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Integration of blockchain and machine learning for safe and efficient autonomous car systems: A survey

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Abstract

The integration of blockchain and machine learning technologies has the potential to enable the development of more secure, reliable, and efficient autonomous car systems. Blockchain can be used to store, manage, and share the large amounts of data generated by autonomous vehicle various sensors and cameras, ensuring the integrity and security of these data. Machine learning algorithms can be used to analyze and fuse these data in real time, allowing the vehicle to make informed decisions about how to navigate its environment and respond to changing conditions. Thus, the combination of these technologies has the potential to improve the safety, performance, and scalability of autonomous car systems, making them a more applicable and attractive option for consumers and industry stakeholders. In this paper, all relevant technologies, such as machine learning, blockchain and autonomous cars, were explored. Various techniques of machine learning were investigated, including reinforcement learning strategies, the evolution of artificial neural networks and main deep learning algorithms. The main features of the blockchain technology, as well as its different types and consensus mechanisms, were discussed briefly. Autonomous cars, their different types of sensors, potential vulnerabilities, sensor data fusion techniques, and decision-making models were addressed, and main problem domains and trends were underlined. Furthermore, relevant research discussing blockchain for intelligent transportation systems and internet of vehicles was examined. Subsequently, papers related to the integration of blockchain with machine learning for autonomous cars and vehicles were compared and summarized. Finally, the main applications, challenges and future trends of this integration were highlighted.

1. Introduction

Blockchain and machine learning are two advanced technologies that researchers are exploring as possible ways to enhance the safety and effectiveness of self-driving cars and vehicles. Blockchain, a decentralized and distributed digital ledger, can provide secure and transparent tracking of data and transactions in autonomous vehicle networks. Machine Learning (ML) algorithms can enable autonomous vehicles to learn from and adapt to their environments in real time, equipping them with required Artificial Intelligence (AI) capabilities. Together, these technologies have the ability to make self-driving cars safer and more efficient so that can coordinate and communicate with other vehicles and infrastructure.

The blockchain technology can provide safe and open record-keeping, and it can maintain data across several distributed nodes using encryption to ensure its consistency. Due to its potential applications in several industries, such as banking, healthcare, transportation, and logistics, the blockchain technology has attracted a lot of interest nowadays. It can offer safe and effective solutions for data interchange and management and it is being investigated by the scientific research community. Because of its decentralized nature, blockchain enables the development of reliable systems that may be used to reduce the risk of data breaches, prevent fraud, and to simplify business operations. Several aspects of the blockchain technology, such as scalability, security, and privacy implications, are now being widely researched [1, 2].

On the other hand, the ways how we work, live, and interact with the environment are all being redefined by emerging machine learning algorithms and techniques. Moreover, machine learning has created a plenty of new opportunities in several industries, such as transportation, banking, healthcare, and cybersecurity. Machine learning and its various algorithms can learn efficiently from available data and then come to the best decision/solution for the addressed problem. The subfield within machine learning, called reinforcement learning, focuses on the decision-making process within an environment where an agent can receive rewards or penalties based on its taken actions. The most important objective for the agent is to enhance its performance over time by attaining knowledge from its experienced errors and maximizing the overall reward it receives. At present, intensive research has been carried out for reinforcement learning that has brought about the development of application fields, such as robotics, control systems, and games [3]. Moreover, the Neuro Evolution Augmenting Topology (NEAT) algorithm [4], one of the genetic algorithm variants designed to evolve neural networks both structures, i.e. the number of neurons in the layers and the number of connections, and the weights of individual connections. The NEAT algorithm and its extensions, like HyberNEAT [5], can be implemented for programming new autonomous cars with increased experiences along the way. This has the ability not only to develop complex neural networks, but also to compact and enhance their effective use, thereby minimizing the computational burdens and the training time of autonomous cars particularly.

To put it in other words, applications of blockchain and machine learning to vehicles can be a new, uprising field of research, resulting in innovative projects and solutions. The integration and adoption of machine-learning technology algorithms that allows learning from data as well the management of data information securely and transparently of the blockchain technology appear to be a potential disruptor in various scientific fields such as autonomous vehicles/cars. To sum up, the combination of blockchain and machine learning may create the technology of the future with regards to autonomous vehicles, and as the technology develops, we just might get to experience the benefits soon enough.

The main contributions of this survey include an overview of blockchain, machine learning, and autonomous cars technologies. It also summarizes relevant research papers that explore the integration of blockchain in intelligent transportation systems, internet of vehicles and autonomous cars. The paper highlights potential applications of this integration, such as secure data management, decision-making, and coordination among vehicles and infrastructure. Finally, the paper addresses and discusses the challenges associated with this integration and anticipates the future directions of this integration.

2. Overview of relevant technologies

2.1. Machine learning

Machine learning is the process of enabling machines/computers to learn and make decisions independently, eliminating the need for explicit programming. It constitutes a main subfield of the artificial intelligence and utilizes statistical models and techniques to assist computers in learning from data inputs, which in turn, facilitates predictions or decision-making. There is a lot of research in this domain, covering various topics and methodologies. Among the central types of machine learning are supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, and deep learning. In the process called supervised learning, a model articulated by an algorithm gets fitted using a dataset that has correct outputs or labels for every training sample. The target is to get sufficient estimation from the given data, and apply it on fresh, unseen data, for getting accurate predictions. Contrarily, in unsupervised learning, the algorithm doesn't have access to labeled training examples. Instead, it has to figure out the inherent structure of the data through methods such as clustering or dimensionality reduction. Semi-supervised learning bridges supervised and unsupervised learning, where the algorithm learns from a dataset that includes both labeled and unlabeled data. During the reinforcement learning [3], a machine is being trained to make sequence wise choices in a particular environment to get the highest possible reward. The training process takes place through a procedure of trial and error, in which rewards occur in case of correct actions, while penalties apply when the actions are wrongly performed. This method is extensively utilized in robotics and autonomous driving.

As a popular reinforcement learning algorithm, known as Q-learning [6], an agent will be ready to select the best action to resolve the Markov Decision Process (MDP) issue even before a model outlines the system dynamics. This is done by reinforcement learning which is discovering their action-value function, known as Q-function. It does by taking an action-value function, also known as a Q function, as an integral part of the machine. The function helps calculate the expected cumulative benefit of performing each action a in each state s under this perfect policy. The Q-function is represented as $\mathrm{Q}(\mathrm{s},\mathrm{a})$ and can be updated using the Temporal Difference (TD) [6] learning rule (Equation 1):

$$\mathrm{TD}(\mathrm{a},\mathrm{s}) = \mathrm{R}(\mathrm{s},\mathrm{a}) + \gamma \sum_{\mathrm{a}'} \mathrm{P}(\mathrm{s},\mathrm{a},\mathrm{s}')^{\max}_{\mathrm{a}'}\mathrm{Q}(\mathrm{s}',\mathrm{a}') - \mathrm{Q}(\mathrm{s},\mathrm{a}) \qquad (1)$$

Where $\mathrm{R}(\mathrm{s},\mathrm{a})$ represents reward of applying action a on state s, $\mathrm{P}(\mathrm{s},\mathrm{a},\mathrm{s}')$ illustrates the to-from transition between a state s and an arising state s' after action a, and γ is the discount factor that belongs to [0,1] range. The equation represents how the environmental sectors are Q-value fair [6] which further gives insights of how and in what ways the environment may change over time. The updated Q(s,a) is then represented as follows (Equation 2):

$$\mathrm{Q}_t(\mathrm{s},\mathrm{a}) = \mathrm{Q}_{t-1}(\mathrm{s},\mathrm{a}) + \alpha\mathrm{TD}_t(\mathrm{a},\mathrm{s}) \qquad (2)$$

The Learning rate, α in this expression, determines the time of adaptation the system requires to get informed about the inconstant changes that the environment imparts on it. The $\mathrm{Q}_t(\mathrm{s},\mathrm{a})$ here stands for the Q-value at time t. The recorded Q-value if we replace $\mathrm{TD}_t(\mathrm{a},\mathrm{s})$ with its full-form Equation 2 [6], we should get (Equation 3):

$$\mathrm{Q}_t(\mathrm{s},\mathrm{a}) = \mathrm{Q}_{t-1}(\mathrm{s},\mathrm{a}) + \alpha(\mathrm{R}(\mathrm{s},\mathrm{a}) + \gamma^{\max}_{\mathrm{a}'}\mathrm{Q}(\mathrm{s}',\mathrm{a}') - \mathrm{Q}_{t-1}(\mathrm{s},\mathrm{a})) \qquad (3)$$

Additionally, Deep Q-Network (DQN) is a Q-learning extension that combines deep neural networks with the

Q-learning technique. The agent in DQN can manage high-dimensional state spaces and complicated situations because a deep neural network roughly approximates the Q-function, which is commonly used in autonomous cars. Furthermore, deep learning, a specialized area within machine learning, focuses on the training of artificial neural networks on extensive datasets. These algorithms have the capability to recognize various patterns and characteristics in provided data, resulting in their success across numerous applications and fields. This includes areas, such as image and speech recognition, natural language processing, and even in game-playing scenarios. There are many other topics and approaches within the field of machine learning, and new research is constantly being published [7]. Figure 1 highlights the intersections and differences among the various types and techniques of machine learning.

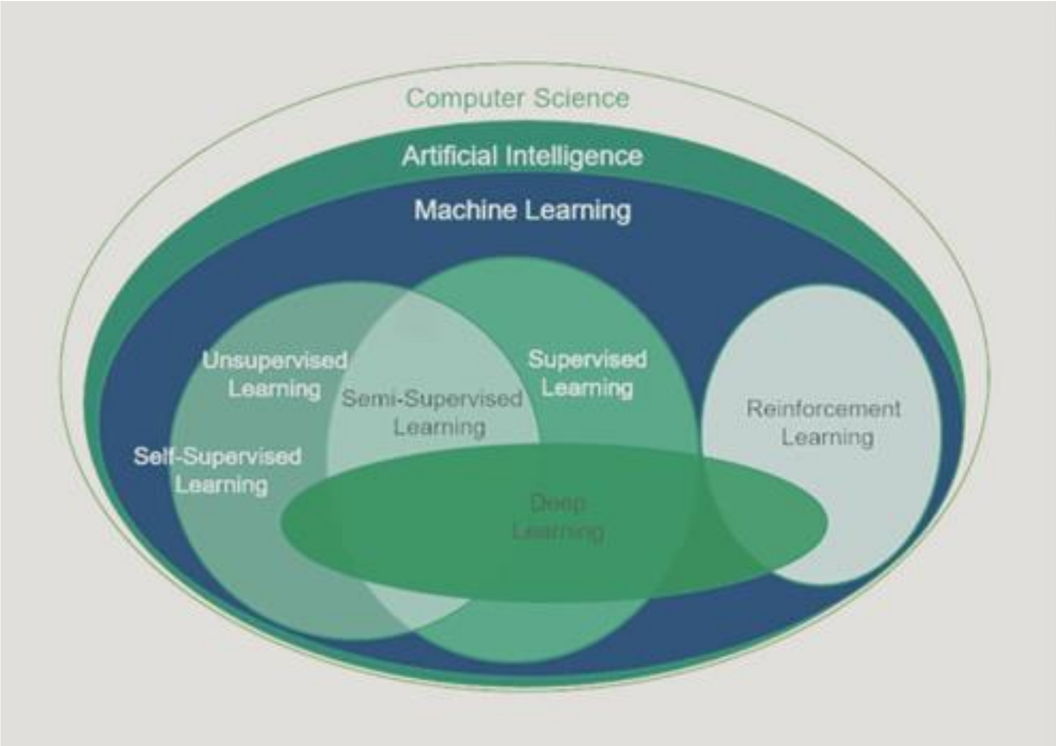

Figure 1. Different types of machine learning [8].

One of the basic algorithms of machine learning is the artificial neural network (ANN) [9], inspired by the structure and function of biological neural networks in the human brain. The ANN models consist of interconnected layers of nodes, artificial neurons, responsible for processing and transmitting information. The basic unit of an ANN is the artificial neuron, which receives input from other neurons or external sources, performs a mathematical computation on the input, and produces an output signal that is transmitted to other neurons or output nodes. The equation for the output of a single neuron in an ANN can be written as (Equation 4):

$$Y = F(\sum W_i * X_i) + b \tag{4}$$

Where Y is the output, F is the activation function applied to the neuron, e.g., ReLU, LeakyReLU, sigmoid, or tanh [10-12], Wi are the weights of the connections, Xi are the input values presented to the neuron, and b is the bias associated with the unit [9].

Furthermore, the neural networks are very accurate in many of the learning algorithms and the development of neural networks has been and is still a very important area of research in artificial intelligence and machine learning. One paper which has specialized on this field by Stanley and Miikkulainen [4] sheds light on the NEAT algorithm. In contradistinction to previous methods that only exploited weight tuning as an optimization tool, NEAT gives rise to both weight and structure optimization. This invention has given rise to neural networks, which unlike before can modify to respond to changes. Such networks can therefore be utilized in some tasks, including object detection, lane keeping, and decision-making. Along with NEAT, another remarkable paper that influenced the growth of large networks was by Stanley et al., [5]. They tackled the problem of matching neural networks for the high level of scalability by proposing a new variant called Hypercube-based NEAT (HyperNEAT). By means of this method, direct encoding is not used. Instead, the encoding exploits domain specific patterns leading evolution towards big neural networks having millions of connections able to display made up of modules, hierarchy, and regularity. Such tricks have opened an entirely new field of investigation into the fields of gentle learning methods and have become one of the leading applications in solving more and more complicated problems. They have motivated AI and ML researchers to explore new approaches for evolving neural networks and improving their structures.

However, some other machine learning techniques and approaches need to be taken into account while considering machine learning and its relevant technologies:

- Active learning: In this approach, the algorithm can request labels for specific examples to improve its performance. This can be more efficient than labeling the entire dataset in a supervised learning setting [13]. This type of learning is primarily associated with supervised learning.
- Online learning: Here, the algorithm receives a stream of data, and it should make predictions or updates on the same data, without the ability to go back and process old data [14]. It is associated with various types of learning, such as supervised learning, unsupervised learning, and reinforcement learning
- In multi-task learning model, a single model is taught how to perform multiple tasks that are interconnected and are at the same time using mathematical processing which is back propagation [15]. It might be associated with both supervised learning as well as unsupervised learning.
- Explainable artificial intelligence: This part of research aims at building machine learning models that bring out the explanations for their prediction or decisions thereby making transparent and humane the whole process [16]. To begin with, it is not deeply coupled to a particular learning kind; rather, it is an approach that is attuned to making AI decisions clearer and more comprehensible across learning paradigms.
- Federated learning: This is a distributed machine learning paradigm that helps parties to jointly train a machine learning model without such entities' direct access to their data [17]. It might refer to many kinds of learning, such as, but not limited to, supervised learning and unsupervised learning.
- Imitation learning: The purpose of such replication is to train a model to imitate the behavior of others, normally resulting in the identical actions or results as ones who are being imitated. It is mostly about supervised learning.
- Transfer learning: The point of this approach is that a model trained on the first task is repurposed and used as the model for a related task. The objective is that knowledge will transfer from the original task to the target task to the end that the model will perform better than if it was trained by scratch [18]. It relates to various ways of learning, such as supervised learning, unsupervised learning and reinforcement learning.

Moreover, familiarization with deep learning (DL) algorithms is becoming trending lately as it is already adopted in several fields of technology including the field of autonomous cars. In Table 1, the basic properties of the most employed deep learning algorithms are shown.

Table 1. Main deep learning algorithms.

Network Type	Features	Pros	Cons	Reference
Convolutional Neural Networks (CNNs)	Spatial hierarchies' recognition, Weight sharing, Feature extraction	Excellent for image and video analysis, Reduced parameters, Translation invariance	Computationally intensive, Limited sequential processing	[19]
Long Short-Term Memory Networks (LSTMs)	Sequential data modeling, Memory retention	Effective for timeseries data, Longterm dependencies capture	Training complexity, Computational demands	[20]
Recurrent Neural Networks (RNNs)	Sequential information processing	Suitable for sequential data modeling, Variable input lengths	Vanishing and exploding gradient problems, Training instability	[21]
Generative Adversarial Networks (GANs)	Generative modeling, Image synthesis	Produces realistic data, Creative content generation	Training instability, Mode collapse	[22]
Radial Basis Function Networks (RBFNs)	Nonlinear mapping, Pattern recognition	Fast training on fixed data sets, Good for radial symmetry	Limited generalization, Sensitivity to kernel selection	[23]
Multilayer Perceptrons (MLPs)	Universal function approximation	Versatile and widely applicable, Good for complex problems	Prone to overfitting, Sensitive to hyperparameters	[24]
Self-Organizing Maps (SOMs)	Unsupervised learning, Topological mapping	Dimensionality reduction, Clustering and visualization	Fixed structure and size, Limited to input topology	[25]
Deep Belief Networks (DBNs)	Layerwise unsupervised pretraining	Effective feature learning, Probabilistic inference	Computationally intensive, Training complexity	[26]
Restricted Boltzmann Machines (RBMs)	Stochastic, generative learning	Feature learning in unsupervised manner, Efficient pretraining	Training complexity, Sensitive to hyperparameters	[27]

2.2. Blockchain

Blockchain is a public database which can be adopted by several parties to record transaction activity on the distributed ledger. Record keeping for each entity is done through a cryptographic protocol. In each case, the transaction is recorded as a block, and then the chains of the blocks are connected to form an unbroken record of all the transactions on the blockchain. One of the crucial factors for blockchain is its distributed feature [1]. Instead of relying on a central authority to verify and validate transactions, a blockchain network relies on a peer-to-peer network of computers to reach consensus on the state of the digital ledger. This makes it difficult to manipulate the record.

Another important aspect of blockchain technology is its use of smart contracts, Figure 2. Smart contracts represent a key element of blockchain technology. They are autonomous contracts, with the terms of the agreement between the involved parties, such as a buyer and seller, encoded directly into the lines of code. This code, along with the enclosed agreements, is stored and duplicated within the blockchain network [28].

Among mathematical representations and equations widely used in smart contracts is cryptographic hash function [1] that takes an input and produces a fixed-size output. Mathematically, it can be represented as (Equation 5):

$$h = H(m) \tag{5}$$

Where h is the hash value, and m is the input message.

Furthermore, there are several different blockchain applications, such as the financial industry, supply chain management, and voting systems. Some of the key benefits of using blockchain technology include increased security, transparency, and efficiency. There has been a lot of research conducted on blockchain technology in recent years, with numerous papers being published on the subject. Some of the key areas of focus in these papers include the technical aspects of blockchain systems, their potential applications, and their economic and social impacts. Blocks and transactions are fundamental elements of blockchain technology, where blocks are digital containers of data, primarily consisting of transactions that document value exchanges across the network. Table 2 provides a comparison of the data elements included in blockchain blocks and transactions.

Figure 2. Smart contracts.

Table 2. Differences between blocks and transactions.

Feature	Blocks	Transactions
Definition	Collection of transactions bundled together and added to blockchain	Record of specific exchange or transfer of data or value on blockchain
Size	Larger than transactions	Smaller than blocks
Frequency of creation	Created less frequently than transactions	Created more frequently than blocks
Data stored	Hash of previous block, timestamp, transaction data	Data specific to transaction being recorded
Examples	Bitcoin block, Ethereum block	Bitcoin transaction, Ethereum transaction

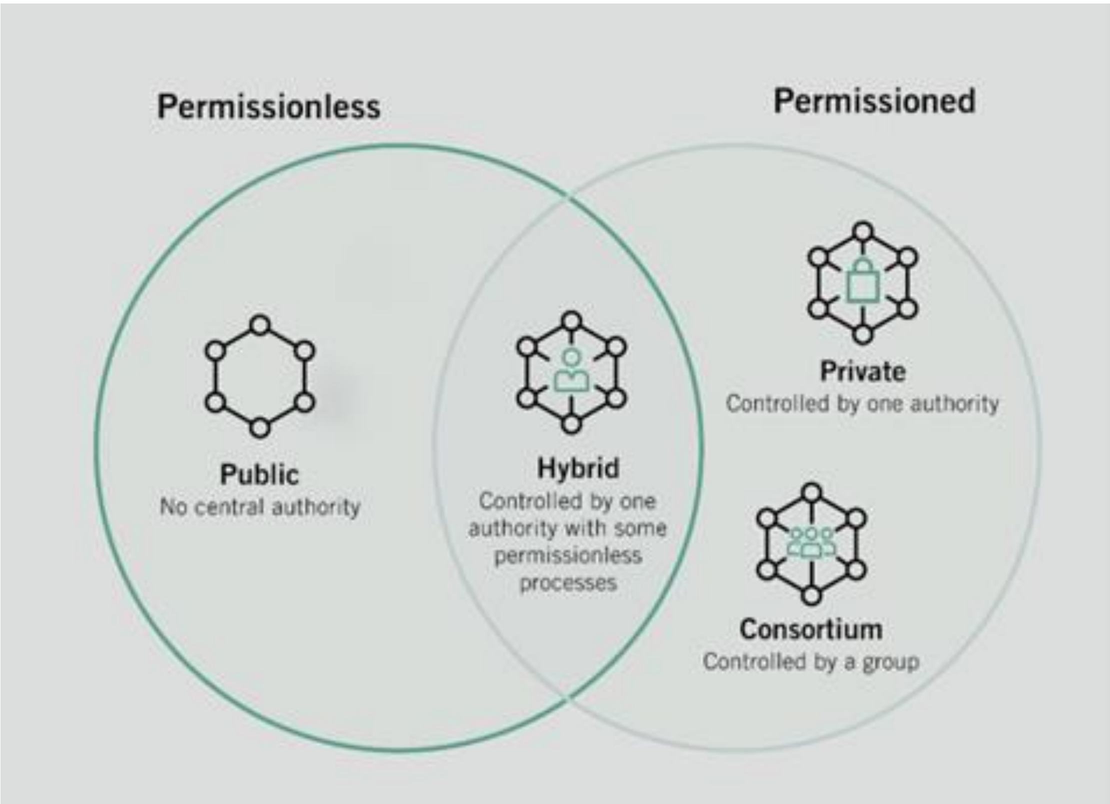

Figure 3. Different types of Blockchain [29].

Blockchains can be classified into four types, Figure 3, based on their accessibility and control:

- Public blockchains are open and decentralized, allowing anyone to participate and are secure.
- Private blockchains are for a specific group or organization and access is restricted to authorized members.
- Consortium blockchains are controlled by a pre-selected group of organizations.
- Hybrid blockchains combine the features of both public and private blockchains for a balance of security, privacy, and decentralization.

In a blockchain network, participants are typically referred to as nodes. Blockchain nodes vary as users, miners, validators, or other participant types. The specific blockchain and consensus algorithm determine the node types. A consensus algorithm ensures network agreement on the shared ledger state. All blockchain network nodes must agree on the current state. Having the same blockchain copy across nodes is crucial. Any new added blocks require most nodes' agreement. This maintains a tamper-proof, secure, and accurate transaction record. When adding a new block, the consensus algorithm determines the allowed node. It also ensures other nodes validate the block. The process may involve complex math problem-solving. A majority vote approach could be used. A combination of methods is also possible [30]. Once a block is added, the consensus algorithm ensures that all nodes in the blockchain network have the same blockchain copy and reach a consensus on its current state. This mechanism is, hence, crucial for ensuring the blockchain's overall authenticity and trustworthiness, irrespective of the individual node's particular intentions to modify the blockchain at will or introduce fake information. Table 3 presents a comparison of main blockchain consensus algorithms.

Table 3. Comparison of the main consensus algorithms.

Algorithm	Pros	Cons
Proof of Work (POW) [31]	Widely used and well-known	Energy-intensive
Proof of Stake (POS) [32]	Energy-efficient	Can be subject to “nothing at stake” issue
Delegated Proof of Stake (DPOS) [32]	Fast transaction speeds	Centralized decision-making
Byzantine Fault Tolerance [33]	Fast transaction speeds	Requires a relatively small and known group of nodes

2.3. Autonomous cars

An autonomous vehicle has sensors that allow its environment to be perceived without the need of a human operator. The array of sensors and complex machine learning algorithms that the autonomous car is equipped with helps in discerning the immediate surroundings and predicting the road ahead. Based on the perception, the machine then navigates the road accordingly. The efforts of developing self-driving cars have been driven by several goals, such as lowering traffic accidents, enhancing fuel efficiency, and offering transport to the people who cannot drive. Potential economic benefits exist with autonomous car usage. Car ownership needs could reduce. More efficient road space utilization may occur. Significant research and development efforts are underway in this field. Intelligent transportation systems are a focus area. Currently, multiple companies test self-driving vehicles on public roads. However, there are also several technical and organizational challenges that must be overcome before autonomous cars can be widely deployed. These challenges include the need to improve the reliability and safety of autonomous systems, develop standards for their operation, and address concerns about cybersecurity and data privacy. One of the key technologies that enables autonomous cars to navigate their environment is sensors. These sensors include lidar, radar, and cameras, which are used to create a high-resolution map of the car’s surroundings [34]. Figure 4 provides a visual representation of the main tasks achieved by different sensors, while Table 4 summarizes the essential properties of the main sensors utilized in autonomous cars.

Table 4. Sensor types in autonomous cars.

Sensor	Pros	Cons	Distance	Reference
Camera	Wide field of view, high resolution, low cost	Sensitive to lighting conditions, easily fooled by camouflage and other visual illusions	Depends on camera resolution and zoom	[36]
Lidar	High resolution and accuracy	Relatively high cost, vulnerable to occlusion and interference from other lidar sources	100-200 m	[37]
Infrared Camera	Can operate in variety of lighting conditions, robust to visual illusions	Limited range, sensitive to temperature changes, vulnerable to occlusion	Depends on camera resolution	[38]
Ultrasound	Can operate in variety of lighting conditions, relatively low cost	Limited range, vulnerable to interference from other ultrasound sources	1-5 m	[39]
Radio Frequency (RF)	Wide range, relatively low cost	Limited accuracy and resolution, vulnerable to interference from other RF sources	Depends on antenna design	[40]
Dedicated Short-Range Communication (DSRC)	Wide range, high accuracy, robust to interference	Limited accuracy and resolution, vulnerable to interference from other RF sources	1,000 m	[41]

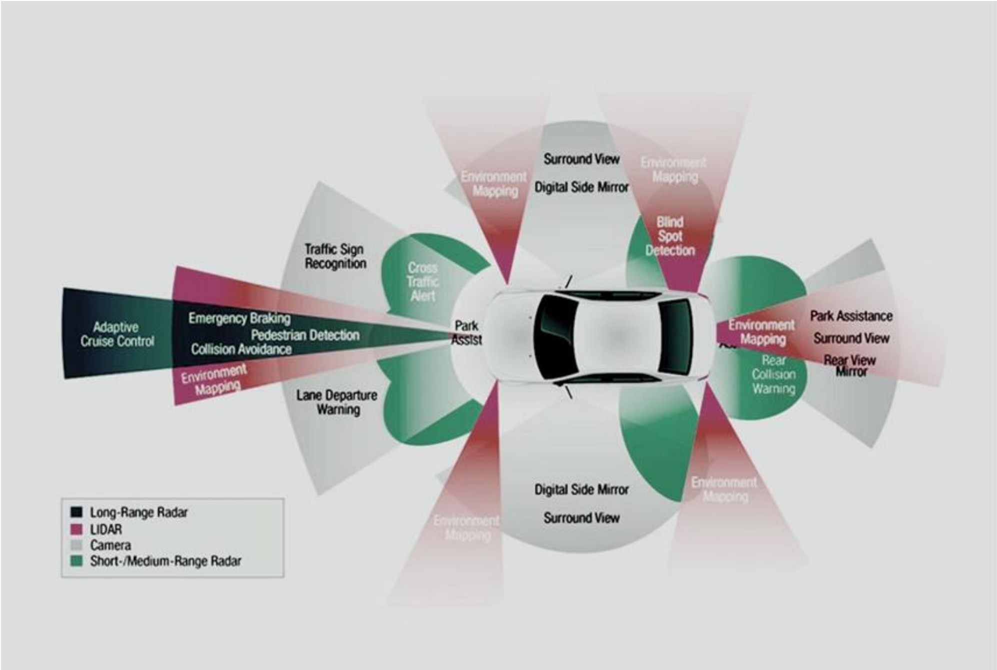

Figure 4. Different sensors used in autonomous cars [35].

Table 5. Sensor data fusion approaches for autonomous cars.

Method	Description	Cons	Pros	Reference
F-Cooper	Uses fully convolutional neural network (FCN) to extract features from both camera and lidar data. Features are then fused using cooperative learning framework	Not effective in complex environments	Handles high-dimensional data	[42]
V2VNet	Uses RNN to model temporal dependencies between frames of camera data. RNN is then augmented with vehicle-to-vehicle (V2V) module that learns to fuse information from neighboring vehicles	Computationally expensive	Improves object detection and tracking	[43]
AttFuse	Uses attention mechanisms to fuse features from camera, lidar, and radar data. The attention weights are learned in an end-to-end manner	Sensitive to noise in data	Improves object classification and localization	[44]
V2X-ViT	Uses ViT (Vision Transformer) encoder to extract features from camera data and FiT (Fusion Transformer) decoder to fuse features with information from V2X communication	Can be difficult to train.	Improves situational awareness	[45]
CoBEVT	Uses contrastive learning framework to learn representation of camera data that is invariant to ego-motion. Learned representation is then used for object detection and tracking	Requires large amount of training data	Improves robustness to ego-motion	[46]
No Fusion	Simply concatenates features from camera, lidar, and radar data before feeding them into classifier or regressor	Less effective than other fusion methods	Simpler to implement.	[47]
Late Fusion	Fuses features from camera, lidar, and radar data after they have been processed by separate networks	More computationally expensive than early fusion.	Preserves more information from original data sources	[48]
Early Fusion	Fuses features from camera, lidar, and radar data at the raw data level before they are processed by any networks	Less effective than other fusion methods when data sources are noisy or unreliable	Less computationally expensive than late fusion	[49]
MACP	Uses multi-attention fusion network to fuse features from camera, lidar, and radar data. The network uses multiple attention mechanisms to capture different types of relationships among features	More complex to implement than other fusion methods	Improves performance of autonomous vehicles in complex environments	[50]

Another important aspect required for autonomous cars is machine learning. Extensive efforts have been made in developing datasets of real driving scenarios for autonomous driving training, such as Kitti [51], Waymo Open [52] and V2V4Real [47] datasets. Other datasets, such as V2X-Sim [53] and OPV2V [54], are built using CARLA simulator [55] for different autonomous driving scenarios. Also, machine learning algorithms allow the car to analyze and fuse data from its different sensors, and then make decisions accordingly. Table 5 shows some utilized approaches for sensor data fusion in autonomous cars. Machine learning and blockchain techniques can further contribute to countermeasures strategies against security vulnerabilities in autonomous cars and vehicles. These can be intra-vehicle threats associated with engine control, transmission units, temperature control, and various Electronic Control Units (ECUs), or Vehicle-to-everything (V2X) threats, which include a spectrum of cyber threats, including DoS attacks, black-hole attacks, replay attacks, Sybil attacks, malware infiltration, falsified-information attacks, timing attacks, and impersonation attacks in V2X communications. Recent surveys [56, 57] provide a detailed exploration of security vulnerabilities and their countermeasure strategies using blockchain and machine learning technologies in Connected Autonomous Vehicles (CAVs).

Furthermore, mathematical models play a crucial role in the decision-making processes of autonomous vehicles. There are several models employed in various aspects of decision-making, such as path planning, control, and prediction. Here are three prominent models used in autonomous vehicle decision-making:

1. Probabilistic Models [58]: Probabilistic models are used to represent and reason about uncertain information, such as sensor noise, localization errors, and prediction of other road users' behavior. Bayesian networks, Markov Decision Processes (MDPs), and Partially Observable Markov Decision Processes (POMDPs) are examples of probabilistic models employed in autonomous driving. For example, in an MDP, the decision-making problem is modeled as a tuple (S,A,P,R), where S is a set of states, A is a set of actions. P(s'|s,a) is the transition probability function, which represents the probability of reaching state s' from state s when taking action a. R(s,a) is the reward function, which assigns a numerical value to each state-action pair. The goal in an MDP is to find a policy (a mapping from states to actions) that maximizes the expected cumulative reward over time.

2. Optimization-based Models: Optimization-based models are used to find optimal trajectories and control actions that minimize a cost function while satisfying constraints, such as vehicle dynamics, road geometry, and traffic rules. Examples of optimization-based models include Model Predictive Control (MPC), convex optimization, and Mixed-Integer Linear Programming (MILP). For example, in an MPC framework, the decision-making problem can be formulated as an optimization problem as follows (Equation 6-9).

$$\text{Minimize } J(x, u) \tag{6}$$

$$\text{Subject to}$$

$$x' = f(x,u) \tag{7}$$

$$g(x,u) \leq 0 \tag{8}$$

$$h(x,u) = 0 \tag{9}$$

where x represents the state vector, u represents the control input vector, $J(x,u)$ is the cost function to be minimized, $f(x,u)$ represents the state dynamics equation that describes the evolution of the state vector over time, $g(x,u)$ represents constraints on the states and control inputs, ensuring they satisfy certain conditions, and $h(x,u)$ represents any additional problem-specific constraints that need to be satisfied. The optimization problem aims to find the values of x and u that minimize the cost function J while satisfying the given constraints. The specific form of the cost function, state dynamics equation, and constraints would depend on the optimization-based model being used.

3. Graph-based Models [59]: Graph-based models are employed in path planning and route selection tasks in autonomous vehicles. The road network, traffic, and vehicle states are represented as graphs, and graph search algorithms, such as Dijkstra's, A*, or RRT (Rapidly exploring Random Trees), are used to find optimal paths or routes.

Figure 5 provides a flowchart for high-level overview of the decision-making process used by an autonomous car. The process of autonomous driving involves several key steps, which can be broadly categorized into perception, prediction, planning, control, actuation, and monitoring. In the perception phase, data are collected from various sensors to identify and track objects in the environment. The motion of other road users and changes in traffic lights are estimated in the prediction phase. In the planning phase, the optimal route and path are determined, and the desired vehicle motion is calculated. In the control stage, control inputs are calculated to achieve the desired motion, and these inputs are applied to the vehicle's actuators in the actuation stage. Finally, the system is continuously monitored and updated in real-time based on sensor data, and errors or unexpected situations are detected and handled appropriately. Overall, the flowchart provides a valuable way for understanding how an autonomous car navigates the road and makes decisions that prioritize the safety of pedestrians and other drivers on the road. Moreover, such or similar decision-making process is utilized in most autonomous vehicles for different purposes, such as self-driving cars, small cleaner robots [60] or autonomous drones [61, 62].

Many studies have utilized different machine learning algorithms for autonomous cars and autonomous driving systems. In [63], the authors provide an in-depth discussion of various deep learning approaches such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) and Generative Adversarial Networks (GANs) and their application in self-driving cars through case studies. The paper provides a comprehensive overview of the considerations and challenges of developing self-driving car systems using deep learning techniques. However, this paper focuses specifically on the use of deep learning and does not provide a complete analysis of other technologies or approaches used in autonomous driving systems. Another paper [64] presents a system for real-time obstacle detection and tracking for autonomous driving. This paper also talked about the sensors and

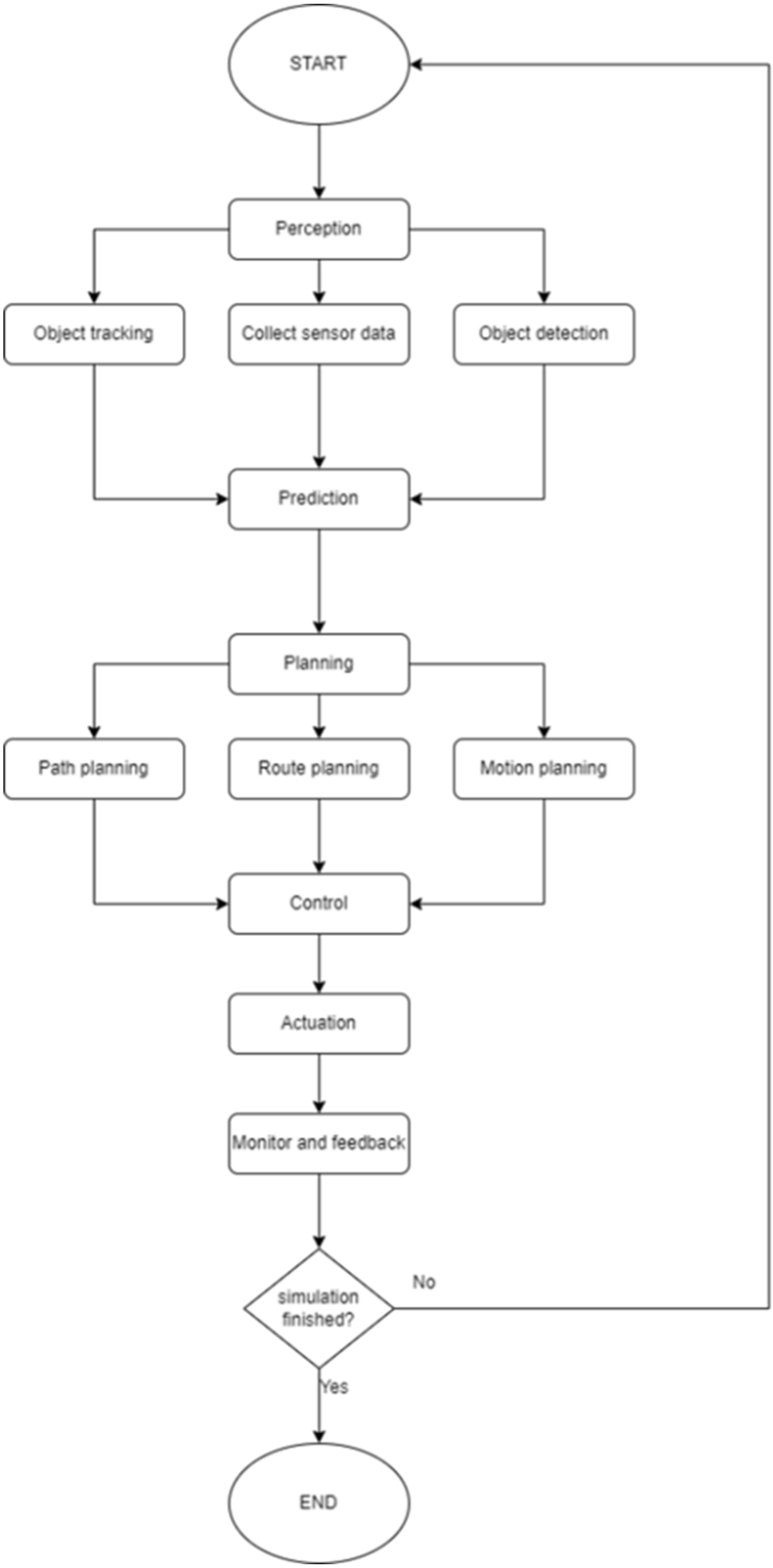

Figure 5. Flowchart of decision-making process in an autonomous car.

algorithms used. However, this paper focuses specifically on the problem of obstacle detection and tracking in autonomous driving and does not provide a comprehensive overview of other aspects of autonomous driving systems. When it comes to improving the autonomous driving systems, the bigger challenge is the amount of data required for learning. However, the authors in [65] discuss the problems such as overfitting and difficulty transferring models between different environments and to overcome these challenges, they provide an overview of several proposed solutions, including data augmentation, transfer learning, and active learning. Also, the authors suggest future directions of using deep learning techniques in autonomous driving by integrating other different technologies, such as edge computing and the internet of things.

To improve the efficiency of lane changing, the authors in [66] provide a machine learning-based approach for lane change intention awareness in assisted and automated driving. An autonomous vehicle learns to predict the lane change intentions of surrounding vehicles by analyzing their motion patterns and contextual information. Kendall et al. [67] present another example of machine learning-based approaches, where an autonomous vehicle learns to drive through interaction with the environment, receiving rewards or penalties. The paper is devoted to assessing the abilities of machine learning-based autonomous driving system using situations, such as like lane switching, lane merging and intersection moving. In [68], the authors investigate about the use of Deep RL (DRL) in the driverless vehicle systems. They provide various applications of DRL for autonomous driving systems, such as perception, decision making, controlling systems. Nevertheless, the employment of DRL in autonomous driving would require quite a big amount of data and computational capability which can result in systems that are more complicated and expensive. Similarly, Ni et al. [69] review the key applications of DRL in autonomous driving and the various evaluation metrics used to improve their performance.

However, all previous studies did not consider or benefit from blockchain technology for developing autonomous car systems or intelligent transportation systems.

3. Integration of blockchain in intelligent transportation systems

3.1. Blockchain and internet of vehicles

The incorporation of blockchain technology into the Internet of Vehicles (IoV) yields comprehensive solutions to security, privacy, and trust related problems, which are all vital to lessen IT intricacies in this domain. In [70], Chen et al suggested a hybrid approach for data trading in IoV that is based on both blockchain as well as edge computing. Blockchain is the basis for security and decentralization while edge computing allows for faster data processing. This technique prefers blockchain to keep track of data consistency and provide dynamic data exchange support among vehicles. In the same way, the authors from [71] propose a blockchain-based information sharing scheme for IoV with a data storage module, a data sharing module and a data access control module. Through the utilization of smart contracts, they were able to increase the smartness within their existing data sharing processes and implement various access control policies that regulate who can access to the shared data. Employing the blockchain for building trust management can help establish trust management among members in vehicular ecosystem by making transaction data transparent as well as immutable. Applications of blockchain in trust management and challenges with blockchain for vehicular networks were explored in [72], including the use of public, private and consortium blockchain. However, using blockchain for trust management may not be the best way or it still needs more studies. This is because of the implementation and maintenance costs and the need to secure trust data privacy, which is provided in more detail in [73]. The authors also explore decentralized decision-making algorithms and reputation systems for determining the trustworthiness of vehicles using blockchain-stored data. Additionally, the authors in [74] proposed a decentralized blockchain-based trust management framework for the IoV that uses smart contracts to automate the trust management process. In terms of communication, blockchain technology has been proposed for enabling secure and trusted communication among vehicles in the IoV.

While other work has elaborated the positive implications of blockchain technology for data sharing, Vattaparambil et al. [75] have also addressed the technical challenges and particularities of data sharing and trading among connected cars. The above paper discusses the improved connected car environment's new challenges, such as the data security and trust, which are vital for the whole system efficiency, and can be used for malicious attack purposes. Blockchain is a revolutionary technology that enables its application in the autonomous car's ecosystem, like the management of computing resources. Lin, et al. [76] introduced the application of a blockchain-based platform for the sharing of on-demand computing resources between each other in the case of smart cities. Among others is the application of smart contracts to regulate the resource management between the cars and other devices thereby, as well the use of distributed ledgers for the security and transparency of the resource trading process. Additionally, they discussed different challenges and the solution limitations, and they made a performance analysis demonstrating the effectiveness of their system.

To develop scalable, highly efficient, and highly safe blockchain-structured devices for IoV, it is imperative to develop the complete framework that allows the optimization of the blockchain use in IoV. The system utilizes a concept of technical optimization to solve issues of scalability, efficiency and the security, which typically crop up when we are designing the IoV blockchain. Being able to gain a perspective of the unique aspects that make the environment stand out like the need for scalability and interoperability and this framework can draw a solution that is specific to this application. Xu et al. [77] have applied edge servers to support the decentralized nature of blockchain-based communications in IoV to facilitate the local processing and help reduce the amount of data that needs to be transmitted. This improves the overall performance of the system and also enables the secure and reliable data exchange among vehicles and other participants. The paper provides the proposed system architecture and each of its components, such as the blockchain, edge server deployment algorithms, and the performance optimization issues.

Consequently, blockchain can also be leveraged for establishing systems that manage the charging stations for electric self-driving vehicles, as in [78]. The writers presented a framework of blockchain-powered software that would deliver charging electric cars in a secure way, and also allow sharing of charging resources among different vehicles. Smart contracts helped them to do the charging resources management in an automatic and direct manner. This reduces the need for manual intervention and improves the speed and accuracy of resource allocation. Also, the use of a consortium blockchain enables the system to scale to large numbers of charging stations and vehicles. It is worth noting that implementing a blockchain-based software system may require significant investment in terms of software development and infrastructure. There may also be regulatory or legal challenges associated with the utilization of blockchain in managing charging resources for electric self-driving cars.

However, very few surveys are recently available in the literature that discuss the application of blockchain in IoVs and Intelligent Transportation Systems (ITSs) [79,80]. Mollah et al. [79] conducted a survey on the latest advancements in blockchain for IoVs, highlighting different application scenarios and investigating key challenges where blockchain is applied in IoVs. They also discussed future opportunities and further research directions. The article emphasizes that the underlying platform of IoVs for information exchange needs to be transparent, secure, and immutable to achieve its required objectives. In [80], the authors systematically reviewed applications of blockchain in ITSs and identified several challenges in the realm of vehicular networks and suggested potential future research directions. Future research paths outlined by the authors encompass enhancing security against Distributed Denial of Service (DDoS) attacks, thorough analysis of the architectures, limitations and challenges of the IoVs as a pivotal facilitator of ITSs, and a focus on data management in smart cars. They foresaw that enhancing blockchain performance will be a significant area of interest in the future, particularly as Blockchain-based IoV (BIoV), with broader applications. They also explored blockchain role in vehicular network cybersecurity and assessed the cybersecurity threats in these networks. However, recent advancements in fifth Generation (5G) technology, big data analytics, and machine learning were not considered.

3.2. Integration of blockchain and machine learning for autonomous cars

The rise of autonomous cars and their intelligence capabilities has brought new challenges in data sharing and security. Blockchain, as decentralized and tamper-proof technology, can address these challenges in a secure and efficient way. In [81,82], the authors propose the utilization of blockchain technology to accelerate the training of autonomous cars. Blockchain technology by itself can be used as an infrastructure for securing the storage devices to store the bulk data requirement of the self-driven vehicles. Moreover, blockchain has opened up new ways of trusting and reconciling the authenticity and integrity of the underlying data.

In the context of supply chain management, the combination of reinforcement learning together with a heuristic search method was explored in [83]. Their purpose was improving the self-driving vehicles routing optimization in a supply chain management system, which would use blockchain technology. The paper has a different perspective which is the use of reinforcement learning and heuristic search for routing optimization of autonomous vehicles. The blockchain technology is going to be employed to create an infrastructure for the storage and sharing of data emanating from vehicles routing as well as for verification of their authenticity and integrity. In addition to this, Liu et al. [84] proposed a strategy based on blockchain technology and deep reinforcement learning to enhance the Industrial IoT (IIoT) systems in terms of data collection and sharing. An innovation with blockchain technology and deep reinforcement learning as a solution for data collection and sharing in industrial internet of things systems. Performance optimization of blockchain-integrated IIoT systems was the main concern of [85], which describes a DRL approach for improving the performance of blockchain-enabled IIoT systems. This paper focused on blockchain usage in IIoT rather than in vehicular networks. However, the use of deep reinforcement learning in such systems can be very useful to adjust the balance between decentralization and performance in IIoT systems.

Furthermore, blockchain technology in the context of federated learning for connected and autonomous vehicles was considered by He et al. [86]. That is, an autonomous car learning from the combined collective data of any given car while retaining the privacy of each individual vehicle data. The smart contracts technology was used behind the scenes to offer an automatic and transaction neutral exchange of data among cars. Moreover, smart contracts were implemented to guarantee the integrity of the data exchange. The paper showed a predictable architecture of federated learning for connected and autonomous vehicles, covering its advantages and disadvantages.

The authors in [87] examined the incorporation of Autonomous Vehicles (AVs) into our daily lives in numerous forms, such as autonomous drone delivery systems, driverless cars, automated vehicles in warehouses, autonomous home assistant devices, and Automated Eligibility Verification System (AEVS) for green energy solutions. The type, usage, and application of these vehicles largely depend on the level of their automation. The authors discussed the progression and feasibility of integrating advanced technologies like blockchain, Industry 4.0, AI, and IoT into these vehicles. They provided a comparative analysis of different types of autonomous vehicles and their various features, including private blockchain autonomous vehicles, public blockchain autonomous vehicles, and electric vehicles. The study also investigated the potential of integrating blockchain technology with networked groups of Unmanned Aerial Vehicles (UAVs) and the application of blockchain-based mutual-healing group key distribution schemes in UAV ad-hoc networks.

Overall, Table 6 summarizes the objectives, contributions, and important considerations of the relevant papers that propose blockchain-based techniques for solving privacy, trust and security issues in the internet of vehicles, vehicular networks, and autonomous car systems. The proposed solutions, as seen in Table 6, include secure and scalable communication protocols, trust management frameworks, data sharing schemes, and reinforcement learning-based optimization methods. Each paper in the table discusses important considerations, such as the trade-off between security and efficiency, the reliance on cloud computing, evaluation techniques, the scalability, and performance limitations of the blockchain technology.

Table 6. Relevant research papers summary.

Reference	Objective	Method	Important considerations
[75]	Secure and scalable vehicular communication protocol	Presents a protocol using blockchain to secure communication in vehicular networks and discusses its performance	Protocol evaluated through simulations. Results-protocol outperforms existing approaches in terms of security and scalability
[74]	Decentralized blockchain-based trust management	Uses decentralized blockchain network and trust evaluation model to enable secure and trusted communication among vehicles in IoV	Effectiveness of proposed framework evaluated through simulations
[71]	Efficient and secure blockchain-based data	Uses decentralized blockchain network to enable efficient and secure data sharing among vehicles in IoV	Efficiency and security of proposed scheme evaluated through simulations
[70]	Secure and scalable data sharing scheme for IoV	Uses blockchain-based trust model and cloud computing-based data storage and retrieval system	Reliance on cloud computing. Availability and reliability of cloud may impact overall performance
[81]	Blockchain-based system for training autonomous cars using AI	Uses blockchain to securely store and share data for training autonomous car AI model	Efficiency of AI model should be carefully evaluated. Scalability and security of blockchain-based data sharing system should also be considered
[82]	Blockchain-based system for training autonomous cars using ML	Proposes using blockchain to securely store and share data for training autonomous car ML model	Efficiency of ML model should be carefully evaluated. No real model was given
[83]	Reinforcement learning (RL)-based method for optimizing routes of self-driving vehicles	Uses RL to learn and adapt to changing conditions. Uses a heuristic search method to find optimal routes. Uses blockchain to store and share data in supply chain securely	Performance of RL should be carefully evaluated. Scalability and security of blockchain-based data sharing system should also be considered
[79]	Overview of current research on blockchain in Internet of Vehicles (IoV) and intelligent transportation systems (ITS)	Reviews various use cases, applications, architectures, challenges and future trends of blockchain in IoV and ITS	Underlying platform of IoV for information exchange needs to be transparent, secure, and immutable to achieve required objectives
[76]	Blockchain-based data sharing and resource trading model	Presents data sharing and trading model utilizes blockchain between connected cars and third parties. Model includes smart contract-based data trading	Potential benefits of model, including security, privacy, and data ownership. Challenges need to be addressed in practice
[72]	Comprehensive review of existing solutions for privacy, security and trust management issues	Presents overview of challenges and opportunities in application of blockchain in vehicular networks. Discusses various techniques for addressing these challenges	Further research in privacy-preserving blockchain design, and efficient and secure consensus mechanisms for vehicular networks needed. Does not consider scalability and performance limitations in large-scale vehicular networks
[80]	Systematic review for blockchain applications in ITSs	Uses private blockchain and deep RL for secure content caching in vehicular networks	Need for enhancing security against DDoS attacks, limitations and challenges of IoV, data management in smart cars, blockchain-based cybersecurity
[87]	Advances and trends of using blockchain in Autonomous Vehicles (AVs)	Comparative analysis of different types of autonomous vehicles, potential utilization of blockchain technology in networked AVs	Level of automation determining AV type, usage, and application of vehicles. Very wide spectrum of different AVs and application trends without focus on integration techniques

4. Challenges of integrating blockchain with autonomous cars

Along with the blockchain technology prospective benefits for self-driven vehicles, there are some challenges and issues to consider as well to fully leverage their impact. The challenge of scaling and performing stage is resulted from the growth of vehicles in networks that eventually enlarges the size of the blockchain and the computational power necessary to compute transactions. In this case, the transactions are run so slow and the latency highly increased that autonomous vehicles are inefficient and even dangerous. Autonomous vehicles have a challenge in reliability too, where they should run virtually error-free and with continuous availability. In case of failures or hacks, the blockchain network used for the cars would undermine platform safety as well as the operation functionality. Privacy and security are also among the major issues, because the central system of autonomous vehicles stores a lot of critical data, which may become available for unreliable or malicious users. Privacy is needed in autonomous vehicles, as they utilize anonymity and confidentiality to shield passengers' identity and location. The process of regulatory and legal compliance as well as maintaining the evolving standards and laws set in this integration is complex. This implies that those involved in the blockchain, and autonomous cars integration have to adhere to data protection laws and other cybersecurity regulations, among other road safety regulations.

Figure 6 provides the major challenges and considerations of blockchain, artificial intelligence and the convergence between them for intelligent transportation systems [88].

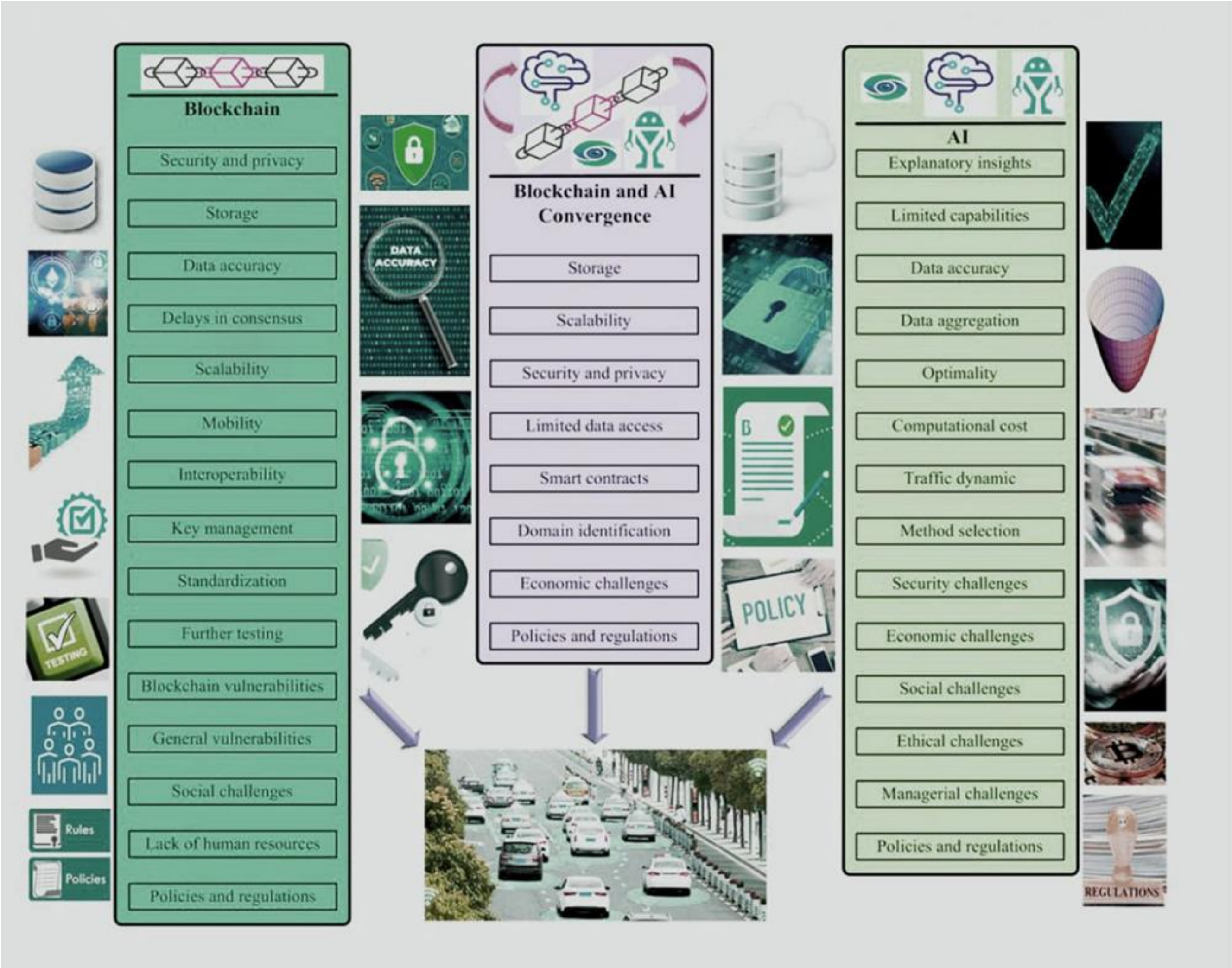

Figure 6. Main challenges in the applications of blockchain, AI, and their convergence for ITSs [88].

Factors that make blockchain challenging include security and privacy as well as data storage, throughput, data consistency, scalability, mobility, interoperability, key management, and standardization. On the AI side of the matter, the related questions involve giving explanatory insights to stakeholders, directing the abilities of AI, guaranteeing data integrity, coordinating data aggregation and, lastly, trying to achieve the highest possible optimality solutions. Other issues, such as bringing computational costs under control, opting for the right strategies to be used alongside the autonomous vehicles, issues of security are among the few obstacles. Their convergence is a double-edged sword affecting both opportunities and the formulation of new challenges and considerations. Such complexity is concerned with among others, ensuring security and privacy of data as well as limited data accessibility in the same process, storage problem, and smart contract system. Besides this, one must also examine the general implications in terms of the economy and policy and regulatory problems.

In this context, researches are working out different alternatives by which blockchain and autonomous vehicle technologies can work together. As such, blockchain could be deployed as an imperative trust management system for vehicle components, e.g. sensors, control systems and networks. It will also contribute in enhancing the security and reliability of autonomous cars. Additionally, reinforcement learning in conjunction with heuristic search methods can be employed to enhance the routes that autonomy vehicles will take within the supply chain management system. This helps in improving efficiencies and reducing the related costs. Blockchain-facilitated data collection and access can drive the improvement in the quality and reliability of the data used for autonomous vehicle learning process, which in turn increases the safety and excellence of their performance. Blockchain is not only used in data management and sharing models but also in trading models for connected cars. This technology can enable IoV-based smart city, on-demand computing resource trading and edge deployment schemes. The directions for the usage of blockchain technology have the possibility to stimulate the understanding of the intelligent transportation systems and autonomous vehicles however the challenges and limitations of the integration of the blockchain with these complex and safety-critical systems must be taken very cautiously into consideration.

5. Conclusion

Integration of blockchain and machine learning for autonomous cars is the uprising field with the capability to bring revolution in the field of self-driving vehicles with respect to safety, efficiency and security. So, this survey was built around three technologies: machine learning, blockchain and self-driving cars, studying how they work and interconnect. The covered literature also revealed that such integrations shall be applied in a multitude of ways in various fields, such as the training of self-driving vehicles and optimizing transportation routes in the supply chain management. The integration of the last-mentioned technologies with blockchain was presented as an innovative approach to address the challenges peculiar to autonomous cars, the internet of vehicles and intelligent transport systems. Additionally, the study ventured into federal learning, offering a secure approach on how connected cars can collaboratively enhance their models whilst still individual user's data privacy. Although the prospects were numerous, various challenges were encountered, such as operational challenges, technical issues, and the ideal balance between safety and efficiency. The blockchain technology has enabled transparency that raises privacy considerations for autonomous vehicles; they require anonymity and confidentiality for their operations. Besides the fact that legal space contributes to complexity, it is necessary to follow the changing rules and regulation in the field of data protection, cybersecurity, and road safety.The future research should be centered on creating scalable solutions that can be quickly replicated accordingly to fit the ever-increasing number of vehicles in the network. During the process, safety and efficiency should be taken into consideration for the sake of development of smart transport systems. Moreover, to ensure service stability, unconditional failure prevention and security protection mechanisms should be deployed. In addition to the privacy-preserving blockchain designs tailored for large-scale networks, further work on the vehicular network should be prioritized for the automobile industry. Alongside this is the need for cooperative efforts among researchers, industry representatives, and policymakers who can create awareness, and understanding of the broad aspects concerning the integration of technology, legality, and societal implications.

Author contributions

Hussam Alkashto: Writing-Original draft preparation, Visualization, Software, Data curation, Investigation. **Abdullah Elewi:** Conceptualization, Visualization, Validation, Supervision, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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