanges, significantly enhancing communication security in autonomous vehicle systems.	Stavdas et al. [39]

operations by incorporating QML algorithms into perception, planning, and decision-making systems, which represents a substantial advancement in real-world applications.

B. PRACTICAL CASE STUDY: INTEGRATION OF QSVM IN ADAS

Quantum computing (QC) is poised to transform ADAS and self-driving vehicles by providing considerable gains in processing speed and accuracy, which are critical for effective real-time decision-making. While conventional vehicular technologies rely heavily on classical computing frameworks, quantum algorithms' unique characteristics enable creative solutions to existing limits, particularly in cases requiring rapid responses with high stakes.

The studies in this paper conducted to evaluate the performance of quantum support vector machines (QSVM) when integrated into advanced driver assistance systems (ADAS), with a focus on improvements in computational speed and accuracy. The experimental set-up was quite similar to real-world vehicle sensory processing conditions. Data for these experiments are obtained from Kaggle, which supplied extensive, diversified datasets on autonomous driving and sensory processing. The simulations were carried out utilizing a hybrid quantum-classical framework. IBM's Qiskit was used to implement quantum algorithms, including QSVM, on cloud quantum computers like Osaka. Preprocessing and interaction with ADAS components were accomplished using Python and Tensor Flow. The hardware setup consisted of a high-performance classical computing system (NVIDIA GPU-enabled server) combined with cloud-based quantum computing capabilities. These experiments demonstrated QSVM's ability to significantly reduce preprocessing latency and improve decision-making accuracy, especially in high-speed computations and dynamic environment. Extreme scenarios in autonomous driving, such as sudden weather changes, emergency maneuvers, and unexpected pedestrian movements, require ADAS to respond quickly and reliably. Classical systems, while capable, frequently have limitations in processing speed and accuracy in such dynamic environments. However, quantum computing introduces a paradigm change by allowing complex information to be processes at unprecedented speeds because to quantum parallelism and entanglement. The following experiment was based on three types of datasets.

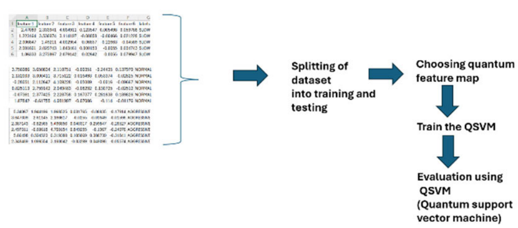

FIGURE 9. Discuss the flowchart of QSVM being implemented for Numerical dataset.

1) Numerical dataset-Inertial Measurement Unit (IMU) sensor to determine driving style- slow, normal aggressive. Fig. 9 gives the detail working of the steps being carried out.

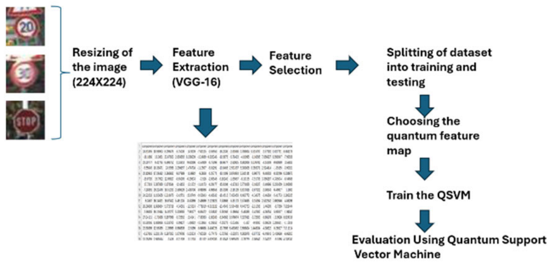

FIGURE 10. Discuss the flowchart of QSVM being implemented for gray scale image datasets.

2) Image dataset-Gray Scale Image to determine driver monitoring system- no-yawn, yawn, eye-open, eye-closed. Fig. 10 gives the detail working of the steps being carried out.
3) Image dataset-RGB Traffic Sign Recognition- only two signs were considered (Speed limit(20,30, 40, 60) and stop signs). Fig. 11 gives the detail working of the steps being carried out.

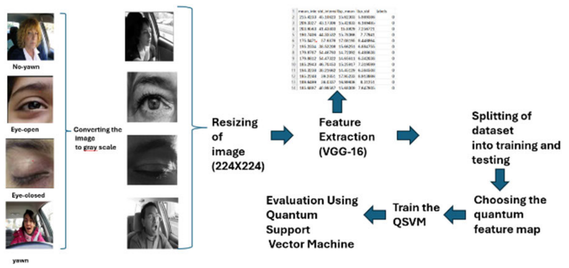

FIGURE 11. Discuss the flowchart of QSVM being implemented for RGB image datasets.

Steps for implementing QSVM

1) Problem Definition:
   - Identify ADAS computational issues.
   - Highlights areas for quantum improvements, here: accuracy and speed.
2) Preprocessing:
   - Clean and normalize the dataset.
   - Handle missing values (if any).
   - Feature extraction (using VGG-16 [153] for image data).
   - Feature selection (using PCA [154] for dimensionality reduction).
3) Quantum Preparation
   - Choose Quantum Feature Maps to transform classical data into quantum data
   - Encode pre-processed data into quantum states.
4) Quantum Computation
   - Build Quantum Kernel to measure data points similarities in quantum space.
   - Calculate Kernel Matrix based on quantum kernel outputs.
5) QSVM Training:
   - Train Quantum Support Vector Machine (QSVM) using the kernel matrix.
6) Performance Evaluation:
   - Compare QSVM with classical SVM.
   - Assess QSVM in terms of computing speed and accuracy.

The following table 6 demonstrates the comparative result between QSVM and classical SVM across different types of datasets.

TABLE 6. Represents the best accuracy and computational time being obtained for three different datasets after doing several iterations.

Type of dataset	QSVM Accuracy (%)	QSVM Computational Time (ms)	Classical SVM Accuracy (%)	Classical SVM Computational Time (ms)
Numerical dataset	53	25	36.67	173
RGB Images	62	62.92	37.50	158
Gray scale images	50	56.98	50	75.1

According to the data from the table, Quantum Support Vector System (QSVM) outperform classical SVM in terms of both accuracy and computing time across a wide range of datasets, particularly numerical and RGB images. These advantages are most likely attributable to quantum computing's inherent features, such as the ability to handle complicated, high-dimensional data sets more efficiently and the possibility of speedups via quantum parallelism.

The fact that grayscale images performed equally well in terms of accuracy implies that the benefits of QSVM may vary depending on the unique qualities of the data being processed. As a result, while QSVM has considerable potential to improve Advanced Driver Assistance Systems (ADAS) through increased speed and accuracy, its use should be tailored to individual demands and data types in order to optimize its benefits.

This experiment reveals that QSVM can be a valuable tool in the creation of more efficient and effective ADAS, helping to enhance autonomous vehicle technologies by enhancing real-time processing capabilities and system accuracy.

C. NEW INSIGHTS AND CONTRIBUTIONS OF QUANTUM APPROACHES

The introduction of quantum techniques in this section offers the groundwork for understanding how quantum machine learning (QML) can overcome the major issues confronting present ADAS systems. By delving into core concepts like qubits, entanglement, superposition, and quantum gates, readers will gain an understanding of the distinct advantages that quantum systems provide, such as improved computational speed, parallelism, and the capacity to process high-dimensional data more efficiently. These features are critical for overcoming the limits of traditional systems, notably in real-time decision-making and data management, which are required for the advancement of self-driving vehicles. As quantum computing advances, integrating QML into ADAS algorithms has the potential to greatly improve safety, accuracy, and efficiency in autonomous driving technologies. The above sections cover the technical background required to comprehend QML's future impact in autonomous systems, as well as its relevance and importance to the overall discussion in this review.

IV. DEVELOPMENT OF ADAS

Advanced Driver Assistance Systems (ADAS) enhance both the safety and comfort of driving. ADAS bounds technologies that are designed to enhance, automate, and optimize the vehicle safety, aiming at assisting drivers in accomplishing an improved and safer driving experience. Numerous ADAS technologies include ACC (Adaptive Cruise Control), forward collision warning system, lane departure warning system, TSR (traffic signal recognition system), TPMS (tire pressure monitoring system), pedestrian detection, night vision, automatic emergency braking system, parking assistance system, Electronic Stability Control (ESC), driver drowsiness detection system, and more [89]. Spicer et al. [90] in their study, estimated the effectiveness of Toyota's Advanced Driver Assistance Systems (ADAS) in preventing crashes using survival analysis. The research analyzed various police crash reports from eight states in the United States, which focus specifically on the types of accidents relevant to the system's capabilities, such as rear-end collisions and incidents related to pedestrians. According to this study, cars with automatic emergency braking (AEB) had a much lower risk of being hit in front-to-rear collisions than cars without the system. Similarly, run-off-road and pedestrian strike accidents were less likely to occur when Lane Keeping Assistance (LKA) and pedestrian AEB systems were installed. Dollorenzo et al. [91] discuss the continuous evolution of the automotive industry and the need for research to increase the system's autonomy. They proposed a novel method to improve Advanced Driver Assistance Systems (ADAS) test maneuvers in line with European regulations. This method involves automating data collection and analysis for Lane Support System, Autonomous Emergency Braking (AEB), and Car to Pedestrian Nearside Child (CPNC) systems. The study attributes a notable decline in fatal traffic accidents to ADAS, highlighting its significance in enhancing vehicle safety and lowering the probability of collisions.

Advanced driver assistance systems' primary focus is to make driving more automated and less stressful for drivers. The key element that enables these technologies is the array of sensors. Numerous sensor types are being employed; some of these include vision sensors, RADAR sensors, LiDAR sensors, ultrasonic sensors, and various other technologies, including global positioning sensors (GPS) and photonic mixer devices (PMD). The vision-based sensors make all the decisions based on the images being acquired, which further undergoes postprocessing techniques for image processing and segmentation for the identification of various features. These segmented images are then used for the identification and classification through different machine learning algorithms and neural networks.

ADAS is a major advancement in vehicle technology that will lead to safer and more automated driving. Advanced computation plays a key part in ADAS capability for processing real-time data from a variety of sensors to carry out essential tasks like navigation, obstacle recognition, and driver assistance. Li et al [92], discuss the algorithms used in ADAS, basically focusing on how they process data from various sensors like radar, cameras etc to perform various functions such as collision avoidance, lane keeping, and object detection. The author highlights the integration of various machine learning techniques for enhancing the accuracy and efficiency of these systems, detailing how these various algorithms can help in interpreting complex environmental data to make real-time driving decisions. The aforementioned aspects are crucial in advancing ADAS towards more autonomous capabilities, which suggests a direction for future research in developing more practical and reliable algorithms. In the subsequent sections, we shall explore the significance of various important ADAS systems.

Computing plays an important part in ADAS by processing massive volumes of data from sensors to improve vehicle safety and driving pleasure. ADAS uses processing capacity to analyze sensor data in real time in order to detect and respond to possible risks such as crashes, lane departures, and pedestrians. Liu et al. [12] in their paper examine the state-of-the-art computing systems for autonomous driving, highlighting seven performance measures, nine essential technologies, and twelve difficulties. The goal is to bridge the gap between existing capabilities and the robust systems required for level-4/level-5 autonomy, encouraging future research in both the computing and automotive fields. Li et al. [93] investigated allocating computing resources for real-time autonomous driving activities like localization and obstacle avoidance. The paper presents a technique that uses a restless multi-arm bandit (RMAB) framework with deep reinforcement learning (DRL) to reduce vehicle travel during data processing delays. This Whittle index-based technique effectively adjusts to dynamic vehicle motion.

In conclusion, integrating modern computing into ADAS is critical for improving vehicle safety and driving experience by processing large amounts of sensor data in real time. The research by Liu et al. [12] and Li et al. [93] underline the recent accomplishments and continued hurdles in autonomous driving. These initiatives by the aforementioned researchers show the crucial role of computing in the advancement of level 4/level 5 autonomous driving, paving the way for future research and development in this rapidly evolving sector.

A. V2X COMMUNICATION

A crucial piece of technology that enables vehicles to communicate with various components of the surrounding traffic system, as well as with each other, is vehicle-to-everything (V2X) communication. This technology covers interactions such as vehicle-to-vehicle (V2V), vehicle-to-pedestrian (V2P), vehicle-to-network (V2N), and vehicle-to-infrastructure (V2I) communications. Various technologies enabling V2X are dedicated short-range communications (DSRC) and cellular V2X (C-V2X). Xu et al. [94] introduced a novel cooperative perception framework for V2X that effectively fuses information across on-road agents, including infrastructure and cars, utilizing a vision transformer. It describes an architecture for reliable and effective perception that makes use of machine learning and LiDAR technologies to enhance autonomous car object identification and classification.

Huang et al. [95] focus on cooperative perception (CP) for autonomous driving and offer a thorough overview of the developments in V2X communication technology. The author discusses the integration of edge computing, blockchain, 6G communications, and digital twin, presenting a new taxonomy and defining a framework for understanding and improving CP in V2X scenarios. Petrov et al. [96] benchmarked the performance of 5G- and long-term evolution (LTE)-based Cellular-V2X (C-V2X) technologies in their study. The author examines how infrastructure density impacts performance measures like end-to-end latency and packet delivery ratio, comparing their efficacy in urban environments under varied circumstances like traffic intensity and communication perimeter.

The powerful computational capacity that underpins V2X communication is critical for real-time data processing, safety, effective communication management, the development of self-driving technologies, and future-proofing systems against changing technical standards. It facilitates the seamless integration of various data sources, guaranteeing that vehicles can adapt quickly and correctly to dynamic driving circumstances, hence improving road safety and traffic flow. Shaer et al. [97] emphasize the relevance of computational capacity in V2X communication by tackling the constraints of sophisticated data processing and low-latency requirements, which are critical for road safety and traffic improvement. They propose using edge computing to distribute computational capabilities closer to the vehicles. This solution addresses the limitations of edge computing power and the independence of V2X services. The authors develop a binary integer linear programming model to optimize the location of V2X services, reducing latency while meeting resource restrictions. Their simulations show that this strategy effectively meets the V2X application latency requirements, outperforming baseline approaches under realistic situations. Gao et al. [98] emphasize the relevance of processing power in V2X communication and propose the weighted minimum mean square error (WMMSE) algorithms as well as a deep learning method for efficient power allocation. While training the deep neural network (DNN) takes time, it significantly decreases computational overhead and gives real-time solutions, which are critical for V2X performance. The authors stated that future studies will entail investigating unsupervised learning approaches.

The investigations emphasize the critical relevance of computational capacity in V2X communication, emphasizing the importance of efficient data processing and low latency to ensure road safety and traffic efficiency. The proposed solutions, which include edge computing and deep learning techniques, show considerable gains in performance and real-time processing capabilities. A future study will investigate advanced computational strategies to improve V2X systems. Below Fig. 12 illustrates the different components involved in V2X communication, such as vehicles, pedestrians, infrastructure, and the types of data exchanged between these entities.

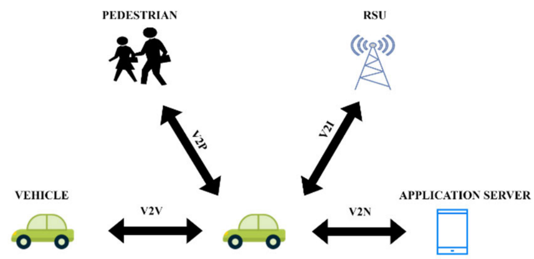

FIGURE 12. Representation of V2X communication.

B. TRANSITION TO QUANTUM COMPUTING FOR V2X COMMUNICATION

Now that the fundamentals of V2X communication have been established, it's critical to investigate how new technologies, in particular quantum computing, have the potential to completely transform this field. Quantum computing has the potential to significantly alter V2X by improving cybersecurity and processing capacity, two vital areas. V2X systems could see significant improvements in processing speed and efficiency because of quantum computing. This improvement is essential since more and more vehicle functions, including route planning, traffic optimization, and real-time decision-making, depend on sophisticated algorithms. The use of quantum bits, or qubits, by quantum computers allows them to calculate at speeds that are not possible for classical computers. This could reduce the amount of time needed for data processing and analysis in V2X systems. Real-time analytics for dynamic routing and congestion control may benefit greatly from this speed. Latency is one of the most crucial challenges in V2X communication, particularly for autonomous vehicles that require real-time data processing and decision-making. Due to high standards for ultra-low latency, current approaches frequently fail to meet this. Quantum communication networks have a considerable computational and latency benefit because they can reduce overall end-to-end delay through distributed quantum computing and entanglement. These technologies enable more efficient in-network distributed computing while overcoming the inherent limitations of traditional communication networks. Ferrara et al. [99] established a quantum communication network that can reduce communication complexity while improving system responsiveness, making them extremely efficient in tackling latency concerns in V2X systems. Furthermore, Chen et al. [100] in the paper investigate novel strategies for entanglement distribution across quantum networks, greatly reducing the latency that affects standard V2X systems. This integration will not only enhance data exchange but also decrease overhead and processing delays, resulting in a solid foundation for next-generation vehicular networks. Zeydan et al. [101] emphasize the need for efficient computation techniques like Toom-Cook or Karatsuba for handling the computational load of quantum-resistant security algorithms (QRSAs) in V2X and other mobile applications. The author also discusses the application of post-quantum secure algorithms in next-generation mobile networks. The paper presents a Service & Computation Orchestrator (SCO) architecture intended to streamline these procedures and provide low-latency, secure communication services. Yu et al. [102] emphasize the security aspects of V2X communication, basically discussing the hindrances faced due to passive and active attacks in the context of quantum computing threats. Additionally, the author covers several tactics like cooperative jamming and beamforming to improve the security and dependability of V2X communications in the event of possible attackers with access to quantum technology. Chen [103] presents the PQCMC scheme, a post-quantum cryptography method built on the McEliece-Chen framework and intended to produce pseudonymous certificates. In order to improve efficiency and security against quantum threats, the author suggests a lattice-based cryptographic solution that solves the shortcomings of conventional elliptic curve encryption for quantum assaults.

As we tread our way into the next frontier of automotive technology, the integration of ADAS and quantum computing for autonomous vehicles presents a transformative opportunity to enhance the vehicle's intelligence and safety. The main market value of V2X technology lies in its ability to enhance road safety and the improvement in traffic efficiency. Quantum computing could accelerate the processing of vast amounts of data from various integrations of sensors and cameras in real-time, which can lead to quicker and more accurate decision-making processes in autonomous and connected vehicles. The security of communications is greatly improved by quantum cryptography, which is crucial for the viability of V2X technologies. Achieving public trust and promoting the broad use of autonomous cars require this high degree of security. For the aforementioned cars to function securely and effectively, there is a constant need for secure data interchange.

But there are eclectic challenges being faced in the development of V2X communication for autonomous vehicles since quantum computing is in its initial stage of development. The integration of quantum resources into current V2X systems is a significant challenge since quantum technology—specifically quantum computing and quantum machine learning—is still in its infancy and requires much study and experimentation before it can be used efficiently in practical settings. The general adoption of quantum-enhanced V2X technologies may be impeded by the high price of creating quantum-safe cryptographic techniques and quantum computing equipment. There is a significant challenge and doubt about the compatibility of quantum-enhanced V2X technologies with existing infrastructure and scalability across various regions. Close collaboration between stakeholders in the automotive and technology industries is needed to overcome these obstacles. The primary goal of this partnership should be to further quantum research, provide affordable quantum computing solutions, and create common standards that make it easier to incorporate these cutting-edge technologies into current systems. By doing this, we can fully realize the promise of V2X technologies that are boosted by quantum mechanics, leading to more intelligent, safer, and efficient transpiration networks that are ready to handle future demand.

C. QUANTUM-INSPIRED EDGE INTELLIGENCE FOR TASK OFFLOADING IN AUTONOMUS PUBLIC TRANSPORT

Quantum-inspired techniques have shown great promise in improving edge intelligence for autonomous public transportation systems, notably in task offloading and resource management. Ansere et al. [104] developed a quantum-empowered deep reinforcement learning (Qe-DRL) framework for optimizing resource allocation in MEC-enabled IoT systems. By incorporating modified Grover's methods for rapid state transitions, the Qe-DRL technique achieved exponential convergence speeds while minimizing computing overhead and latency. This makes it ideal for real-time applications such as route planning, fleet coordination, and predictive maintenance in public transportation systems. Wang et al. [105] proposed a quantum-inspired reinforcement learning (QRL) framework for MEC environments, with the goal of maximizing end-to-end delay in task offloading scenarios. Their hybrid network concept, which combines 5G and WiFi technologies, offers a scalable solution for dynamic vehicular networks. QRL's adaptive task allocation solutions efficiently handled issues in managing large traffic loads and real-time computational and real-time computational needs, exceeding traditional resource management methods. Zhao et al. [47] extended these advances by focusing on quantum communication networks and their application on the Internet of Vehicles (IoV). Their research demonstrated how quantum entanglement distribution might dramatically improve system responsiveness and minimize communication latency, resulting in seamless task offloading and efficient data exchange in distributed vehicular environments. They also investigated he use of quantum-resistant cryptographic methods to solve security concerns, emphasizing the importance of reliable and secure communications in IoV systems. Collectively, this research demonstrates quantum-inspired techniques' transformational potential in handling the high computing and communication needs of autonomous public transportation. These approaches pave the way for future intelligent transportation systems that can handle the complexities of urban mobility and make real-time decisions by allowing for scalable and efficient job management.

D. ADAPTIVE CRUISE CONTROL (ACC)

ACC (Adaptive Cruise Control) assists the driver in maintaining the longitudinal control of their vehicles basically during motorway driving. The system takes control of the accelerator, powertrain, and vehicle brakes to maintain the specific time gap relative to the vehicle in front. The adaptive cruise control operates continuously by adjusting the vehicle's speed to maintain a safe distance based on the changing dynamics of traffic flow [106]. Ren et al. [107] focus on the goal of managing both longitudinal and lateral control in autonomous vehicles (AVs). The author presents the cooperative adaptive cruise control (CACC) method, which uses the Frenet frame. The approach reduces complexity in control design and boosts efficiency by disentangling vehicle movement into two dimensions. The above-mentioned author discusses a Frenet frame-based vehicle dynamics model, which creates control rules for both lateral and longitudinal directions and uses the simulation to verify the algorithm's efficacy. The above method tackles issues with vehicle coupling during lane changes or turns.

Lu et al. [108] present the Smart Drive Model (SDM), a novel adaptive cruise control technique that aims to improve traffic flow stability. The research shows that SDM performs better than traditional models in stabilizing homogeneous traffic flow through simulations and linear stability analysis. This is accomplished by improving the vehicle's reaction to traffic dynamics, relieving traffic, and possibly raising road efficiency and safety. Fig. 8 illustrates the block diagram of ACC, showing how the system uses radar sensors to alert the driver to either accelerate or apply brake following distance based on real-time measurements. ACC systems rely heavily on computing for their usefulness and efficacy. ACC systems use modern sensor data processing to integrate and evaluate inputs from lidar, radar, and cameras, resulting in an accurate real-time picture of the driving environment. Li et al. [109] underline the relevance of computation by pointing out the inherent high computational complexity of model predictive control (MPC) in sophisticated vehicle control systems. They emphasize the importance of tackling this complexity in order to achieve real-time implementation, demonstrating that efficient computation is critical for practical use. The research proposes a scale reduction methodology to reduce the computing cost and allow MPC controllers to perform successfully in real-time applications. This emphasizes the importance of computing efficiency in assuring the viability and performance of sophisticated vehicle automation systems. In exploring the functionality of adaptive cruise control (ACC) systems, Fig. 13 states the block diagram for its working, and Fig. 14 illustrates the working example for reference.

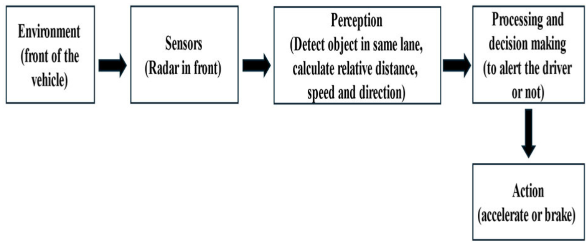

FIGURE 13. Block diagram for the working of ACC.

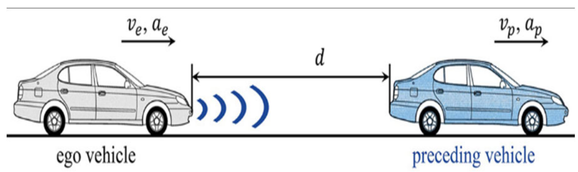

FIGURE 14. Working of ACC, v_e, a_e, v_p, a_p are velocity and acceleration of ego and preceding vehicle respectively [110].

E. REAR CROSS TRAFFIC ALERT SYSTEM (RCTA)

Rear Cross Traffic Alert System (RCTA), an ADAS system, specializes in assisting drivers during vehicle reversing maneuvers, particularly when exiting parking spaces. In scenarios where there is perpendicular traffic, like pedestrians, moving vehicles, and bicycles, it can be challenging for drivers to see these obstacles through the side mirror if their view has been blocked by the other parked vehicles. The Rear Cross Traffic Alert (RCTA) systems employ mid-range sensors mounted at the rear corners or short-range radar sensors that cover the area directly behind the vehicles. These sensors are basically designed to detect objects such as bicycles, cars, and pedestrians, providing audio or visual warnings to the driver to prevent accidents [111].

Takahashi et al. [112] suggest a novel method for optimizing the alert timing of the Rear Cross Traffic Alert (RCTA) system, specifically that tailored to the parking environments in North America. The above-mentioned approach addresses challenges such as the higher prevalence of front-in parking and larger lot sizes that result in varying speeds of cross traffic. The system attempts to enhance driver response times, increasing safety during backup operations by estimating how long it will take a cross-traffic vehicle to pass behind the reversing car. Computation is essential in all aspects of RCTA systems, including data processing, alarm generation and system optimization. RCTA systems can successfully improve driver awareness and safety by utilizing advanced computational approaches, especially in situations where sight is limited, such as backing out of parking spaces or traversing congested parking lots.

Kamal et al. [113] emphasise the importance of computation by highlighting the deep neural networks (DNNs) and their function in object detection and semantic segmentation for self-driving applications. The research highlights the importance of computing improvements in AI and DNNs for improving autonomous vehicle system performance, especially in diverse and challenging environments. Fig. 15 depicts the simplified block diagram for the working of a traffic alert system, illustrating the integration of sensors, data processing units, and alert mechanisms to enhance driver awareness and safety. In the study of rear cross traffic (RCT) detection system, Fig. 16 depicts the hardware setup for the reference.

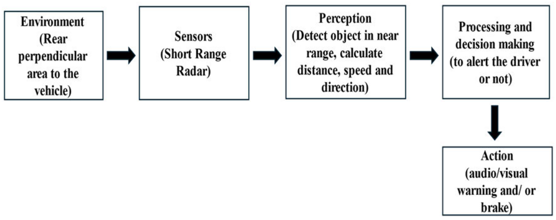

FIGURE 15. Depicts the simplified block diagram for the working of the traffic alert system.

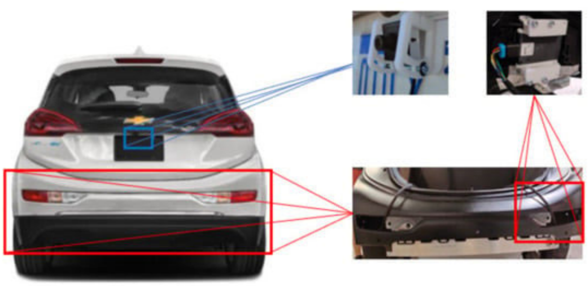

FIGURE 16. Depicts the hardware setup for the RCT detection system [90].

V. PARKING ASSISTANCE SYSTEM

Parking Assist is an ADAS system that assists the drivers to park their vehicles with greater precision using guidance system technology and path planning technique. This technology not only reduces the stress that is associated with maneuvering in confined areas, but it also helps in minimizing the risk of causing significant scratches and dings while parking in narrow spots. This system reduces the burden by automatically searching for a proper parking space and then assisting in parking. Massaki Wada et al. [114] proposed the architecture for this driver assistance system, which focuses on the Human Machine Interface (HMI) and path planning. Their paper outlines the development of a prototype parking assistance system, including the selection of hardware and software along with implementation details.

Ma et al. [115] examine various methods for detecting parking spaces, which emphasize the importance of parking efficiency and address parking shortages. The paper reviews the different detection systems, discussing the advantages and disadvantages of each approach, including those that are based on the identification of the empty spaces, recognizing parking space markings, and utilizing user interfaces and infrastructure. The focus of the paper is to provide a comprehensive overview of the current state-of-the-art and to propose future directions for research in parking space detection. Yang et al. [116] suggest a multi-model LiDAR-based parking sensing system that includes a perceptron, building free-space parking lots, parking space tracking, and obstacle identification to increase the robustness and efficacy of free parking space recognition. Numerous experiments show that the LiDAR-based parking sensing system can achieve superior performance in terms of recall rate and accuracy of detected parking spaces, in addition to being able to predict free parking spots at a distance. Computation is critical to the performance and efficiency of a parking assistance system. It allows for real-time processing, cost minimization, advanced algorithm implementation, adaptability, and the incorporation of new features, all of which contribute to a more intelligent and user-friendly parking solution. Fig. 17 depicts the simplified block diagram for the working of the parking assistance system, highlighting the interaction between various sensors, actuators, and control units to facilitate accurate vehicle parking. In the above context of discussing advancements in automated parking solutions, Fig. 18 illustrates a garage parking system.

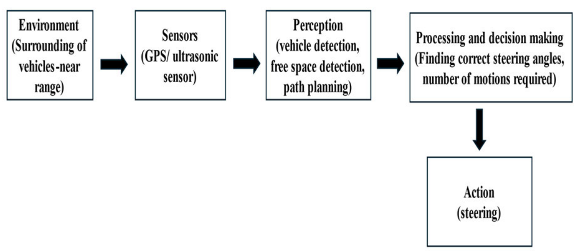

FIGURE 17. Depicts the simplified block diagram for the working of the parking assistance system.

FIGURE 18. Garage Parking system, an example [117].

A. TRAFFIC SIGN RECOGNITION SYSTEM

Drivers need to follow numerous rules and regulations while driving on the road, and all these rules are notified to drivers through various traffic signs. These traffic signs and their interpretations can subsequently vary from one place to another. Therefore, it is crucial for drivers to see and understand traffic signs from a good distance to ensure safe driving. Missing important signs like "Speed Limit" or "No Overtaking" can lead to dangerous situations on the road. Failure to observe these signs can result in severe consequences, including legal penalties and accidents. Thus, prompt interpretation of traffic signs and attentive driving are essential for maintaining road safety. Hengliang Luo et al. [118] discuss the development of a new data-driven system to recognize various types of traffic signs using video sequences captured by a camera mounted on a car. The system is structured into three stages, which include traffic sign regions of interest (ROI) extraction, ROIs refinement and classification, and post-processing. The paper proposes a multi-task convolutional neural network for classifying these regions. The neural network trains a diverse dataset, which includes labeled images and traffic signs from street views. The resultant post-processing stage combines the result from all frames to form a decision-making system for recognition. Triki et al. [119], in their paper, introduce an attention-based deep convolutional neural network (CNN) approach for traffic sign detection (TSR). The method focuses on real-time detection of different road sign categories. This method uses a deep CNN model for classification that was trained on the GTSRB dataset to achieve excellent accuracy, together with Haar cascade techniques for detection. The author conducted multiple tests on the system using a Raspberry Pi 4 board, which is designed to recognize 43 different types of indicators.

Wan et al. [120] present a novel architecture in the research paper that aimed at improving the identification and detection of traffic signs, particularly in challenging environments such as poorly lit areas or adverse weather conditions. The method being proposed by the author employs a detection system, a neck network for feature fusion, and a backbone network to enhance the accuracy of traffic sign recognition. Kim et al. [121] discuss the challenge of accurately identifying the traffic signs across diverse urban road conditions. In the research paper, the author develops a framework that employs deep learning-based models for object detection and tracking. Specifically, highlighting the effectiveness of the SORT tracking model and the YOLOv5 detector, noting their superior processing speed and accuracy in traffic sin identification. The study emphasizes the value of real-world validation and suggests a fresh approach to urban road scene categorization.

Wali et al. [122] provide in-depth information about algorithms, techniques, and applications related to traffic sign detection, tracking, and classification. In addition to discussing difficulties such as changing weather impacting vision, it covers traffic sign databases and emphasizes the need for traffic sign recognition for advanced driver assistance systems (ADAS). In addition to discussing existing problems and potential future research paths in this area, the paper classifies and contrasts various methods for traffic sign recognition, tracking, and categorization. Computing is critical for the design and implementation of good traffic sign recognition systems. It provides real-time processing, improved algorithm implementation, data management, integration with vehicle systems, and ensures TSR systems' robustness and dependability, making them critical for modern driver assistance and autonomous driving technologies. Fig. 19 depicts the simplified block diagram for the traffic sign recognition system, illustrating the key components and their interconnections, and Fig. 20 states an example for the traffic sign detection system.

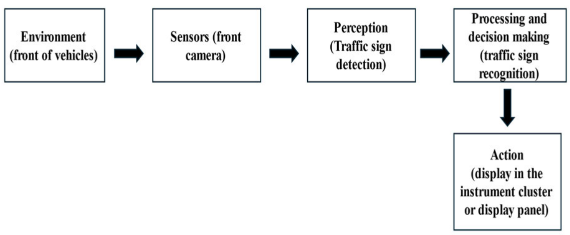

FIGURE 19. Depicts the simplified block diagram for the traffic sign recognition system.

FIGURE 20. Traffic sign detection example [123].

B. LANE DEPARTURE WARNING SYSTEM (LDWS)

This system uses a video camera mounted on the car, which is used to detect the markings ahead of the vehicle and assist in monitoring the vehicle's position with respect to that particular lane. When this function detects that the vehicle is about to unintentionally move out of the lane, it warns the driver by means of a visual, audible, and/or haptic signal, such as steering wheel vibration. Vijay Gaikwad et al. [124] proposed a method that utilizes contrast enhancement and segmentation for the detection of lane markings. The Euclidean distance approach is used to measure departure distance from the lane. This technique effectively identifies and warns the driver. This technique showcases promising results in various real-world scenarios. Gao et al. [125], suggest a technique that incorporates machine learning for the detection of inadvertent lane changes and forecasting the possibility of driver rectification. In order to limit false alarms, it integrates long short-term memory (LSTM), extreme learning, and a deep residual network.

Luo et al. [126] present a distinctive vision-based Lane Departure Warning System (LDWS) that leverages a 3D camera imaging model to enhance calibration and accuracy. This technology particularly relies on a single lane marking to assess lane departure, simplifying calibration and enabling more precise determination of camera height. Anbalagan et al. [127] focus on autonomous vehicles (AVs) and present a vision-based lane departure warning system that makes use of LSTM and Generative Adversarial Network (GAN). The system is made to predict missing lanes, improve the accuracy of the AV's trajectory, and deal with issues including fluctuating brightness, blur, and occlusion. The proposed LDWS requires significant computational capacity to handle real-time image processing, implement complex algorithms, provide seedy inference and decision-making, and maintain high accuracy and performance.

Gamal et al. [128] propose a real-time, calibration-free lane departure warning system (LDWS) algorithm that uses advanced computational approaches to achieve excellent accuracy and efficiency. The real-time calibration-free lane departure warning system (RTCFLDWS) algorithm is scalable, thus it can handle a wide range of input sizes and driving circumstances. The algorithm's high-performance metrics and efficiency make it suitable for inclusion into self-driving systems in Original Equipment Manufacturer (OEM) vehicles, highlighting the need for processing power in real-time lane departure warning systems. In the discussion of lane departure warning systems, Fig. 21 provides a simplified explanation of their operation, and Fig. 22 showcases the example for the lane detection system. In the context of discussing lane detection systems.

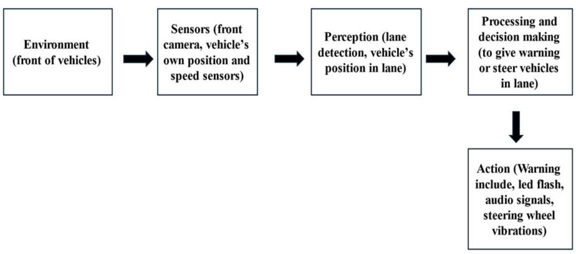

FIGURE 21. Presents a simplified explanation of the workings of the lane departure warning system.

C. FROM DRIVING ASSISTANCE TO AUTONOMY: THE EVOLUTION OF AUTONOMOUS VEHICLES

Autonomous Vehicles (AVs) represent a substantial advancement from ADAS, which marks a shift from partial automation to full autonomy. Various ADAS technologies, like adaptive cruise control, automatic emergency braking systems, lane-keeping assistance systems etc., laid the groundwork for the development of fully autonomous driving solutions. These systems hold the transition from merely supporting the driver to taking complete control of the vehicles in different driving scenarios. This transition involves the enhancements in sensor technology, computational power, and machine learning algorithms that enables vehicles to perceive their environment, decision-making, and operate without human intervention. This advancement not only promises to increase road safety by reducing human error but also focuses on improving traffic efficiency and mobility accessibility. Below table 7 promulgates the contributions being made in the advancement of security, communication, and cloud technologies for autonomous vehicles and vehicular networks.

FIGURE 22. Represents lane detection example [129].

TABLE 7. Literature regarding the advancement in security, communication, and cloud technologies for autonomous vehicles and vehicular networks.

Research paper	Contributions being done in the field of vehicular networks and autonomous systems
Sharma et al. [130]	It examines intrusion detection systems (IDS) for VANETs and VANET Clouds for traffic systems, with an emphasis on security risks and IDS strategies such as signature-based, anomaly-based, and hybrid approaches. The author proposes a Honeypot-based proactive IDS that detects both known and zero-day attacks with minimum overhead.
Pang et al. [131]	The research presents a deep reinforcement learning (DRL)-base task offloading system for vehicle-edge-cloud collaboration, which optimizes task scheduling to reduce latency and energy consumption in multi-task vehicle applications.
Tian et al. [132]	The researcher describes a cloud-based highway traffic safety early warning system that utilizes IoT and BP neural networks for real-time data processing. It increases node categorization by 13%, resulting in more rapid and accurate traffic safety warnings and accident forecasts.
Yusuf et al. [133]	The author proposes a deep learning-based AV motion control architecture to improve vulnerable road user (VRU) safety, including technologies such as LSTM, 3D-CNN, and GRUs for trajectory prediction. It combines modern sensors like radar, cameras, and LiDAR with C-V2X communication to provide real-time VRU tracking and identification, enhancing safety through efficient data sharing and exact localization.

Reimer et al. [134] speak about the potential of the driver assistance systems for enhancing the safety and mobility of older adults as the technology advances towards fully automated vehicles. The papers focus on how these systems can address specific challenges faced by the old drivers, who might experience declines in cognitive, visual, and motor abilities. The integration of ADAS technologies, including lane-keeping assistance, collision avoidance, and adaptive cruise control, enables older drivers to maintain road independence and safety for longer periods. Ongoing research aims to integrate these technologies into everyday driving while addressing associated challenges.

Computing is critical for ADAS for real-time data processing and sensor fusion to combine inputs from many sensors (cameras, lidar, radar, and ultrasonic sensors) to produce an accurate representation of the environment, enabling instant response to dynamic conditions like unexpected obstructions. Advanced algorithms, notably machine learning and artificial intelligence (AI), require extensive processing resources to identify objects, recognize traffic signs, and detect lane markings, allowing for intelligent decision-making and predictive analytics to foresee future hazards. High computational capabilities improve accuracy and dependability through high-resolution mapping and continual sensor calibration.

Ziebinski et al. [135] examined the capabilities of current ADAS systems and considered the future of sensor fusion on autonomous mobile platforms. Computing is highlighted through the integration of various sensors, real-time data processing, improved control units, and the development of strong hardware and software structures. Furthermore, the utilization of common computing platforms, such as the CAN interface and Raspberry Pi, highlights the accessibility and scalability of ADAS technology. This continual advancement and innovation in ADS emphasizes the importance of computing in improving vehicle safety and efficiency. In discussing the evolution of autonomous systems, it is salient to consider Fig. 23, which provides a representation of various levels of autonomy.

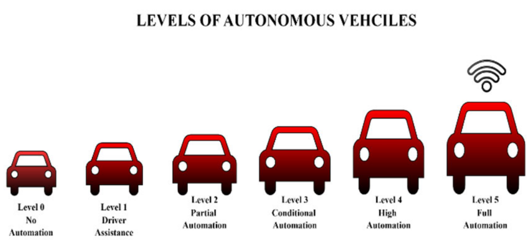

FIGURE 23. Representation of various levels of autonomy.

D. FUTURE CHALLENGES

The development of autonomous vehicles has created various opportunities for smart urban mobility. These vehicles have become a focal point, aligning with the growing concept of smart cities. Faisal et al. [136] proposed a methodology for reviewing the existing evidence base to better understand the impacts, capabilities, planning requirements, and policy issues associated with autonomous vehicles. This approach focuses on providing a comprehensive understanding of how autonomous vehicles could influence various aspects of society and infrastructure. The review conducted by Asif Faisal [108] delves into the evolution of technology, detailing its development trajectory, the disruptions it causes, and various other strategies to address these disruptions. Furthermore, the paper explores numerous gaps in the existing literature. Faisal further presents a framework that outlines the connections among various driving forces, impacts, uptake forces, and potential interventions related to the technology in question. This comprehensive approach assists in understanding both the benefits and obstacles brought about by technological advancements.

The advancement in the development of autonomous vehicles has encountered a myriad of obstacles, which necessitate sophisticated answers to various surmount impediments, which range from ensuring safety in dynamic environments to addressing myriad regulatory complexities, cybersecurity concerns, copious ethical dilemmas, and the need for the widespread public acceptance. Parekh et al. [18] discuss how one of the major obstacles in the field of autonomous vehicles (AV) stems from the inadequate implementation of proposed algorithms, which is primarily due to the lack of data within the domain. This shortage of data hampers the development and testing of effective solutions, which could otherwise advance AV technology. The author states that certain algorithms face various obstacles in achieving both accuracy and speed and often corroborate errors in the orientation estimation. The model predictive control algorithm plays a crucial role in lateral motion control. However, its effectiveness is hindered by its inability to detect faults adequately. Additionally, uncertainties that deviate from predetermined conditions remain unaddressed, further constraining the algorithm's efficacy.

Khan et al. [137] discuss the implementation and security aspects of autonomous vehicles (AVs). The author outlines various challenges and benefits that are associated with AVs. Significant implementation obstacles include advancements in current technology, vehicle costs, security and privacy concerns, legal and liability issues, and ethical considerations.

Lin et al. [138] investigate the constraints and acceleration challenges associated with (AVs). The authors analyze a range of design limitations, encompassing performance, storage (pertaining to managing previous data), predictability (instances where processing exceeds predefined timeframes), power restrictions, and thermal concerns. Their primary objective is to develop an end-to-end autonomous driving system utilizing cutting-edge, award-winning algorithms.

Another paper by Garikapati [20] discusses various challenges in developing AVs, such as integration of AI technologies, resolution of moral dilemmas, dealing with biases in AI research, and defining the role of AI in the Internet of Things (IoT) ecosystem for these cars. These obstacles involve the development of sophisticated algorithms, addressing safety issues, ensuring equity, and effectively integrating vehicles into larger smart infrastructure networks. Padmaja et al. [139] analyze the challenges in building AVs from both technical and non-technical perspectives. These obstacles include real-time deployment, security, privacy, regulatory issues, and customer satisfaction. The paper emphasizes that for overcoming these challenges and successfully commercializing autonomous vehicles, advancements in computing and communication technologies are salient. Parekh et al. [18] discuss various hindrances related to autonomous vehicles (AVs). These include ensuring accurate and reliable positioning for navigating uncertainties that include different road types and pedestrian behavior, integrating advancements in computing and communication technologies for enhancing vehicle autonomy, and resolving issues related to security, privacy, and regulatory compliance. The paper focuses on increasing public confidence while effectively addressing societal and technological barriers in the development of fully autonomous vehicles.

In his paper, Biswas [140] discusses the challenges of creating AVs that integrate blockchain, the Internet of Things (IoT), 5G, and edge intelligence. The paper highlights difficulties related to technological obstacles, safety, trust, and the need for breakthroughs in computing and communication. The complexity of AV infrastructure presents significant challenges, necessitating safe, reliable, and efficient solutions. Dong et al. [141] in their study examine the issues with data processing and storage in the context of autonomous cars, emphasizing the necessity of effective data management techniques to deal with the massive volumes of data produced by sensors and cameras in cars. These difficulties include guaranteeing data integrity, reducing data processing latency, and streamlining storage options to provide the instantaneous decision-making necessary for safe autonomous driving.

Observing the various aspects of the autonomous vehicles, it became evident that latency, speed, and accuracy of algorithms, as well as the security and privacy measures, play a paramount role. To overcome these issues, we proposed a methodology based on quantum machine learning, which can overcome most of the challenges currently faced in the development of Autonomous vehicles. Quantum machine learning holds the promise of addressing the issues related to security and privacy. Quantum computing has the potential to significantly impact cryptography. Shor's algorithm is the prominent one, which can factorize the large numbers efficiently. Further development of quantum-resistant cryptographic algorithms could provide enhanced security for communications with autonomous vehicles.

VI. CHALLENGES FOR IMPLEMENTING QML TECHNOLOGIES

Recently, quantum computers faced various obstacles due to the inherent noise, which causes qubits to be error-prone and due to which their states decay rapidly. The implementation of the gates for the manipulation of the qubit introduces many errors, which leads to deviating from the expected result; this phenomenon is known as gate infidelity. Decoherence, which arises from the gate infidelity and qubit errors, hinders the execution of the algorithm. Beyond these obstacles, recent quantum technologies encounter various shortcomings in scaling, with disturbances introduced as the number of qubits on a single device increases. This constraint in scalability has led to the term, which was coined by John Preskill [142] as "noisy intermediate-scale quantum (NISQ) computers," reflecting the technology's current state characterized by noise, intermediate scaling capabilities, and limited scaling.

Technological Barriers to Integration:

- Hardware limitations: Current quantum processors are prone to rapid decoherence and require extremely low working temperatures, hindering their integration into vehicle systems that must operate in a variety of environments. Furthermore, the physical size and energy requirements of quantum hardware are not yet suitable for on-board vehicle integration.
- Software maturity: Quantum programming languages and frameworks are still in their early stages of development. While libraries like Qiskit, Cirq, and others are evolving, they still lack the scalability, standardization, and support seen in traditional computing counterparts, which are critical for automotive industry applications.
- Scalability Challenges: It is difficult to scale quantum systems to the amount of qubits required for practical applications without increasing error rates and decoherence times significantly. This scaling issues must be resolved in order to fulfil the computing needs of ADAS and AV systems.

To overcome the challenges of applying quantum machine learning (QML) in ADAS, an organized roadmap is required. The integration can start with hybrid quantum-classical systems that use existing quantum algorithms like Quantum Support Vector Machines (QSVM) for non-critical tasks like traffic prediction or route optimization. This stepwise strategy allows quantum technologies to be added without overhauling existing infrastructure, maintaining reliability and scalability. Hardware developments must favor portable, energy-efficient quantum processors that can operate in vehicular situations. Simultaneously, software development should concentrate on developing domain-specific quantum programming libraries and simulation environments specialized for ADAS, allowing for seamless testing and deployment. A major component of this roadmap is the collection of extensive datasets that contain real-world scenarios and edges cases, allowing for robust training of quantum algorithms under a variety of driving conditions. Collaboration across industries is critical to success. Automotive manufacturers, quantum computing firms, and regulatory bodies must establish common standards and protocols to ensure interoperability and scalability. Pilot studies in controlled conditions will help to benchmark the performance of QML algorithms and refine their deployment. Over time, these technologies can be applied to real-world applications, improving processing speed, decision-making accuracy, and cybersecurity in ADAS. By adopting this road map, stakeholder can systematically remove the technical and practical challenge to incorporating quantum technologies into ADAS, thereby unlocking their disruptive potential in the automotive sector.

While technical limits in quantum computing, such as noise, scalability, gate infidelity, are significant obstacles, the broader implications of ethical, security, and privacy concerns must also be addressed to enable the responsible implementation of quantum technologies. AVs that rely primarily on data-driven decision-making, are especially sensitive to these risks. To prevent harmful outcomes, ethical problem such as elimination of bias in decision-making and maintenance of transparency in the working of QML models work must be addressed. Another concern is security problems, as quantum computers have the potential to bypass conventional encryption methods, endangering vehicle communication networks. Furthermore, privacy problems arise because of the massive amounts of sensitive data collected by these cars, necessitating strict data protection methods and compliance with rules like as GDPR. Addressing these issues is critical to responsibly integrating quantum technologies into autonomous systems.

While quantum computing has transformative potential, it is limited in terms of cost. Scaling quantum systems, particularly fault-tolerant ones, incurs large, fixed costs, which vary significantly between technologies. Camps et al. [143] found that superconducting qubits are less expensive than ion trap systems, which can cost up to four orders of magnitude more. Furthermore, mistake correction remains a major cost driver, necessitating significant developments to reduce operational costs. Despite these hurdles, quantum computers can gain an economic advantage without showing quantum supremacy. According to Bova et al. [144] quantum systems can be economically viable in niche markets due to lower variables costs in specialized applications like Grover's method, which provides quadratic speedups over classical systems. However, these gains come at a larger fixed cost for expanding hardware, thus delaying widespread adoption. Future advances in error correction techniques and quantum algorithm developments are projected to lower prices, opening the way for realistic quantum computing applications that are both economically viable and scalable for real-world use.

With the advancement of quantum computation technology, by overcoming the current hindrances, there will likely be remarkable progress in the development of autonomous vehicles. The evolution in computing can lead to more practical and reliable autonomous systems in the near future. The following researchers discuss the potential of quantum computing and quantum machine learning algorithms.

Goto et al. [145] explored the potential of quantum machine learning (QML) models for handling a broad class of machine learning problems. The paper delves that QML models with the universal approximation property (UAP) and classification performance based on quantum-enhanced feature spaces. The universal approximation property (UAP) for quantum machine learning (QML) models is proven by the authors in standard quantum feature map settings, suggesting that these models may accurately approximate any continuous function and classify disjoint regions. This significant paper underlines the theoretical capabilities of QML in handling tasks that classical machine learning models can handle in classical scenarios to provide insights into generating expressive QML models. Noori et al. [45] contribute to the development of an innovative hybrid-quantum-classical machine learning technique known as "analog-quantum kitchen sinks" (AQKS). The researcher uses an analog-quantum computer for feature mapping; this technique improves the efficiency of traditional machine learning algorithms for problem solving in classification by generating new, nonlinear features from input data. Through the implementation of AQKS on synthetic and Modified National Institute of Standards and Technology (MNIST) datasets, their study shows significant advances in classification accuracy, demonstrating the potential of quantum annealers in real-world machine-learning applications by offering a distinctive solution to feature transformation and issues with classification. Biamonte et al. [43] examine how machine learning and quantum computing might work together and make the case that machine learning tasks could be greatly improved by quantum computers. The author explores the development of machine learning techniques and the history of data analysis, proposing that quantum mechanics could produce intricate patterns that are beyond the reach of classical computing. The study examines several quantum algorithms and how they perform better than their classical equivalents in certain situations, especially when handling big datasets and intricate computations. Biswas et al. [146] highlight Quantum AI's potential in improving efficiency and safety of self-driving vehicles, particularly in circumstances such as truck platooning. The authors suggest quantum artificial intelligence (AI) as a more efficient solution, which improves learning efficiency, capacity, and runtime. They created and tested both Long Short-Term Memory Networks (LSTM) and a hybrid quantum-classical LSTM (QLSTM) model. While comparing the two algorithms, it's observed that QLSTM used less data for training and had fewer parameters than LSTM while producing equivalent results. They also evaluated the operational efficacy and string stability of autonomous truck platoons using trajectory predictions from both LSTM and QLSTM, with QLSTM outperforming string stability.

Kuppusamy et al. [147] examined how machine learning and quantum computing might work together, particularly for image categorization applications. It draws attention to the developing role of quantum computing in speeding up computational operations in a variety of fields, such as security and optimization. A new subject called quantum machine learning (QML) aims to improve machine learning algorithms by utilizing quantum physics, perhaps leading to faster and more efficient computations. The report notes issues including qubit stability and the limitations of existing quantum devices, even with hopeful advances. It illustrates how QML has the ability to provide faster image classification by contrasting its algorithms with traditional methods. The survey indicates a substantial but early-stage potential for quantum computing in real-time problem solving across multiple sectors, and it makes recommendations for future research areas in tailoring QML algorithms and investigating quantum devices for wider applications.

As the reliance on autonomous vehicle networks develops, it is critical to have strong security and privacy safeguards in place. Quantum cryptography, specifically Quantum Key Distribution (QKD), provides theoretically unbreakable encryption based on physical laws. Stavdas et al. [39] suggest that incorporating QKD into Vehicle-to-Infrastructure (V2I) networks via Free Space Optical (FSO) technology to enable secure key exchange and prevent eavesdropping attempts. Al Mamun et al. [148] stress on post-quantum cryptographic (PQC) approaches, such as CRYSTALS-kyber, for safeguarding Transportation Cyber-Physical Systems (TCPS) from quantum threats while preserving low latency. Furthermore, Sutradhar [149] developed a secure vehicular quantum communication protocol that takes advantage of quantum phenomena such as the quantum Fourier transform and Shamir's secret sharing, with the goal of countering threats such as man-in-the-middle, Trojan horse, and collusion attacks. The above studies demonstrate that by incorporating quantum cryptography algorithms, it is possible to resolve ethical concerns, increase security, and protect sensitive data in autonomous vehicle systems, paving the road for their safe and responsible implementation.

Recent advances in quantum machine learning (QML) offer exciting potential for improving the capabilities of autonomous vehicles. Researchers have demonstrated the potential of QML in improving decision-making processes and classification accuracy in dynamic environments by investigating models with the universal approximation property (UAP) and innovative hybrid-quantum-classical techniques such as 'analog-quantum kitchen sinks' (AQKS). These advancements demonstrate QML's ability to address real-world difficulties in AVs, paving the path for more efficient and effective autonomous systems. Further investigation states that with the convergence of quantum computing and machine learning, it becomes clear that QML has enormous potential for changing the future of autonomous vehicles. In discussing the potential application of quantum computing with respect to computational power, Fig. 24 provides a representation of an exemplary use case in the field.

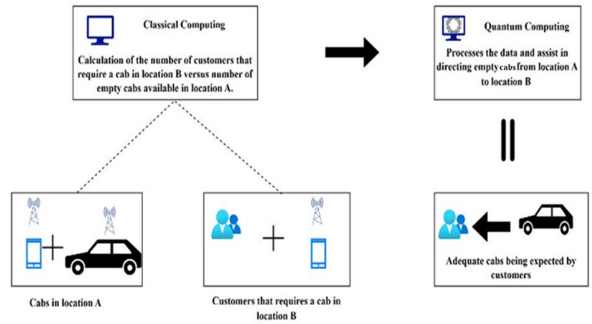

FIGURE 24. Representation of quantum computing exemplary used case.

VII. MAJOR CONTRIBUTIONS OF THE PAPER

This paper contributes significantly to bridging the gap between the traditional Advanced Driver Assistance Systems (ADAS) and the fast-developing fields of quantum computing and quantum machine learning (QML). It addresses fundamental computing hurdles associated with traditional ADAS, such as latency issues, limited accuracy, and inefficiencies in real-time decision-making. Our research shows that by harnessing quantum systems' exponential processing advantages—primarily through principles like superposition and entanglement—we may improve sensor fusion, trajectory planning, and object identification in autonomous cars.

The paper delves deeply into how several QML techniques, such as Quantum Support Vector Machines (QSVMs), Quantum Neural Networks (QNNs), and Quantum Reinforcement Learning (QRL), can improve the performance and dependability of ADAS. In addition, the study presents a thorough analysis of known quantum algorithms, emphasizing their importance in both ADAS and Vehicle-to-Everything (V2X) communication systems. We also discuss the potential of quantum cryptography to transform data security in automobile systems.

Quantum Computing is expected to play an important role in the future development of self-driving cars with improvements in data processing, secure communications and efficient vehicle control. Figure 25 depicts the methodical integration of quantum technologies into automobile systems which promises to improve autonomous vehicle accuracy, efficiency, and safety by leveraging quantum algorithms' higher computational capacity and real-time processing capabilities.

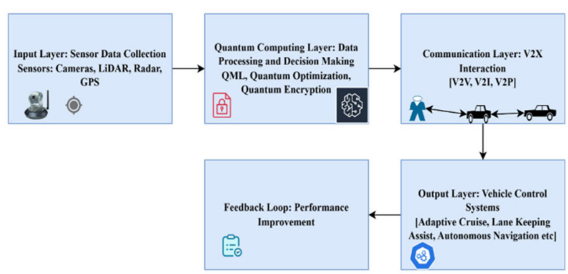

FIGURE 25. Proposed quantum-enhanced autonomous vehicle system architecture.

This study's significant practical implication is the proposed framework that integrates QSVMs into ADAS applications. This integration not only makes use of existing information, but it also creates opportunities for revolutionary future study in this field. By adding quantum machine learning, our framework paves the way for next-generation ADAS that are more accurate, faster, and secure, resulting in safer autonomous driving technologies.

VIII. EMERGING TRENDS AND FUTURE RESEARCH DIRECTIONS

Finding future research avenues is crucial because the integration of quantum computing in ADAS and V2X communications is poised to bring about a revolutionary shift in the automobile sector. Quantum computing uses quantum mechanics law, which gives us subsequently high computational algorithms and intense security in a faster and more reliable way. In order to safeguard communications between connected automobiles, strong quantum-resistant cryptographic algorithms must be developed. There is an interesting research direction to investigate how quantum computing can exemplarily handle vast amounts of data. Data forms the crucial part in the development of autonomous vehicles; based on the analyses of the algorithm using these data, the decision is taken by the vehicle. Further, development in the integration of quantum-based sensors can increase the precision, which could be beneficial for the vehicle's perception system. Further research also should focus on developing and adopting quantum solutions without completely sacrificing performance or integrity. The hybrid quantum-classical models will be able to diminish the gaps and the challenges being faced using the current technology. By addressing the aforementioned objectives, we may contribute to the research and developments of quantum systems, which further can assist in developing safer, more sophisticated, and more effective autonomous mobility technology.

IX. CONCLUSION

In conclusion, this review paper explored the prospects of quantum computing while focusing on how quantum breakthroughs could transform Advanced Driver Assistance Systems (ADAS) and self-driving automobiles. Quantum Machine Learning (QML) has demonstrated the potential to overcome traditional computing limitations by improving real-time decision-making, security, and computational efficiency, all of which are critical for the development of self-driving technology. Key findings indicate that quantum computing may handle enormous datasets and complex computational processes more quickly and securely than traditional approaches, providing considerable benefits in sensor fusion, trajectory planning, and vehicle-to-everything (V2X) communications. The most prominent issue confronting the autonomous vehicle dwells in the realm of security, since the multitude of communication devices are involved— from inter-vehicle communication to interactions within various internal components. The hackers can infiltrate the system, manipulating the vehicle's actions, by executing a spectrum of actions, ranging from manipulating sensor information to assuming complete control over the vehicle's operation. The solution to this problem can be the implementation of quantum machine learning. QML (Quantum Machine learning), promises to address various security and privacy concerns by enhancing encrypted algorithms, improving various machine learning models, and providing QKD (Quantum Key Distribution).

Future research should focus on completely integrating these quantum capabilities into practical automotive applications in order to realize the full potential of quantum-enhanced vehicular systems. This work establishes the groundwork for future quantum technology advancements, with the goal of accelerating their implementation to improve vehicular safety and efficiency.

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