Journal of Scientific Insight
E-ISSN: 3062-8571
DOI: https://doi.org/10.69930/jsi.v1i4.232
Review Article

Vol. 1 (4), 2024
Page: 155-169

Revolutionizing Automotive Engineering with Artificial Neural Networks: Applications, Challenges, and Future Directions

Mohamed H. Abdelati [1,*], Ebram F.F. Mokbel [1], Hilal A. Abdelwali [2], Al-Hussein Matar [1], M. Rabie [1]

[1] Department of Automotive and Tractors, Faculty of Engineering, Minia University, Egypt
[2] Department of Automotive and Marine, College of Technological Studies, Kuwait

*Email (corresponding author): m.hilal@mu.edu.eg

Abstract
Artificial neural networks (ANNs) have emerged as the technology that provides solutions to key issues arising in the field of automobile engineering regarding autonomous driving, predictive maintenance, energy control, and vehicle protection. This paper aims to present various uses of ANNs in car industry concerning data handling for continuous decision-making and adaptation. Convolutional Neural Networks (CNNs), Long Short-Term Memory networks (LSTMs), and Generative Adversarial Networks (GANs) are all explored in relation to their ANN specific relevance to automobiles. The identified limitation also responds to issues associated with the integration of ANN such as data dependency, the computational load required, and questions related to the ethical use of AI decision making. This paper compares ANN techniques in an automotive context, explaining where they excel and where they could use improvement in terms of the tasks they are applied to. The strategies for phased implementation of the ANN framework, the performance evaluation for each stage of implementation, and the optimization methodologies are discussed below. Future direction highlights the future development of transformers, energy efficient models and raising concerns of ethical regulatory frameworks with regards to ANN driven systems. Thus, by such barriers overcoming, ANNs have a potential to significantly influence the further development of automotive engineering and make automobiles safer, more efficient and environmentally friendly. This study advances the discussion around intelligent mobility and provides the foundation on which future research in the field can build from.

Keywords: *Artificial neural networks, automotive engineering, autonomous vehicles, intelligent systems, smart transportation*

1. Introduction

Artificial intelligence, especially artificial neural networks (ANNs), are key technology across various sectors(Rankovic, Đonić, & Geroski, 2024; Abdelati, 2024). In automotive engineering, ANNs offer unique capabilities by mimicking the human brain's processing network(Prathiba, Saravanan, David, & Thangaraj, 2024), enabling the creation of intelligent vehicle systems that can process large amounts of data and make autonomous decisions, advancing beyond traditional engineering methods. The growing demand for safer, more efficient, and environmentally friendly transport systems necessitates the adoption of ANN-

Received: 19 November 2024 / Accepted: 23 December 2024

powered solutions, which are crucial in transforming vehicle design, control, and maintenance(Qu et al., 2024; El-Wahab, Rabie, Abdelati, Khalil, & Abdelgawwad, 2021).

The automotive industry is at a pivotal point, driven by technological advancements and societal pressures for sustainability and safety(Zamoum, Baiche, Benkeddad, Bouzida, & Boushaki, 2025; Shi, Wei, Wang, Liu, & Jiang, 2024). What was once considered futuristic, such as autonomous driving, predictive maintenance, and optimized energy management, is now an immediate need.

ANNs play a crucial role in enhancing automotive engineering, particularly in self-driving systems and electric vehicle energy management. For example, Convolutional Neural Networks (CNNs) are used for object detection to help vehicles recognize obstacles, while Recurrent Neural Networks (RNNs) predict battery life, enhancing energy efficiency and extending vehicle range. ANNs significantly improve safety, increase system efficiency, and promote sustainability by reducing emissions and conserving fuel(Li et al., 2024).

ANNs, capable of processing complex and unstructured data, are uniquely positioned to address these challenges. This paper explores various applications of ANNs in automotive engineering, including the development of intelligent systems, safety protocols, and energy-efficient solutions, while also identifying implementation barriers and proposing strategies to overcome them.

This paper contributes new insights into the application of ANNs in automotive engineering. Unlike prior studies that focus on single ANN types, this research integrates multiple ANN architectures, such as CNNs, RNNs, and GANs, to address challenges in autonomous driving, predictive maintenance, and energy efficiency. It also proposes a new framework for designing lightweight, energy-efficient ANN architectures, which have not been extensively explored in automotive contexts. This contribution provides fresh ideas for developing smarter, more sustainable vehicle systems.

The aim of this research is to examine how ANNs are integrated into automotive engineering, identifying challenges and proposing solutions to enhance future transportation. This paper is structured as follows: Section 2 provides the theoretical framework by describing ANN architectures and their applicability to automotive applications. Section 3 discusses several applications, including autonomous systems, maintenance, energy optimization, and safety. Section 4 explores the challenges of implementing ANNs in the automotive sector. Section 5 compares different ANN techniques and their suitability for various tasks. Section 6 outlines a framework for implementing ANNs in automotive systems, and Section 7 addresses emerging technologies and ethical considerations.

2. Theoretical Framework

2.1. Overview of Artificial Neural Networks

Artificial neural networks are computational models inspired by the structure and functioning of biological neural systems (Rankovic, Đonić, & Geroski, 2024; Wang, 2024). They consist of layers of interconnected nodes, or neurons, that process information by assigning weights and biases to inputs. In effect, their ability to learn and generalize from data has positioned them uniquely for complex and data-driven applications in automotive engineering (Carrio, Sampedro, Rodriguez-Ramos, & Campoy, 2017; Ammour et al., 2017; Zhang, Hu, Xiao, & Zhang, 2020). However, to improve specificity let me explain that ANNs are trained from data through a process known as training. In training the network the internal patterns adjusts to these modifications of the weights to help improve on the accuracy of its predictions. Learning process is a ubiquitous concept and is generally assisted by algorithms like back propagation; where the network strives to make corrections to its weights for the purpose of minimizing the difference between ideal and anticipated results. This process gives ANNs the ability to perform such functions as pattern recognition and decision making which are very complex in nature. The main types of ANNs applied in this domain are Convolutional Neural Networks, Recurrent Neural Networks, Long Short-Term Memory networks, and Generative Adversarial Networks. Each of these architectures provides specific capabilities (image recognition, time-series prediction, and data generation) that are very important in solving unique automotive challenges(Kishore, Rao, Nayak, & Behera, 2024; Abdelwali & Abdelati, 2024).

2.2. Relevance of ANNs in Automotive Engineering

The power of ANNs is derived from their capability to process a wide range of data types, including visual, temporal, and numerical inputs. Accordingly, in automotive engineering, this is helpful for the implementation of detecting objects in a road environment, traffic prediction, or fault diagnosis in mechanical elements(Paheding et al., 2024; Martínez, Casas-Roma, Subirats, & Parada, 2024). CNNs are very powerful in visual tasks; they can be used to analyze images from cameras installed in vehicles for the detection of lane markings or pedestrian identification. On the other hand, RNNs and LSTMs are potent in the handling of sequences, thus enabling RNNs and LSTMs to predict vehicle behavior, flow of traffic, or a failure in the system by considering past history(Lolas & Olatunbosun, 2008; Zhang et al., 2019). GANs have found application in generating synthetic data for training autonomous systems, reducing reliance on expensive real-world datasets(Yordanov, Zhilevski, & Mikhov, 2024; Corrochano, 2024).

2.3. Key Metrics for Evaluating ANN Performance

The performances of ANN in automotive applications depend on a few metrics: accuracy and precision, which are fundamental to safety-critical systems like collision detection and obstacle recognition; computational efficiency, which is a necessary condition for real-time applications where latency can bring major effects on performances; scalability and adaptability of ANN models remain critical to be widely deployed across diverse vehicle types and various operational conditions. Besides, robustness against noise and environmental variability is paramount for ANN-driven systems operating in real-world automotive scenarios(Lolas & Olatunbosun, 2008; Datta, Das, & Mukhopadhyay, 2019).

3. Applications of Artificial Neural Networks in Automotive Engineering

3.1. Autonomous Driving Systems

The Artificial Neural Network ANNs are central in the platform of autonomous driving, processing streams from cameras, LiDAR, radar, and other sensors. CNNs are employed in a general way in the image and video feature extraction where roads signs, lane markers, pedestrians, and other vehicles are detected(Abdelati & Abdelhafeez, 2023; Levinson et al., 2011). RNNs and LSTMs enhances a decision by providing a sequential analysis of data, for instance, the movement of vehicles and growth of traffic jam in order to predict dynamic traffic conditions on the road. Together, these types of ANNs allow the systems to detect objects in real-time, plan routes, and exhibit flexibility of dynamic interactions in the environment(Bhat, Aoki, & Rajkumar, 2018).

3.2. Predictive Maintenance and Fault Detection

ANNs have taken a significant leap in the area of condition monitoring of vehicles to allow for efficient predictive maintenance by estimating the possible mechanical and electrical failures on the basis of data harvested from the vehicle's sensors. These systems keep track of factors like temperature, dynamic behavior, and life of the battery to detect changes that are indicative of a growing problem before it becomes big. For instance, ANNs can estimate the RUL of components such as batteries and motors of electric vehicles, lower the maintenance time, and costs. The ability to distinguish between faults on the basis of patterns in sensor data guarantees timely and accurate diagnosis(He & Rutland, 2004; Turkson, Yan, Ali, & Hu, 2016).

3.3. Energy Management in Electric and Hybrid Vehicles

The reduction of energy consumption of electric and hybrid cars is one of the very important among the applications of ANNs(Shayler, Goodman, & Ma, 2000; Smyl, 2020). The neural network calculates a driving pattern with battery and environmental inputs in order to suggest an optimal strategy for energy management. Besides improving regenerative braking systems, they can also predict braking patterns for maximum energy recovery. In hybrid automobiles, they balance power distribution between internal combustion engines and electric motors to improve fuel economy and extend the reach of vehicles. These contributions save wasting energy and improve sustainability for transportation(Ribbens, Park, & Kim, 1994; Ahmed, El Sayed, Gadsden, Tjong, & Habibi, 2014).

3.4. Safety and Driver Assistance Systems

ANN-driven safety has improved vehicle safety significantly due to the use of advanced driver-assistance systems (ADAS). Such examples include automatic emergency braking, lane-keep assist, adaptive cruise control, and blind-spot monitoring(Jiménez et al., 2016). CNNs process real-time visual data about obstacles, lane positioning, and driver fatigue. LSTMs are used to predict driver behavior, such as panic braking or steering, for proactive activation of such safety features. Response times are greatly reduced with the integration of ANNs, thereby reducing potential accidents in the application of ADAS(Sultan, Alsarraf, Alfeeli, & Alghanemi, 2024; Mohamed, 2023; Wagner, 2024).

3.5. Other Applications

Beyond these core areas, ANNs have been employed in vehicle design optimization, traffic flow management, and personalized in-car experiences. Neural networks optimize aerodynamics and material selection through performance simulation in an array of conditions(Li, Ida, Gen, & Kobuchi, 1997; Ida, Gen, & Li, 1996). In smart traffic systems, ANNs predict congestion patterns and dynamically adjust the signal timings to ease the flow of traffic. Inside the vehicle, ANNs power in-car user experiences on everything from voice recognition systems, adaptive climate control, and infotainment recommendations that adapt to a driver's preference(Maass, Deng, & Stobart, 2011).

Figure 1 illustrates the workflow of neural networks in autonomous driving. The chart sequentially represents the process, starting from environmental sensing using cameras, LiDAR, and radar, followed by sensor fusion, data preprocessing, object detection and classification, path planning, neural network decision-making, and concluding with vehicle control through automated actuation systems.

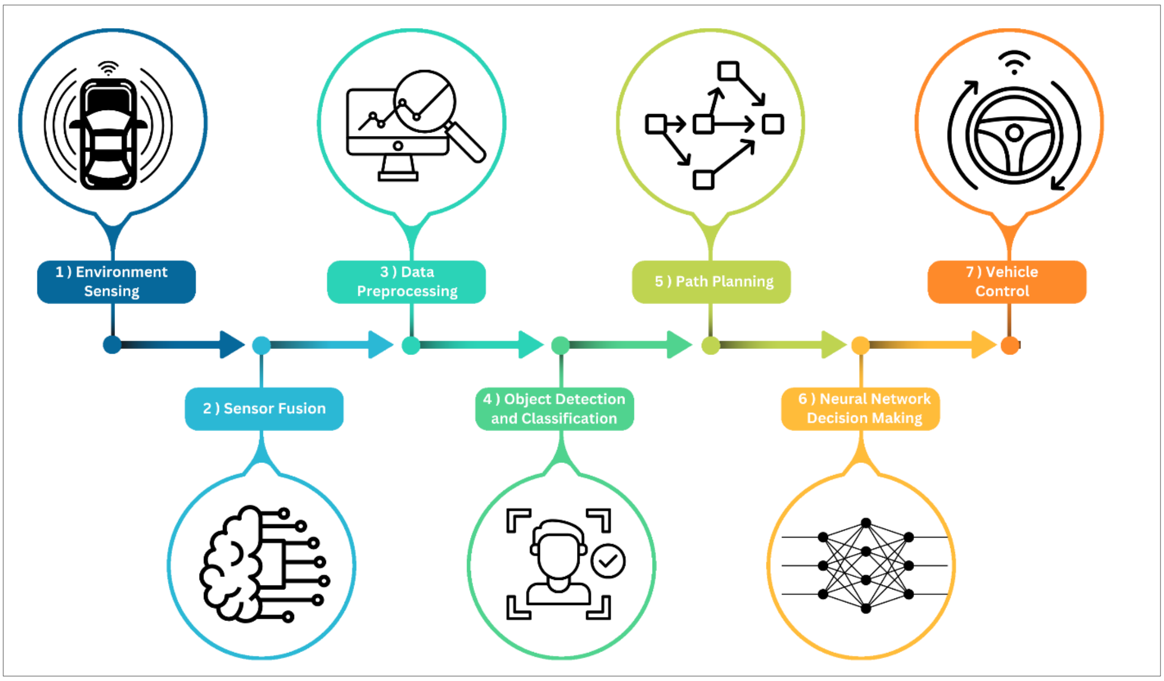

Figure 1. Neural networks in autonomous driving systems

4. Challenges and Barriers

4.1. Technical Challenges

Artificial neural networks face great technical obstacles in their implementation within automobile engineering. One of the largest is that the models are dependent on the quantity of high-quality data. For example, the system of autonomous driving needs such complex databases as the changes in road condition, in climate, and other trends of traffic to have high performance(Bathla et al., 2022; Zöldy, Szalay, & Tihanyi, 2020). To this day, gathering and labeling such datasets continues to be a very tedious and costly affair. ANN models are also very repetitive and time consuming most of the time they need high hardware complex hardware such as GPUs and TPUs which is expensive in terms of real time application thus less usable. Besides, the problem of making them resistant to noise, other unknown environmental factors, and adversarial inputs remains a concern, even more, if the ANNs are applied in safety-critical systems such as self-driving vehicles(Mei, 2023).

To curb data dependency there are several methods that are available one of which is synthetic data from one or simulation or augmentation. Also there are improvements in the system optimization with new improved hardware like energy-efficient GPUs, TPUs, etc; which make computation and hence the cost lower.

4.2. Economic Constraints

ANN based systems when used in automotive applications it has a drawback of its high cost of deployment. Below it is clear that the high-performance computing infrastructure, together with training and inference, raises the cost of development(Ziółkowski, Oszczypała, Małachowski, & Szkutnik-Rogoż, 2021). Also, the provision of sensors, such as LiDARs, radars, and high-definition cameras put extra expenses towards the construction of the vehicle. These financial burdens are the barriers to the utilization of ANN-powered solutions among manufacturers, especially for the budget or mid-range vehicle models*(Jahangir et al., 2019)*. In addition, the costs required to update ANN models for those dynamic environments in which the models are to be used incur long-term economic costs*(Riha, Nemec, & Sousek, 2014)*.

Such approaches as the cloud computing, and deep learning as a service can serve to help lower these infrastructure costs and thereby make ANN systems more deployable. Furthermore, by employing the synthetic data, the dependence on expensive sensors is reduced resulting in reduced general financial implications.

4.3. Ethical and Regulatory Issues

There are several tricky ethical and regulatory questions surrounding the applications of ANN in automotive systems. However, the problem of deliberation for autonomous vehicles remains one of the most significant issues when driving in life-critical events(Fedorov & Curran, 2024). For instance, if there is an unavoidable collision, then ethical dilemmas about whose safety should be prioritized by the system must be addressed. Second, accountability for accidents where the vehicle is powered by ANNs is still an open issue, as liability-that is, whether it falls under the manufacturer, developer, or user-remains ambiguous. Other pressing concerns include data privacy, as most ANNs rely on real-time data collection from users and their environment, which may lead to misuse or breaches of sensitive information(O'Sullivan et al., 2019; Martinho, Herber, Kroesen, & Chorus, 2021). Due to the rapid development of ANN technologies, regulatory frameworks have fallen behind the curve, with large lacunas in oversight and standardization.

Solutions to the issue of morality in choice-making must encompass clear rotas for specific jurisdiction of autonomous cars. Furthermore, data privacy can be protected better by using more a stringent algorithm in encryption and conforming to data security laws.

4.4. Environmental Impacts

ANN model training and deployment consume a lot of computational power, which adds to environmental issues. The nature of the training of large-scale neural networks requires enormous energy supply that, in turn, contributes to substantial carbon emission(Fahim, 2024). The production and waste management of hardware components that contain GPUs and other special processing units raise sustainability issues. These are increasingly being reviewed in light of global sustainability targets, of which the automotive industry also needs to take note. These have points of concern that include energy-efficient ANN modeling and utilization of renewable energy in computational infrastructure(Alardhi, Abdelwali, Khalfan, & Abdelati, 2024).

On the ANN models that are efficient in energy usage, as well as energy from renewable sources for the computing resources, the environmental impacts are considerably offset.

Furthermore, hardware manufacturing, specifically the sustainable, eco-friendly approach to their fabrication, and recycling of these devices will contribute to decreasing the carbon emissions of ANN deployment.

5. Comparative Analysis of ANN Techniques for Automotive Applications

5.1. Overview of Comparison Criteria

It is evident that in automotive applications, the correct selection of the ANN architecture bears paramount importance in obtaining the best results. Different ANN methods serve specific purposes, depending on the data nature and application complexity. In this regard, this section compares different major ANN types based on criteria such as accuracy, computational efficiency, robustness, and suitability for various automotive use cases.

5.2. Convolutional Neural Networks (CNNs)

CNN is particularly effective for image and video processing tasks, which makes them one of the vital parts of autonomous driving systems. Extracting features from visual data spatially allows it to run applications like lane detection, object recognition, and traffic sign classification. This will do wonders in terms of accuracy but is highly computation-intensive, requiring a lot of processing power to be able to work real-time. While CNN models have their strong points, they are less suitable for sequential or temporal data, which limits their applicability for a broader automotive application.

5.3. Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs)

RNNs and LSTMs are designed to process sequential data, making them ideal for analyzing time-series information such as vehicle dynamics, traffic patterns, and driver behavior. LSTMs are a kind of RNN that handles the issue of vanishing gradients; hence, these models can learn long-term dependencies in data. These are particularly useful in predictive maintenance, where models analyze sensor readings over time and use it for predicting potential failures. However, in general, RNNs and LSTMs are slower to train as compared to CNNs and may require careful tuning to avoid overfitting, especially in noisy datasets.

5.4. Generative Adversarial Networks (GANs)

The application of GANs in automotive engineering is based on their capabilities for generating synthetic data. GANs alleviate the need for expensive and labor-intensive data collection by creating realistic simulations of road environments and traffic conditions. These networks also increase the capabilities for training autonomous systems for rare or hazardous scenarios, such as extreme weather conditions or near-collision events. Yet, GANs are computationally intensive and often require thorough calibration to balance the realistic value and utility of the generated data.

5.5. Hybrid ANN Models

Hybrid models, which incorporate various elements of CNNs, RNNs, and other architectures, also provide a flexible approach to solving such multifaceted automotive tasks. Consider, for example, the development of autonomous vehicles that make real-time decisions based on both spatial and sequential data by incorporating CNNs for visual processing with LSTMs for temporal analysis. Applications like driver assistance systems are another common use for hybrid models, where diverse data types must be integrated seamlessly. While being versatile, hybrid models tend to be more complex, require significantly more computational resources, and careful optimization in order to balance performance with efficiency.

5.6. Insights and Recommendations

The choice of ANN technique should be guided by the application requirements. While CNNs are most fitted for visual tasks, including object detection and scene recognition, RNNs and LSTMs are suited for predictive tasks, especially of sequential data. Although GANs come with considerable advantages in both simulation and training environments, they should be combined with other models for real-world deployment. While computationally intensive, hybrid models provide an integrated solution for complex systems where multiple data types are involved. Future research on lightweight and energy-efficient ANN architectures will further alleviate the computational bottlenecks and thereby broaden their applicability to many automotive applications. Table 1 illustrates a comparative analysis of various artificial neural network (ANN) techniques used in automotive applications, highlighting their signal-handling capabilities, strengths, and limitations.

Table 1. Comparative analysis of an techniques for automotive applications

ANN Type	Signal Type Handled	Capabilities	Strengths	Limitations	Key Applications in Automotive Systems
Convolutional Neural Networks (CNNs)	Images, Videos	Processes spatial data like images and videos.	High accuracy in visual tasks, suitable for real-time applications.	Computationally intensive, limited for sequential data.	Object detection, lane recognition, and traffic sign classification in autonomous driving systems.
Recurrent Neural Networks (RNNs)	Sequential Signals (e.g., Text, Time-Series Data)	Handles sequential data, including time-series information.	Effective for analyzing sequential patterns, suitable for predictive tasks.	Slower training, prone to vanishing gradients, requires fine-tuning.	Traffic flow prediction, vehicle behavior analysis, and predictive maintenance.

Long Short-Term Memory (LSTM)	Sequential Signals (e.g., Text, Time-Series Data)	Specialized RNN for learning long-term dependencies in sequential data.	Addresses vanishing gradient issue, ideal for long-term sequence prediction.	Higher computational requirements, slower training compared to traditional RNNs.	Predictive maintenance and traffic condition forecasting.
Generative Adversarial Networks (GANs)	Images, Synthetic Signals	Generates synthetic data, simulates real-world conditions for training.	Reduces reliance on real-world datasets, suitable for rare or extreme scenario training.	High computational demand, requires careful calibration for data realism.	Synthetic data generation for training autonomous systems, particularly in hazardous conditions.
Hybrid Models (e.g., CNN + LSTM)	Mixed Signals (e.g., Image + Sequential Data)	Combines capabilities of multiple ANN types for integrated tasks involving diverse data types.	Versatile and highly adaptable for complex, multifaceted tasks.	Requires significant computational resources and optimization for seamless integration.	Autonomous vehicle systems combining visual and sequential data processing for dynamic decision-making.

6. Proposed Framework

6.1. Conceptual Model for ANN Integration

The model framework provides the integration of ANN into automotive systems to improve the functionalities related to autonomous driving, predictive maintenance, energy management, and safety. This model framework is based on three cores: inputs, processing layers, and outputs.

It acquires inputs from various sensors including cameras, LIDAR, radar, and vehicle onboard emissions. Other information relating to the environment, such as the status of traffic and weather, is also incorporated into the development of a detailed picture of the operating environment. The processing layers employ diverse ANN structures depending on the suggested usefulness. Among them, CNNs perform the processing of the visual data related to the object detection and lane recognition task and LSTMs for solving the predictive analytical tasks where sequential data are involved. These architectures are employed by hybrid models and are further extended to more complex systems such as integrated driver assist and traffic control systems. Outputs are in the form of decisions which also contain route changes, safety interventions and maintenance signals to allow the vehicle to remain outsmarted and self-sufficient in light of current conditions.

6.2. Implementation Roadmap

Designed for phased implementation, the framework is adaptable and scalable. In the first phase, pilot systems will evaluate ANN models in ‘sanitized’ conditions for instance in a simulated traffic environment or on test tracks. The last phase involves model training and testing on actual data and dataset and synthetic datasets and data created by the generative adversarial network (GANs) tools. The second phase involves limited deployment where the ANN-powered systems are applied mostly in areas of application such as predicting vehicle health conditions for maintenance or as support systems for the drivers in a small car fleet. During this phase, tuning of the models takes place according to the operational feedback received. The final phase is total integration where deployment of ANN increases to cover other systems in consumer vehicles. This phase makes it possible to check compatibility in the operation of subsystems including autonomous navigation and energy management, and integrate new information collected from the real world to improve the performance of the system.

6.3. Evaluation and Optimization

The evaluation will be necessary to confirm the framework’s effectiveness, as mentioned in this work. Metrics comprise accuracy which refers to the extent of reliability of ANN predictions, particularly in safety-sensitive activities like obstacle detection and traffic prediction. Responsiveness is also measured to establish the capability of systems to respond to input and develop an output in the same measure of time. Scalability tests the framework’s capability of handling increased data load and integration with even more systems, without compromises to efficiency. These are normally done to ascertain functionality in various situations especially when there is high noise and other phenomena.

Other approaches are implemented that are related to the use of lightweight ANN structures, the use of efficient structures, and the use of edge computing to minimize the dependence on the cloud-based setup. Thus, the framework remains productive and flexible to changes that requirements in automotive engineering offer.

7. Future Directions

7.1. Emerging Technologies in Neural Networks

ANN holds a bright future in automotive engineering only if it can be implemented in conjunction with another technology, which improves its performance. Transformers, on the other hand, have demonstrated superb performance in operations involving the natural language processing and are currently applied to time series analysis and vision tasks in self-driving automobiles. Hybrid neural networks that combine the strengths of CNNs, LSTMs, and reinforcement learning will handle complex multidimensional data in real time. Lightweight and energy-efficient ANN architectures also have significant traction and enable deployment on resource-constrained environments such as budget-friendly vehicles. Quantum computing advances hold great promise for drastically reducing the time it takes to train ANN models and will allow for quick iteration and rapid deployments.

7.2. Sustainable AI Practices

The environmental impact of the training and deployment of large-scale ANN models will come under increasing scrutiny as sustainability becomes a growing priority. In this regard, much future effort will be centered around developing models at lower computational resources without a loss in performance. Model pruning, knowledge distillation, and hardware optimization are envisioned to play a pivotal role in developing energy-efficient neural networks. Other directions involve using renewable energy sources to power data centers handling ANN training and inference. These efforts fall in line with the automotive industry's goals of reducing its overall carbon footprint while advancing intelligent systems.

7.3. Ethical and Regulatory Considerations

Ethical and regulatory frameworks for ANN-powered automotive systems will change as the technology advances. How autonomous vehicles decide in situations where there is an unavoidable collision is one of the biggest challenges to ethical dilemmas in this aspect. Explanatory algorithms that are transparent about their decisions will likely be a future regulatory requirement. Furthermore, privacy concerns about the data gathered by ANN-driven vehicles need to be protected, with much more restrictive legislation that ensures misuse and hackers do not gain access to users' information. These will have to be addressed in concert by governments, industries, and academia if there is to be a set of complete standards for the deployment of ANN technologies in safety-critical applications.

7.4. Expanding Applications of ANNs

The potential application in the automotive field using ANNs is quite widespread compared to what is currently being done. By enhancing neural network architectures, there is a great expectation of advancements in real-time navigation, predictive analytics to perform infrastructure maintenance, and personalization of user experience inside the vehicle. Neural networks could also allow vehicle-to-everything (V2X) communication where complete smooth interaction between vehicles, infrastructure, and pedestrians will be developed. The contributions that ANN-powered systems can make toward integrated traffic management in smart cities will, in turn, optimize the flow of vehicles and reduce congestion. These types of innovations will transcend transportation systems themselves and basically reformulate the broader mobility landscape.

Conclusions

The integration of Artificial Neural Networks (ANNs) in automotive engineering has significantly advanced intelligent and adaptive vehicle systems. This paper highlights their applications in autonomous driving, predictive maintenance, energy optimization, and safety systems, demonstrating their potential to enhance efficiency, safety, and sustainability in transportation. Despite these advancements, challenges remain, including the need for large datasets and high computational power, as well as ethical and regulatory issues surrounding autonomous decision-making and data privacy.

To maximize the benefits of ANNs, it is recommended to: 1) Develop lightweight, energy-efficient ANN architectures to reduce costs and environmental impact. 2) Increase the use of synthetic data and hybrid models to minimize reliance on large datasets. 3) Promote collaboration among policymakers, researchers, and industry leaders to create ethical and regulatory standards for ANN-powered systems. Looking ahead, ANNs will continue to shape the future of automotive engineering, with emerging technologies like quantum computing and transformers further enhancing their capabilities. By addressing current challenges and leveraging recent innovations, the automotive industry can realize safer, smarter, and more sustainable mobility solutions.

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