Review Article

A Critical Review on the Use of Artificial Intelligence in the Automotive Industry

Mbatha Abednigo Jabu¹, AA Alugongo², NZ Nkomo³

^{1,2,3}Vaal University of Technology, Department of Mechanical Engineering, Industrial Engineering and Operation Management, South Africa.

¹Corresponding Author : abednigom@vut.ac.za

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Abstract - Artificial Intelligence has been used as an effective approach to processing data because of the growing volume of data and calls to speed up its processing. Artificial Intelligence has the potential to transform the automotive industry like no other technology, and it is gaining an increasingly important role in the current automotive industry. Due to this, automobiles have an increasing number of sensors installed in them, turning them into machines that can gather, process, and display data in real-time. The convenience that automobiles provide for individuals on their trips, the designs of the vehicles themselves, and, most importantly these days, the technology advances, technical malfunctions become more common. As a result, testing has become a crucial step in the production of any vehicle. As a result, businesses have begun investing in automated testing to cut down on both labor costs and long-term expenses. This paper reviews the use of artificial intelligence in the automotive industry and its application, limitations, and potential use. Furthermore, this paper discusses machine learning and deep learning technology used. There is a need to create efficient ways to process data. Further research is still needed to make artificial intelligence as advanced as the human mind and solve complex problems.

Keywords - Artificial Intelligence, Automotive industry, Deep Learning, Machine learning, Industry 4.0.

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1. Introduction

Artificial Intelligence (AI) is the ability of a system to accurately understand outside input, learn from that data, and use that learning data to accomplish particular tasks and goals through adaptable change [1]. Artificial intelligence implies making programmed machines to perform human tasks, evolve from experience to understand situations, and make appropriate decisions [2]. Humans play a vital role in the automotive industry since automated machines cannot think and make decisions themselves [3]. The purpose of artificial intelligence in the automotive industry is to reduce risk and limit human intervention [4]. It has been reported that approximately 1.24 million people die annually due to traffic accidents. These fatalities can be minimised by using artificial intelligence. Furthermore, the use of AI technology can contribute to fuel savings of approximately 10% [5]. Artificial intelligence is mostly used in domains where diverse data must be promptly and accurately analysed in order to make competent conclusions, process data analytically, and perform monotonous tasks but demand constant attention [6]. The automotive industry is motivated by numerous potential technologies such as deep learning algorithms, sensor technology, machine learning and communication techniques. In the automobile industry, AI has been used to build many

innovative devices and applications that have reduced human errors, including aggressive driving, accidents, and traffic incidents [7]. Artificial Intelligence applications in the automotive industry go far beyond the development, engineering, logistics, production, supply chain, customer experience, marketing, sales, after-sales, and mobility services in the automobile industry. AI is the key to a new future of value for the automotive industry [8]. People often associate AI with self-driving cars right, but the full scope and depth of its impact on the automobile industry's basis are often missed. Artificial Intelligence refers to the process of programming a computer or software to think intelligently at a level comparable to that of a human.

This process is mostly based on scientific discoveries in biology, statistics, and mathematics, with algorithms and models being developed [9]. Robots are being used extensively in automotive manufacturing; they are programmed to carry out a predetermined set of tasks in a restricted number of situations in accordance with rigidly laid down guidelines. More sophisticated artificial intelligence technologies have the ability to learn from past experiences and make judgments on their own using processed data [1]. Artificial intelligence will perform better in the future because of advancements in algorithmic research and more potent computer technology. We can anticipate more autonomy from AI and new applications in the automobile sector [1]. However, Artificial intelligence systems are still limited to some areas of knowledge, such as picture identification, speech recognition, and conversation response. The limitations of artificial intelligence technologies contrast with the human brain's capacity for self-awareness, self-control, self-understanding, and self-motivation. Artificial intelligence will encounter more challenges in algorithm bias and transparency ethics, privacy and personal information security, and the economic impact of job losses.

There has never been more support for fairness research focusing on methods to counteract algorithmic prejudice. Tools that machine learning practitioners can use to audit for bias when constructing their algorithms have been developed using a significant amount of fairness research. However, these justice solutions are rarely used in real-world situations [10]. The automotive sector faces challenges in improving efficiency, quality, productivity, and time management due to a lack of knowledge about new technology, such as artificial intelligence [11],[12].

2. Deep learning

Deep learning is a machine learning approaches that use neural networks with numerous hidden layers to perform tasks like speech recognition, language interpretation, and image categorisation [13][14]. Deep learning is the understanding of neural networks, which come in two varieties: hybrid (a combination of convolutional (CNN) and recurrent neural networks) and recurrent (LSTM, GRU) [15][16][17]. In the automotive industry, machine learning and deep learning have many different potential applications. These include operations that take place outside the vehicle, such as during development, manufacture, and sales and aftersales, as well as inside the vehicle, such as autonomous driving and improved driving assistance systems.

Furthermore, deep learning can be used in location-based services, personalised infotainment, supply chain management, automated business processes, and predictive auto maintenance. Due to the large data volumes to store and process, together with handling unstructured data (text, photos, and videos) from sources like camera-based sensors in cars or manufacturing equipment, it presents a typical problem for these applications. In order to make the most of this type of data, new techniques like deep learning are required [18],[19]. AI-trained vehicle algorithms using neural networks by analysing information from a camera, a laser rangefinder, and a human driver facilitate autonomous vehicles.

3. Machine Learning

Machine learning, a branch of artificial intelligence, is the capacity of computers to learn via the manipulation of algorithms and the organisation of the knowledge they produce from processed data. Pattern recognition, natural language processing, cognitive computing, image processing, etc., are the main areas of interest for machine learning. Machine learning may autonomously carry out intellectual tasks that are typically completed by humans with the help of mathematics and statistics [13].

A programmable neural network is used in deep learning, enabling robots to make judgments without human interaction. Application areas for deep learning in the automobile sector include object detection, face and speech recognition, driver identification, and different driver monitoring systems. Design optimisation and engineering are two areas where artificial intelligence is used in the design and development of vehicles. It is feasible to pinpoint areas for development using machine learning algorithms, leading to the eventual construction of automobiles and other vehicles that are more dependable and efficient [14]. Machine learning is a developing field of computational algorithms that uses environmental learning to simulate human intelligence [20][21]. Machine learning trains machines to handle data more effectively [20]. Machine learning (ML) is a promising field that can increase quality control and process optimisation in predictive manufacturing systems [22].

The fact that machine learning algorithms can manage high-dimensional, multivariate data and comprehend implicit linkages in enormous data sets in intricate and dynamic situations is a major reason they are gaining increased attention [23]. A number of examples exist of the effective application of machine learning and data mining to address issues in manufacturing contexts, including process optimisation [24], defect detection [25], and predictive maintenance [26]. Machine learning (ML) allows for the use of several distinct types of algorithms. It determines which to employ based on the output needed. There are different types of learning that ML algorithms typically belong to, such as supervised and unsupervised learning, as shown in Figure 1 [27]. Various algorithms are used by machine learning to solve data problems.

The type of method used relies on the type of problem and the number of variables.

3.1. Supervised Learning

Supervised learning is the machine learning task of learning a function that maps an input to an output based on example input-output pairs. Algorithms for supervised machine learning require outside help. There is a need to train and test datasets that are separated from the input dataset. The output variable from the training dataset must be categorised or forecasted. From the training dataset, the algorithms extract patterns, which they then use to predict or classify. Figure 2 shows the supervised machine learning algorithms' procedure. Supervised learning involves a data scientist providing labeled data, such as pictures of cars with tags attached [28]



3.2. Unsupervised Learning

Unsupervised learning establishes a learning paradigm. Unsupervised learning is motivated by the fact that while the material that feeds its algorithms has a rich intrinsic structure, the training metrics and ground truth are usually sparse [29]. The data scientist provides photographs in unsupervised learning, leaving it to the machine to analyse the information and decide whether the images displayed are relevant.

In autonomous driving, the algorithm can then decide if the pictures of obstacles hinder the vehicle from proceeding. Unsupervised machine learning requires vast volumes of data [28]. Unsupervised learning overcomes the need for data tagging, which requires human participation. It is useful for handling large data sets and finding patterns [30].

3.3. Semi-Supervised Learning

In semi-supervised learning, unlabeled data and supervised learning tasks and methodologies are also used for training. Typically, a small amount of labeled data is combined with a big amount of unlabeled data [31].

3.4. Reinforcement Learning

Reinforcement Learning (RL) assumes an autonomous agent exploring its surroundings and acting upon what it considers to be knowledge about its current condition. In exchange, the environment sends a reward signal, which may be favourable or unfavourable. During the interaction, the agent's goal is to maximise the anticipated cumulative reward signal [32].

3.5. Multitask Learning

A method of inductive transfer known as multitask learning uses the domain knowledge in the training signals of related tasks as an inductive bias to enhance generalisation. It accomplishes this by employing a shared representation to learn tasks in parallel, with the knowledge gained from each task improving the learning of subsequent tasks. [33].

3.6. Ensemble Learning

By integrating results with different choosing mechanisms, ensemble learning techniques improve performance over any single constituent algorithm by utilising multiple machine learning algorithms to produce weak predictive results based on features extracted through diverse data projections [34].

3.7. Neutral Base Learning

Large volumes of data are used to train a neural network, the foundation of deep learning models. Usually, the purpose of using data is to find patterns that will enable the model to forecast new data, that is, data that it has never seen before with greater accuracy. Applications for deep learning models are numerous and include personal digital assistants and selfdriving autos.

3.8. Instance-Based Learning

Machine learning systems classified as instance-based learning memorise training examples before extrapolating to new cases based on a similar metric. Because the hypotheses are constructed from training cases, they are known as instance-based. It is sometimes referred to as lazy Learning or memory-based Learning since it postpones processing until a fresh instance needs to be categorised. The size of the training data affects this algorithm's time complexity. Its previously stored data is analysed each time a new query is encountered. And allocate value to a target function for the newly created instance. The broad algorithm known as Instance-Based Learning Theory (IBLT) seeks to capture the entire human cognitive process of experiential choice in dynamic tasks[35]. More recently, IBLT has been applied to tasks other than dynamic decision-making. Simple binary choice puzzles are among them [36], challenges involving game theory in two persons [37], and other activities involving dynamic control [38].

4. Theory of Mind AI

This refers to the kind of artificial intelligence (AI) systems that are genuinely clever and able to carry out humanlike functions, such as making judgments based on other people around them. They can recognise emotions and modify their actions accordingly.

Robots using this kind of AI can communicate with people in the same way as people. Theory of mind is still mostly a theoretical AI system, but some robots like Kismet and Sophia can understand human emotions and imitate them. Because of their rapid processing speeds, computers are incredibly skilled at playing strategic games like chess better than humans [39].

5. Limitation of Artificial Intelligence

Artificial intelligence technologies are still restricted to some knowledge domains, like conversation response, speech recognition, and image recognition. Artificial intelligence technologies are limited, unlike the human brain, which possesses self-awareness, self-control, self-understanding, and self-motivation as part of its domains, as shown in Figure 3.



Fig. 3 Shortage in artificial intelligence [40]

5.1. Frame Problem

AI is usually restricted to a single frame or problem type because it requires a lot of time owing to massive data training, considering all the possible events that could occur in the real world. Only specific outcomes can be anticipated; for instance, the algorithm can be limited to image or speech recognition but not the full spectrum of senses.

However, there are an endless number of scenarios that we must consider when dealing with every occurrence that arises in the actual world, which causes the database to become overloaded and the extraction time to become infinite.

5.2. Association Function Problem

Artificial Intelligence and machine learning are quite good at identifying patterns. However, it is simple to abuse machine learning's output.

Modern artificial intelligence technology lacks the association function of the human brain and is dependent on massive amounts of data to produce results that can only be expressed as numerical values.

5.3. Symbol Grounding Problem

Connecting symbols to their meanings is essential, yet currently, artificial intelligence struggles with this. For instance, if you are aware of the distinct meanings of the words "horse" and "striped," you will be able to comprehend the concept of "zebra," which is defined as "a horse with stripes," when you are taught that zebra = horse + stripes. But, machine learning cannot draw the same abstract conclusions about concepts.

6. Challenges and Solutions for Implementing Artificial Intelligence

The rate of artificial intelligence use in emerging economies has been limited by challenges such as data quality, privacy, and a shortage of qualified personnel [41]. The factors, changes and solutions are discussed in Table 1.

Factors	Challenges	Solutions
Technical	Technical inefficiency	Update of academic syllabus
Socio- Economical	Fear of losing jobs	Humans can learn to design systems for artificial intelligence
Lack of research and update	While other industries are moving toward Industry 5.0, we are still working toward Industry 4.0 and missing Industry 3.0.	Research and development in hardware and software, as well as competence, should be value- driven and applicable to the industry.
Fragmented and Complex	Not having the capacity to create an ordinary system or design.	Every organisation should have a framework created according to its structure and function.

Table 1. Challenges and solution for implementing artificial intelligence -[42],[43],[44],[42],[45],[46],[47]

7. Conclusion

The technological availability of artificial intelligence to automobile manufacturers is growing exponentially worldwide. As a result, the market for automotive artificial intelligence is expected to grow rapidly as these tools are integrated into production, maintenance, and product usage. The automotive sector is focused on introducing modern technologies to boost productivity and more innovative and safer cars. Artificial Intelligence is already a part of everyday life. Machine learning cannot replace human beings to achieve singularity; however, it can limit the number of people needed in the industry and increase efficiency. Machines can only learn from humans and facilitate speed in various processes. Users can have more free time to do other things when artificial intelligence is applied in the form of driverless cars, and the technology also offers superior transportation services. Manufacturing operations can become more efficient with the help of artificial intelligence. When employed in the automobile assembly process, robots with artificial intelligence built into them can do tasks more precisely and productively than humans. These robots can be used for a variety of tasks, including welding and automobile painting. Robots can also adjust to modifications in the production process thanks to machine learning algorithms. Implementing training and academic programs that include multidisciplinary projects, studies on job role transformation, and workplaces that support human-centred systems as well as Sustainability. Future research should try to include technology to get successful results. The study has also identified future research areas to explore these technologies' potential further in the development industry. The construction industry is expected to benefit from this study's promotion of new technology adoption and enhancement of productivity, accuracy, operational efficacy, and quality.

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