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RESEARCH ARTICLE

Enhancing Autonomous Vehicle Intelligence Through Conversational Artificial Intelligence

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Abstract: Conversational artificial intelligence (AI) is rapidly changing how people interact with digital systems and its integration into smart mobility systems. It creates new opportunities for smart transportation systems. The large language models (LLMs) in autonomous connected vehicles (ACVs) play an important role in automotive research. The LLMs and their natural language processing capabilities can improve the ability of vehicles to communicate and interact with other vehicles and transportation systems efficiently. Recently, the automotive industry has made huge investments in ACV research, recognizing AI as a key driver in advancing smart mobility systems. Even though LLMs cannot directly process real-time sensor data from ACV, they can still contribute to decision-making when integrated within a controlled ACV system. First of all, the sensors collect live data, and then it is processed by perception models and transforms raw inputs into structured semantic representations. These structured representations are then passed to the LLM, which performs reasoning based on contextual and symbolic information. In these proposed integrated systems, ChatGPT supports high-level reasoning, while deep reinforcement learning handles real-time control and decision-making tasks in ACVs. This research also explores the conversational AI opportunities and challenges in smart mobility.

Keywords: LLM, autonomous connected vehicles, natural language processing, vehicle's communication, reinforcement learning

1. Introduction

The emerging technologies have reached the mainstream market and are extremely affecting the ways in which individuals, businesses, and governments interact with each other. Recently, the use of artificial intelligence (AI) as a tool for automating communication across different types of devices has become increasingly popular in today's world [1]. Emerging technologies are used in data discovery, communication, and transfer by enabling faster, more reliable, and intelligent information exchange. AI tools can reduce costs, maximize throughput, and improve transparency, access to more accurate data, analytics, and the ability to communicate securely. Connectivity is one of the most important aspects of autonomous connected vehicles (ACVs). ACV can communicate with other ACVs, which will improve the flow of traffic and the efficiency of transportation [2]. However, there is a security challenge in the connectivity of autonomous vehicles that presents a significant security risk and is attractive for cyberattacks. These challenges can be carried out even if the hacker does not actively hack the hardware, software, or physical components of the vehicle that is the target of the attack. It is sufficient to simply transmit inaccurate or fraudulent information in order to confuse either the communication or the sensing systems. Figure 1 shows the connected vehicles.

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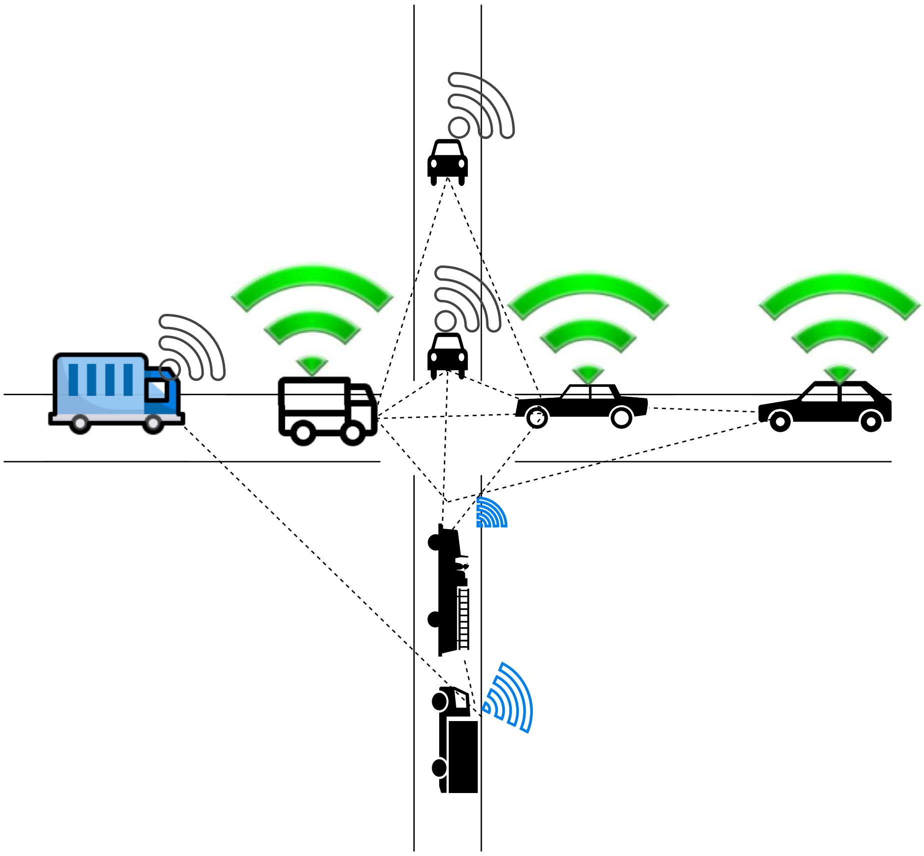
1.1. ChatGPT

The ChatGPT AI chatbot is based on the Generative Pre-trained Transformer (GPT) of large language models (LLMs). ChatGPT is based on OpenAI's core GPT models (GPT-3.5 and GPT-4) and was built using supervised learning and reinforcement learning [3]. It was then customized for chatting uses. ChatGPT, an AI chatbot that OpenAI had developed, was made available to the public in November of 2022. ChatGPT is a combination of Chat, which indicates the system's capacity to function as a chatbot, and GPT, which is a subtype of the LLM. ChatGPT is one of the reasons why it has sparked so much interest among users. The automobile industry is excited because the advancements in AI have had a direct positive impact on the development of autonomous vehicles. OpenAI has made AI models open in recent years [4].

1.1.1. ChatGPT versions

OpenAI continued to develop and improve ChatGPT [5], releasing many new versions of ChatGPT. OpenAI announced the release of GPT-3 in June 2020, the most recent and improved version of ChatGPT [6]. GPT-3 was indicated as a huge step forward in the field of NLP. GPT-3 was the most advanced NLP model in 2020, and it had been integrated into a wide range of applications. Certain models of these applications involve chatbots, virtual assistants, content generation, and language translation. OpenAI released GPT-4 on March 14, 2023 [7]. It is capable of processing images and text inputs, and it can produce text outputs. In comparison to GPT-3, it has 100 trillion parameters and gives more enhancements. On the most important NLP benchmarks, GPT-4

Figure 1
Connected vehicles



achieves better results than both older large-scale language models and state-of-the-art systems. GPT-4 performs better than cutting-edge models when it comes to translated variants of the massive multitask language understanding (MMLU) dataset [8]. AI agents may now self-reflect and self-evaluate in a manner similar to that of humans. To put it more clearly, it is necessary to conduct more tests where GPT-4 evaluates its own responses [9]. This reveals any weaknesses and makes it possible to revise the solutions that it has developed.

1.1.2. ChatGPT utilization

Through the utilization of ChatGPT, extremely accurate methods of translating text between languages have been developed. These systems could deliver translations that are situation-specific and sensitive to the subtleties of many languages, making it easier for people from different cultural and linguistic backgrounds to communicate with one another. ChatGPT can translate code between Python and Java as well as between any other programming languages [10]. ChatGPT has the potential to be of considerable assistance by accelerating the text creation process [11], which often requires significant time and effort from humans. When it comes to creating, summarizing, translating, authoring, and editing information in English, there is no cause to be concerned about the efficacy of ChatGPT.

ChatGPT can deliver a range of dynamic replies because of its conversational nature using AI [12]. Because of its AI, ChatGPT is able to carry out a variety of tasks, including the writing of emails and video scripts, translation, scripting, and copyediting [13].

1.2. AI advancement toward ACVs

The AI advancement technology nowadays has attracted attention to improvements in ACVs. AI is capable of simulating the structure and functioning of neural networks inspired by the human brain [14]. The use of neural networks in real-world autonomous driving was initiated in the late 1980s. In 1989, Carnegie Mellon University launched the ALVINN (Autonomous Land Vehicle in a Neural Network) project [15]. They were successful in accomplishing their goal by meticulously programming in every conceivable driving technique and laying down precise driving directions for all potential scenarios. The development of better computer vision models, like ALVINN, was another factor that was critical to the expansion of the autonomous vehicles sector. Alex Krizhevsky and Ilya Sutskever, two students of Professor Jeff Hinton's, triumphed in the ImageNet image recognition competition in 2012 and took first place [16]. In addition to this, they published a paper describing the AlexNet procedure. This research marked a pivotal turning point for the global information technology industry as well as for AI in general. Object identification and picture recognition are two more technologies that are essential to the development of autonomous driving, and both have benefited from advancements in computer vision algorithms [17].

1.3. ChatGPT and its implications for the future of machine learning

ChatGPT is opening new frontiers in human–computer interaction for vehicles [18]. There are different modes of action, such as gestures, and speech interaction that enables users to communicate efficiently [19]. ChatGPT enables vehicles to hold two-way talks with their drivers, either audibly or textually, concerning topics such as the vehicle's current state and forthcoming turns [20]. These conversations can take place either while the vehicle is in motion or after it has stopped. Before this, there were a lot of different in-car engagement systems, but the industry's main challenge has always been trying to comprehend the responses. As a result of their inability to correctly interpret user responses, most automobile voice interfaces offer fewer command phrases and fewer system actions than their text-based counterparts.

1.4. The success of ChatGPT is a sign that AI has a bright future

Computer vision plays a vital role in perception, whereas generative methods like ChatGPT play a pivotal role in cognition [21]. The majority of a vehicle's capabilities are comprised of its ability to perceive its environment and think about the vision. As a result, the revolutionary impact of ChatGPT has been to pave the way for a future in which models of AI have access to knowledge and the ability to think [22]. The lack of sufficient intelligence in planning and decision-making is now the most significant challenge that must be overcome by autonomous driving.

Autonomous driving can be continuously improved until it approaches the standards of human driving [23] if the concept of human feedback reinforcement learning is also incorporated into its development, and a reward model is trained to check and evaluate the output of autonomous driving models. In other words, autonomous driving can be brought up to human driving standards [24].

The rest of the paper is organized as follows: Section 2 represents Why ChatGPT, Section 3 represents the methods, Section 4 represents the results and discussion, Section 5 shows the challenges, and Section 6 represents the opportunities.

2. Why ChatGPT

Is it possible to train completely autonomous vehicles with human drivers? In theory, it is completely true. We can create a model and train it end to end (from the sensor to action) without making use of any perceptual annotations by relying entirely on data collected from drivers' behaviors and various sensors [25]. Due to the high safety standards for autonomous driving and the difficulties of modern learning algorithms in learning several components simultaneously, the performance of this type of end-to-end learning has not yet been shown to be suitable for the production of ACVs. Many manufacturers of autonomous vehicles are aware of this fact, and as a result, their primary focus is on developing perception, planning, and control systems that can be improved independently before being combined into a single system. Figure 2 represents the manual driving car vs. ACVs.

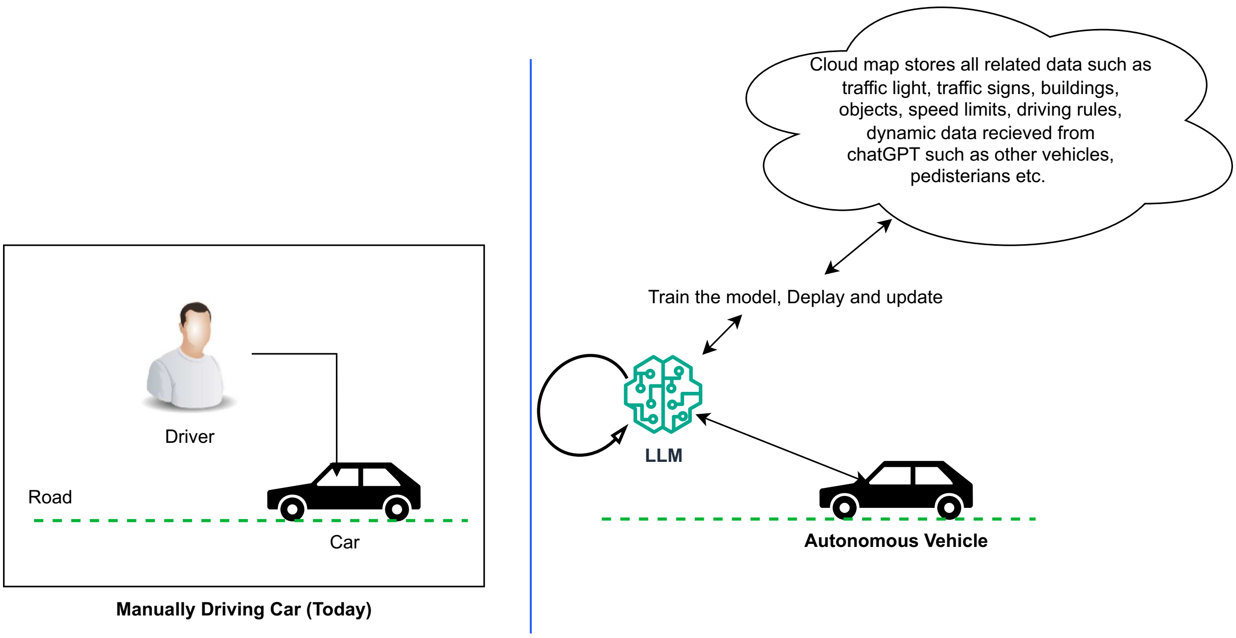
2.1. ChatGPT's contribution to self-driving cars

ChatGPT contributes to the advancement of self-driving cars [26]. ChatGPT and a deep learning system can enhance both the perception-based driving capabilities and the security infrastructure of ACVs [27]. ChatGPT employs NLP to understand and carry out spoken orders. It can be used to instruct an autonomous vehicle on when to turn, how quickly to travel, and when to stop. Autonomous vehicles can thus be trained to operate safely and efficiently using deep reinforcement learning (DRL) algorithms [28].

2.2. ChatGPT-based autonomous vehicle assistant

Because of the numerous advantages that autonomous vehicles have over traditional autos, an increasing number of individuals are choosing them as their primary form of

Figure 2
Manual driving car vs. ACVs



transportation [29]. To protect both its passengers and other drivers on the road, autonomous vehicles must be able to make quick and right decisions [30]. ChatGPT is an NLP system that recognizes spoken language and creates context-sensitive answers. With the help of these advanced technologies, autonomous vehicles will be able to learn from their experiences and make quick, informed decisions. ChatGPT-enabled autonomous vehicles can answer swiftly to questions, recognize things in their surroundings, and follow spoken commands [31]. Furthermore, ChatGPT can be utilized to assist autonomous vehicles in determining how to proceed in difficult settings. This could increase overall road safety and give an added level of security for passengers [32].

2.3. How ChatGPT has aided in the safety of ACVs

People are increasingly interested in adopting self-driving vehicles, but many are concerned about their safety [33]. With the help of ChatGPT, autonomous vehicles may learn more about their surroundings and adapt to them. ChatGPT is a method for evaluating conversational text. It employs a deep learning model that has been trained to identify and respond appropriately to natural human language [34]. ChatGPT can be used to increase autonomous vehicles' understanding of their environment. It improves the vehicle's ability to avoid dangerous situations such as accidents. Using deep learning algorithms, ACVs could better recognize traffic signs and road conditions [35]. The ACVs improved their knowledge of their surroundings and their responses to the directions. This could increase the reliability and security of ACVs for everyone.

2.4. How has ChatGPT enhanced the development of ACVs

ChatGPT has the potential to improve the way ACVs are performed [36]. ChatGPT is driven by powerful AI, which allows it to respond to enquiries and requests in English [37]. Using this technology to develop autonomous vehicle interfaces could result in improved user experience and increased security. A more natural dialogue between the driver and the vehicle might be built using ChatGPT. This could enable more precise direction of the vehicle as well as a better understanding of the user's objectives. An advanced GPT model employs a transformer architecture, which consists of an encoder-processed input sequence and an output sequence created by the decoder. The model may infer meaning and context by assigning various weights to different parts of the sequence. The steps are written as follows:

1) The model generates requests, keys, and value vectors for each character in the input series.
2) Second, it computes a query vector that is like all other tokens by taking the dot product of the query vector and each token's key vector.
3) After that, it generates normalized weights by sending the result through a function.
4) Multiply the weights by the value vector of every token to produce a final vector reflecting the token's relevance in the series. The multiheaded consideration approach developed by GPT goes beyond self-attention.
5) The model executes steps 1–4 in parallel, every time producing a new linear projection of the requests, keys, and values. By growing its self-awareness, the model may find nuances and subtler correlations in the incoming data [38].

GPT model may produce conclusions such as:

1) Not helpful, implying that it doesn't track the user's directions.
2) Difficult to comprehend, implying that consumers do not recognize how the model appeared at a specific result. These visions may contain disrespectful, harmful, or discriminative content, as well as misinformation or erroneous information.
3) ChatGPT promises to use cutting-edge instructional approaches to alleviate some challenges inherent in traditional LLM programs. ChatGPT is a descendant of InstructGPT, which pioneered an innovative technique for integrating human feedback into the training activity to advance support model production through operator intention.

3. Methods

In the process of the ChatGPT model, first of all, prepare a dataset for Fine-tuneGPT, which is the process of training a pre-trained model and generating the reward model. The Proximal Policy Optimization (PPO) method is used to optimize the model using the reinforcement learning method and generate the trained model [39].

1) **Step-1: gather experiment data and train a pre-trained model**

The following is the description of training language models to obey commands through input data. The initial stage is to employ a model of supervised fine-tuning (SFT). To begin, construct a supervised training dataset with known, predictable outcomes from which the GPT model could learn. To collect inputs (or prompts) from genuine user entries, OpenAI was employed. The labelers then completed their tasks and provided a recognized production for every feedback. GPT model adjusted with the newfound supervised dataset to produce an advanced GPT model, commonly known as SFT [40]. After being trained, the SFT model provides more coherent responses to customers' enquiries. The next step is to create a reward model, with the model inputs consisting of a series of questions and their answers and the reward being a scaled value. To take advantage of reinforcement, the reward model must be used. In the learning process, the model is trained to provide outputs that maximize its reward. Figure 3 generates the fine-tuned GPT model.

2) **Step-2: gather parallel data and train the reward model**

Reinforcement learning is revolutionizing AI [41]. The Reinforcement Learning Model gets randomized stimuli and responses. The model's "policy" is used to construct the response. The policy is the method by which the system has been instructed to use in order to reach its target, which is to maximize its reward. Figure 4 shows the training of the reward model.

3) **Step-3: optimize a policy against the reward model using reinforcement learning**

The reward model is applied to the ready and response datasets. It motivates the model to implement policy changes. The PPO method represents altering the model's policy with each response. PPO includes the per-token Kullback–Leibler (KL) penalty from the SFT standard to deviate assesses the similarity of two distribution functions and penalizes extreme closeness [42]. It introduces a KL penalty that reduces the maximum distance that replies can be from the SFT model outputs created, limiting reward model over-optimization and considerable deviation from the human intention dataset. Figure 5 shows the optimization using reinforcement learning.

Figure 3
Generate the fine-tuned GPT model

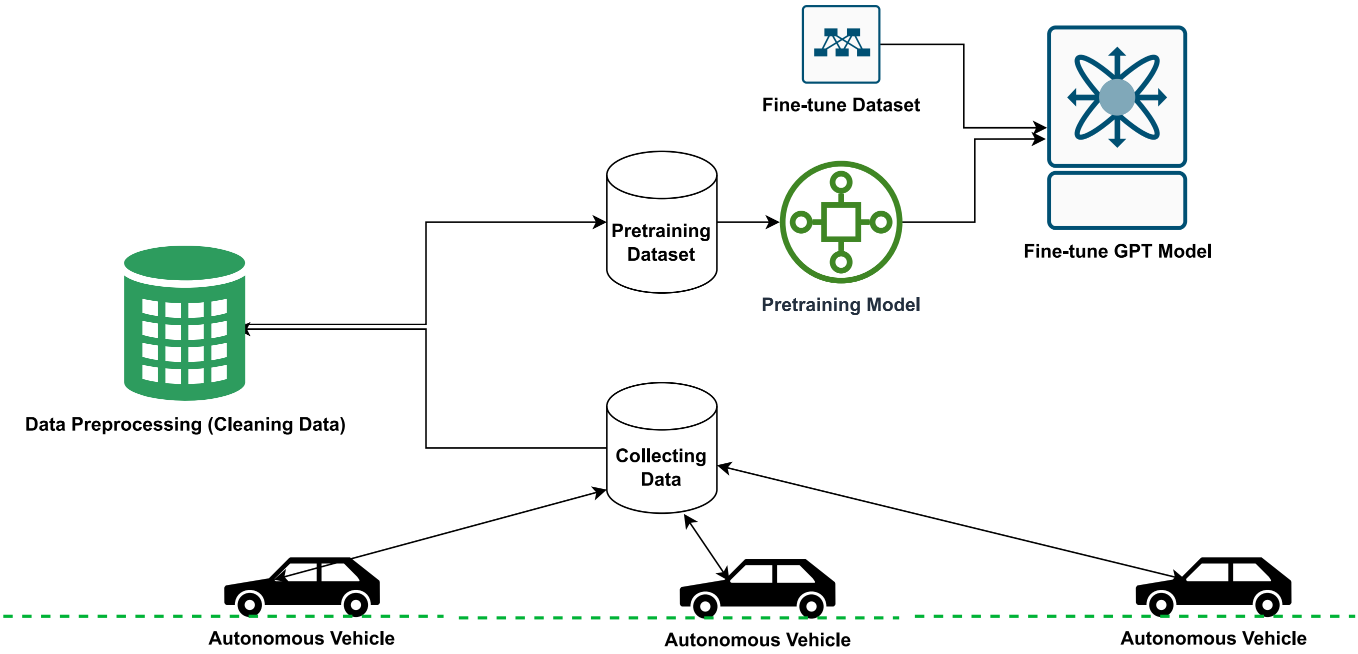


Figure 4
Train the reward model

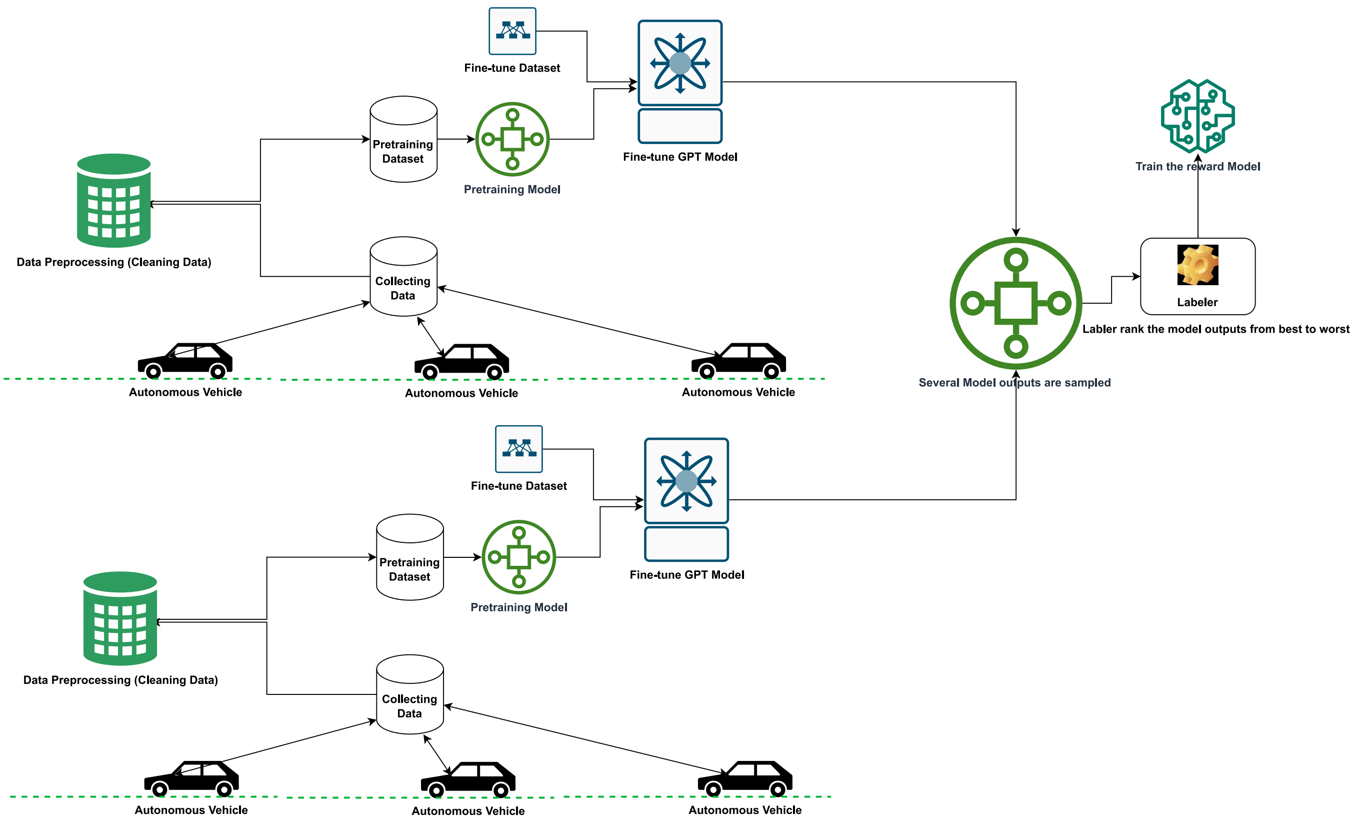
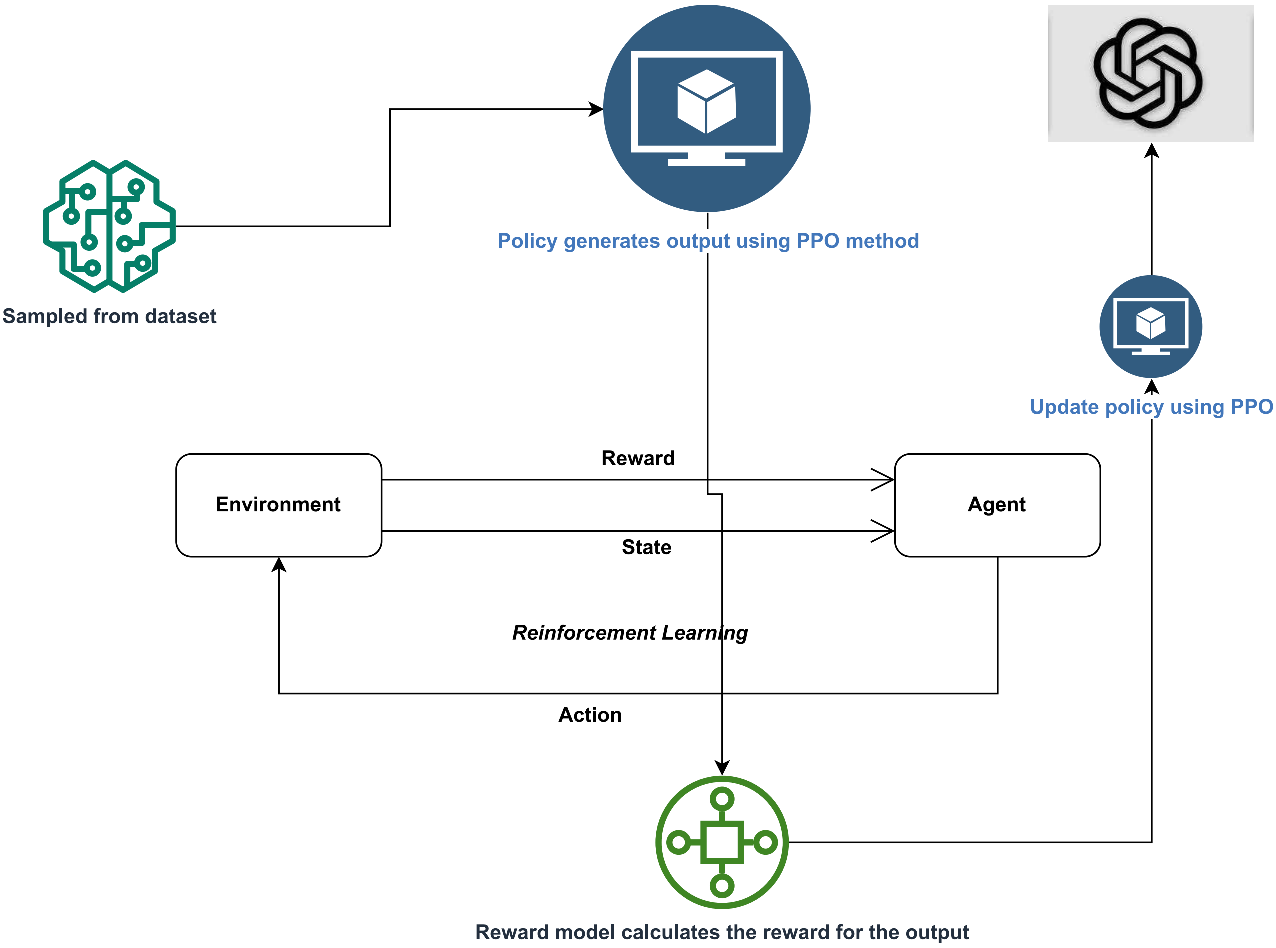


Figure 5
Optimize using deep reinforcement learning



Reinforcement learning training consists of the following steps.

1) Consider the agent (A).
2) For each episode (E):

a. Reset the environment of vehicles.
b. Consider the observation (O).
c. The initial action, Ai = Ω(P), would be established, where Ω(P) represents the current policy.
d. Place Ai the current action and O the current observation at the beginning of the sequence.
e. Do the following while the episode is working on or has not yet ended.

   i. Use the following action Ai on the environment to get the resulting observation O' and reward R.
   ii. Learn more about the O, A, R, and O' collection of experiences.
   iii. Next Action A' = Ω(P')
   iv. Change A to A' and O to O'
   v. If the environment's prerequisites for ending the episode have been met, the episode will end.

f. Stop training if the conditions for doing so have been met. If not, continue to the next episode.

The specifics of how the system performs these tasks are determined by the agent's and environment's configuration.

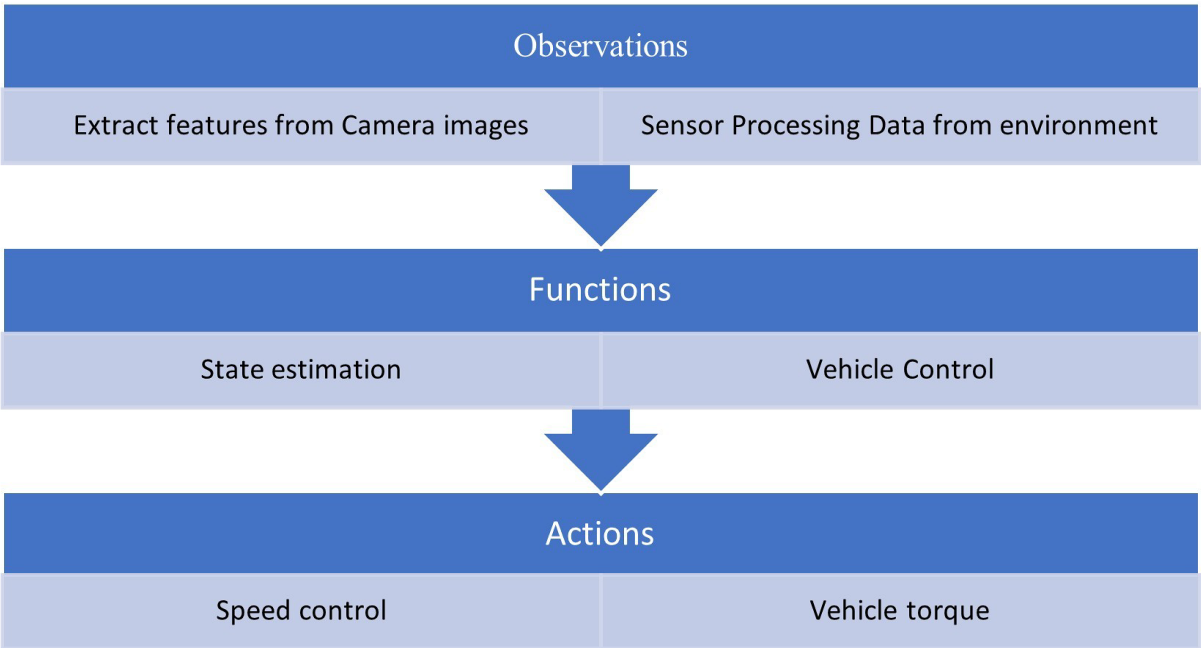
Model Evaluation: During the previous procedure, data was separated into a training set and a test set to assess the model's performance. Determining the model is more accurate than its predecessor. A series of tests on the training data is utilized. PPO improved the accuracy and informativeness of its results by a little margin when evaluated on the dataset. The model's ability to avoid content that could be interpreted as offensive, lowering, or degrading is referred to as harmlessness.

A technique for extracting features from photographic images, for instance, may be developed. They might include information on the obstacle itself or its specific location in the world where the ACV is. Figure 6 shows the observations, functions, and actions.

These states enable a more detailed assessment of the overall status when they are paired with the other sensors' processed data. The reference and estimated states are fed into the controller, which is most likely a complex hierarchy of nested control loops. While the inner loops regulate individual actuators and low-level behaviors, the outer loop regulates high-level automaton behavior.

Q-learning and Policy Gradient are prominent among the several techniques employed in contemporary reinforcement learning [43]. In all scenarios, the ultimate objective is to train

Figure 6
Observations, functions, and actions



a neural network to ascertain the optimal policy, that is, the most favorable course of action to be taken. Both *Q*-learning and Policy Gradients aim to optimize decision-making, although utilizing distinct methodologies. Through the implementation of *Q*-learning, we can acquire a function *Q*(s,a) that associates each system state s with an estimated value representing the cumulative future rewards. Let's examine the scenario where the distance sensor consistently generates a high output. Consequently, the *Q* value will be elevated, indicating that all objects are situated at a considerable distance and the likelihood of an imminent collision is low. After achieving proficiency in the *Q* function, we can determine the optimal action in a particular state by maximizing the *Q* function over all available actions in that state, denoted as a_optimal = argmax *Q*(s,a). In essence, we execute the operation with the utmost *Q* value at every time step. Consequently, the *Q* function inherently defines our policy.

The policy gradient technique is more comprehensible than the policy of *Q*-implicit learning. In this scenario, a policy network is trained to substitute the initial use of the *Q* function with a probability distribution on the actions for every state. Due to the presence of three distance sensors on the vehicle, our policy network can observe and analyze its surroundings. It accomplishes this by converting a three-dimensional input, consisting of the distances on the left, front, and right sides, into a corresponding three-dimensional output. The output options include moving left, moving right, or continuing straight. Based on the input state, each of the three actions will be assigned a probability that represents their possibility of being executed. As an example, if the state was represented by the values [8, 18, 100], a highly skilled policy example might provide the values [0.91, 0.05 0.04]. Based on a 91% confidence interval, if an item is detected by the left and front sensors in proximity, the best action to do is to turn left. Figure 7 represents the effective decision-making process.

One limitation of reinforcement learning is that it requires the machine to autonomously determine the appropriate courses of action. However, consider a training set that consists of the proper moves; the vehicle has only two alternatives (e.g., left and right) rather than the usual three (left, right, straight). Consequently, the precision of action 1 or action 2 determines whether each state is labeled with a 1 or a 0.

A linear model assumes that the connection between the input variables (X) and the output variable (Y) is linear. The term used to refer to this particular model is linear regression. The objective of linear regression is to train a model that can accurately forecast a new Y value based on an unknown X value, while minimizing the amount of error. Y could be predicted by using the following formula:

$$Y = \alpha_0 + X_1\alpha_1 + X_2\alpha_2 + \ldots\ldots\ldots\ldots\ldots\ldots X_i\alpha_i$$

where $\alpha_0, \alpha_1 \ldots\ldots\ldots\ldots \alpha_i$ are the coefficients of the regression.

By optimizing the log-likelihood of the parameters of our policy network, we can transform this into a supervised learning issue by training a logistic regression classifier.

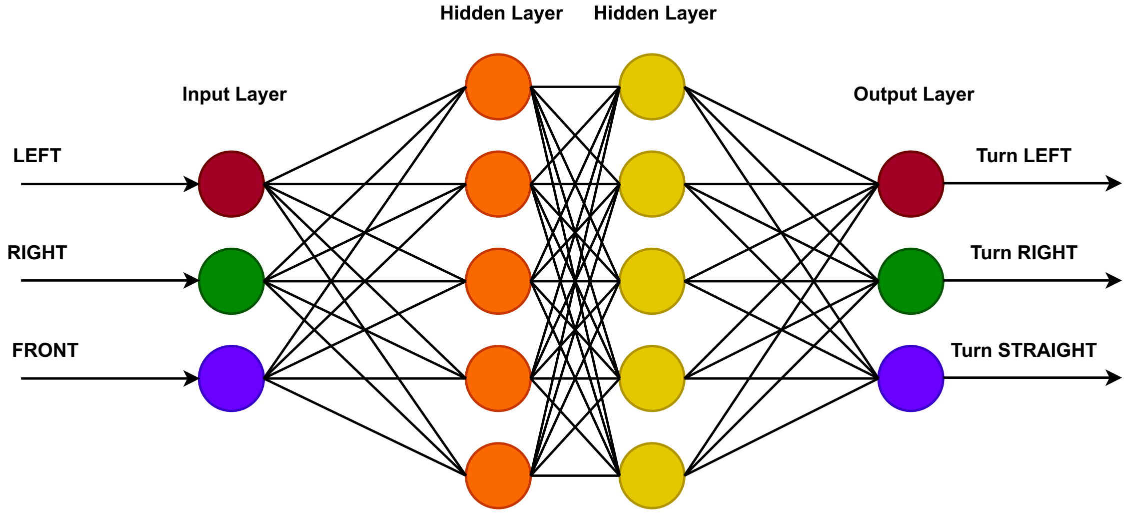
$$Z = \sum_{k=0}^{n} Y^k log(a^k) + (1 - Y^k) log(1 - a^k)$$

For the supervised label Y^k, a value of 1 indicates action 1 is deemed suitable for state a^k, while a value of 0 indicates action 2 is deemed improper. The policy network allocates an acting probability of one. The parameter vector for the policy network is represented by S and the size of our training set, or the total number of times the policy is applied, is given by Z.

$$Z = \sum_{k=0}^{n} log(S(a^k))$$

In this context, S denotes the probability that the policy network would select the action associated with the supervised "right" label. The gradient of this function is computed in order to optimize it.

Figure 7
Effective decision-making



$$\Omega Z = \sum_{k=0}^{n} \Omega log(S(a^k))$$

It is desirable to employ backpropagation and gradient descent (Ω) techniques. Consequently, our policy will possess enhanced predictive capability regarding the labels employed in our training set.

Consider the relationship between this and the Policy Gradient methods. One key differentiation is that our objective is to promote greater engagement in activities that yield substantial benefits. Consequently, the aforementioned computation permits the substitution of the uncertainly chosen proper actions with the actions actually selected by the policy at each time step. These actions are subsequently assigned weights according to the discounted sum of rewards, yielding the subsequent expression:

$$\Omega Z = \sum_{k=0}^{n} \Omega' log(S(a^k))$$

This gradient incentivizes trajectories that lead to substantial payouts and penalizes those that provide reduced payouts. It is possible that the situation could be improved. One issue pertains to the fact that each positive reward trajectory amplifies the probability of the generating policy, notwithstanding the policy's suboptimal performance due to the low reward. In reality, a baseline is therefore eliminated from the incentive at each time step. Additionally, the dynamic nature of the data distribution during each policy network update poses a difficulty in determining an optimal gradient descent step size that maintains efficiency during the optimization process. Table 1 represents the comparison among traditional, ChatGPT, and proposed approach.

4. Results and Discussion

ACVs operating on highways are undergoing advancements to fulfill increasing user demands, adhere to stricter safety regulations, and effectively navigate intricate scenarios [44]. To achieve optimal performance and effectively respond to dynamic road circumstances, it is imperative for these systems to possess the capability to make real-time decisions. The conventional methodologies for autonomous system decision-making are reliant on pre-established rules and algorithms, which impose constraints on their adaptability to novel situations and provide data privacy and security [45]. On the contrary, techniques enhanced by ChatGPT utilize language comprehension to provide responses that are contextually aware and adaptable, enabling more natural conversations and potentially leading to improved decision-making. However, the final option may imply more computational demands and might introduce inherent biases present in the training dataset. The key factors that contribute to optimal performance in various domains include speed, precision, versatility, and communication with others.

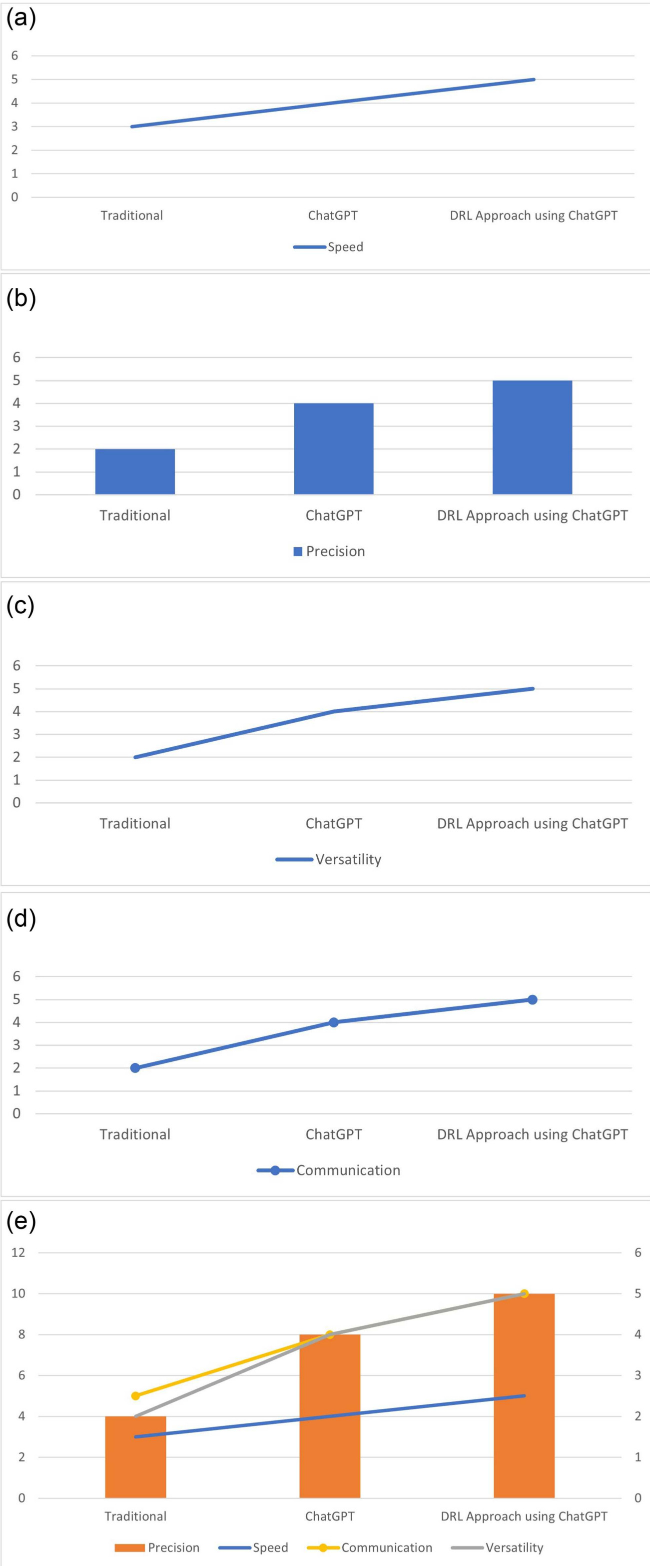
Language models can be described as probability distributions that are based on word sequences. The acquisition of linguistic knowledge by the model is facilitated through the computational analysis and integration of a substantial amount of textual data. Consequently, the language model will assign a probability to the entire sequence by considering the length of the words in the collection. To generate a textual response to a user query, the model employs a probabilistic approach to determine the most likely word tokens based on the preceding words. Figure 8(a)–(d) and e represents the theoretical results comparison among traditional, ChatGPT, and proposed approach.

Supervised learning and reinforcement learning rely on the empirical behavior of an agent within its environment. When an

Table 1
Comparison among traditional, ChatGPT, and proposed approach

	Speed	Precision	Versatility	Communication
Traditional	Average	Low	Low	Low
ChatGPT	High	High	High	High
DRL approach using ChatGPT	Extensive	Extensive	Extensive	Extensive

Figure 8
(a) Speed comparison among traditional, ChatGPT, and proposed approach; (b) precision comparison among traditional, ChatGPT, and proposed approach; (c) versatility comparison among traditional, ChatGPT, and proposed approach; (d) communication comparison among traditional, ChatGPT, and proposed approach; and (e) results comparison among traditional, ChatGPT, and proposed approach



AI agent adheres to a given policy, it receives a reward in the form of a singular numerical value, which it strives to maximize. To operationalize this policy, a set of parameters is defined to encapsulate the weights and biases of a neural network, unlike other configurations commonly used in machine learning. Reinforcement learning is employed as a technique to instruct a system in the optimization of an expected reward through adherence to a predefined set of parameters. The total reward of a trajectory refers to the cumulative sum of rewards obtained by an agent throughout its interactions with the environment, which is represented as a sequence of (state, action) pairs. A suitable candidate for the position will ultimately become accessible. The parameter is updated using a gradient descent-style approach due to the prominence of gradient slope as a strategy for solving this maximization problem.

The initial stage involves gathering sample data for the purpose of supervised policy training. In order to develop an effective monitoring policy, it is imperative to commence the data collection process. Trainers fulfil the dual role of assuming the user's perspective and embodying the ideal AI assistant, facilitating meaningful exchanges between the two parties. Additionally, individuals have the option to utilize the suggested responses provided by the model as a valuable tool for formulating their own ideas. The subsequent phase involves constructing a reward model by utilizing supplementary data. The task of formulating the reward function has been previously acknowledged. The second step is to develop a model that can accept a pair consisting of a prompt and text and generate a single numerical reward that is intended to represent human preferences. The present model provides an approximation of the true reward function. In the training process of the reward model, each comparison made in response to a prompt is treated as an individual batch element. This approach demonstrates enhanced computational efficiency as it necessitates only a singular forward pass of the reward model. Finally, the supervised fine-tuned model is provided with a prompt and a response, resulting in the generation of a scalar reward. The incentive system can be utilized as a learning tool. Next, refine a policy based on the reward model by employing the PPO algorithm in the context of reinforcement learning. The location of the supervised fine-tuned model and the RL policy acquired during the initial round of supervision is unknown. The magnitude of the KL penalty is contingent upon the KL incentive coefficient. The second term functions as a regularizing factor, guaranteeing its persistent proximity. The coefficient for pretraining loss regulates the magnitude of the gradients during pretraining and the strength of the KL penalty. The results or consequences of a particular event, action, or situation.

5. Challenges

When conversational intelligence meets smart mobility, it has several challenges.

5.1. Confidentiality of passengers' information

Continuous passenger interaction is crucial to connect to the ACV system for accuracy and performance. Because of this, it is necessary to collect a substantial amount of data pertaining to the users. However, OpenAI has not yet provided a dependable notification system prior to the gathering of user data for processing. As a consequence of this finding, there is no compelling need to collect and store such information.

5.2. Concerned about their own personal safety

ACVs are especially vulnerable to network breaches because to the fact that they rely on wireless networks for the delivery of their data that might lead to serious traffic accidents brought on by drivers.

5.3. Heavy use of processing power

Because of its extensive network and numerous configuration options, ChatGPT makes heavy use of the computer's processing power. However, the processing capability of today's vehicle network is limited within the vehicle itself. On the other hand, the GPT-4 paradigm can be successfully implemented using remote cloud servers. As a consequence of this, it will be essential for vehicle-to-everything (V2X) communication to find a solution to the challenge of effectively transmitting the outcomes of model processing performed backward.

5.4. Concerning ethics

AI in the decision-making process of ChatGPT-based autonomous vehicles presents some very serious ethical concerns. It is essential to address problems such as the potential of exploitation for malicious intent, the accountability of making decisions that may result in big losses, and the prevalence of bias in training datasets if one wishes to steer clear of ethical challenges. These issues need to be tackled in order to prevent ethical problems. Even though ChatGPT might significantly speed up and enhance the efficacy and effectiveness of such decisions, individuals should still be the ones to make ethical decisions regarding autonomous vehicles, just as they should be the ones to make decisions regarding AI-based traffic solutions.

6. Opportunities

ChatGPT can improve the level of communication between drivers and their vehicles. ACVs' decision-making can be operated by ChatGPT's core large-scale deep learning network, which gives the platform the ability to evaluate massive amounts of data. The following are the opportunities for conversational intelligence that meet the smart mobility.

6.1. Automobiles equipped with voice-activated assistants

Most vehicle networking services will concentrate on providing assistance to the users while they are driving until self-driving vehicles become more popular. For drivers to make use of vehicles and remote server services, they need to be able to communicate information in a concise and timely manner. Because of its superior language processing capabilities, ChatGPT is an excellent tool for implementation in a vehicular voice assistant system [46].

6.2. Understanding a challenging circumstance

In-vehicle sensors such as cameras, speed, and position are just some of the technologies that make it possible for vehicles to collect enormous amounts of data regarding their surroundings [47]. Unfortunately, the computational resources of the vehicle are not capable of quickly processing such a vast volume of data. By deploying GPT-4 models to edge network devices near the ACV and combining them with the local machine learning model of the vehicle, it can effectively process numerous types of information of the ACV and acquire inclusive and comprehensive conservational information.

6.3. Capability to make choices while driving

When trained with reinforcement learning with a feedback mechanism, ChatGPT performs significantly better. This method requires the initial instruction of a reward model established through collective response. The fine-tuning of the pre-trained language models is subsequently accomplished through the use of reinforcement learning and the reward model. Because ACVs will learn from human drivers' driving patterns and behaviors with the support of human feedback, they will be able to increase driving safety and security. It is greatly enticing for autonomous vehicle decision-making because ACVs will learn these things.

6.4. Identifying irregularities with perceptive analysis

Because ChatGPT has such extensive learning capabilities, it is able to provide intelligent recognition of irregular information and exterior dangers that are sensed by the vehicle while driving. This makes it possible to deploy an intelligent anomaly detection technique that is based on advancements to ChatGPT in order to provide a stronger defense for ACVs.

6.5. Hostile defensive mechanisms

Hostile defensive mechanisms for ACVs refer to proactive, offensive-style cybersecurity and safety features. Attackers may use ChatGPT to quickly launch attacks against ACVs that have the possibility to cause catastrophic damage. ChatGPT for ACVs is used to create hostile defensive mechanisms that can essure safe vehicle operations. DRL with ChatGPT can access dynamic data from sensors, cameras, and other resources to optimize the performance of vehicles and improve route planning and traffic control. ACVs produce a huge amount of data using numerous sensors while driving. ACVs are able to see the traffic light, understand its significance, and make the decision to slow down or stop. Using AI makes it easier to provide additional information for such decisions.

7. Conclusions

This study explores how conversational intelligence, particularly LLMs, can enhance ACV capabilities. ChatGPT is a conversational AI that has the ability to improve communication in ACVs. Due to the improvement of AI technologies such as chatbots, LLMs, and even image-generating neural networks, AI has evolved into the development of ACVs. However, there are many challenges to implement it in ACVs. A vehicle based on AI can learn from its experiences and act accordingly. This study shows that LLMs are increasingly important in smart mobility systems supported by advanced AI. However, LLMs cannot directly process real-time sensor data from vehicles. While sensor data is first interpreted by perception models into structured semantic information, which is then passed to the LLM for reasoning and decision support. The paper also reviews key opportunities and challenges in LLM-based conversational systems in autonomous mobility environments.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by the author.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Tanweer Alam: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

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