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AUTONOMOUS VEHICLES USING NEURALNETWORKS

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ABSTRACT

Autonomous vehicles (AVs) have emerged as a disruptive force in the transportation industry, promising a revolutionary shift in mobility. This paper provides a comprehensive overview of the technological advancements, societal implications, and prospects of autonomous vehicles. The development of AVs is propelled by breakthroughs in artificial intelligence, sensor technology, and connectivity. Machine learning algorithms enable AVs to perceive and interpret their surroundings with unprecedented accuracy, while LiDAR, radar, and cameras provide real-time data crucial for navigation and decision-making. Moreover, advancements in vehicle-to-everything (V2X) communication systems facilitate coordination between AVs and infrastructure, enhancing safety and efficiency. The adoptionof AVs stands to revolutionize various sectors, including transportation, urban planning, and logistics. Improved traffic flow, reduced congestion, and lower accident rates are anticipated benefits, leading to enhanced productivity and quality of life. Furthermore, AVs offer newfound independence to individuals with disabilities and the elderly, transforming accessibility and inclusivity in transportation. However, the widespread deployment of AVs raises complex ethical, regulatory, and cybersecurity challenges. Questions surrounding liability in the event of accidents, data privacy concerns, and job displacement in the transportation sector necessitate careful consideration. Additionally, ensuring the resilience of AVs against cyber threats is imperative to prevent potential malicious attacks.

Keywords: Biometrics Technology, Fingerprint Reader, Money Pad, Digital or Electronic Casher Digi- cash or E-cash or E-Cash or Digital Money.

[1] INTRODUCTION

In recent years there has been a confluence of ideas and methodologies from several different disciplinary areas to give rise to an extremely interesting research area called Autonomous

Vehicle (AV) [1]. In the rapidly evolving landscape of transportation, autonomous vehicles (AVs) stand as a beacon of innovation, promising to redefine mobility in ways previously unimaginable. With the convergence of cutting-edge technologies such as artificial intelligence, sensor systems, and connectivity, AVs represent a transformative leap forward in how we perceive, interact with, and utilize transportation systems. The concept ofautonomous vehicles traces its roots back to the early 20th century, but it's only in recent years that significant strides have been made towards practical implementation. Spearheaded by visionary engineers and researchers, AV development has accelerated, fueled by a shared vision of safer, more efficient, and sustainable transportation solutions.

A neuron is the fundamental building block of the nervous system that performs computational and communication functions. The ANN is a functional imitation of a simplified model of the biological neurons and their goal is to reproduce intelligent data evaluation techniques like pattern recognition, classification and generalization by using simple, distributed and robust processing units called artificial neurons or Processing Elements (PE) [2]. The artificial neuron was designed to mimic the first- order characteristics of biological neurons. The intelligence of ANN and its capability to solve hard problems emerges from the high degree of connectivity that gives neuronsits high computational power (processing capability) through its massive parallel- distributed structure or architecture, each neuron of which performs only very limited operation. Even though individual neurons work very slowly, they can still quickly finda solution by working in parallel.

[2] RELATED WORK

The data set is first processed so that the information can be mapped to any number of nodes in the input layer to represent the available information. For images, this often results in a node for each pixel and a value for each node that corresponds to the color of the pixel. This information is then sent to the hidden layer, which decides through a series of weights, one for each input node, how the previous combination will be represented and what value it will have in its nodes. This data is then passed to nodes in the output layer where it is converted into output data to predict what information was given to them in the input layer. This represents the advantage of the model. Predictions are a direct result of the hidden layer's ability to transform information from the input layer. The prediction is then measured, and the quantitative error is determined to update the weights. This happens repeatedly through backward propagation and repetition of forward flows. As the model receives more data to train, its weights will eventually be updated enough to minimize the number of inaccurate predictions. Once the network is trained, it can be used to predict other similar datasets in the future.

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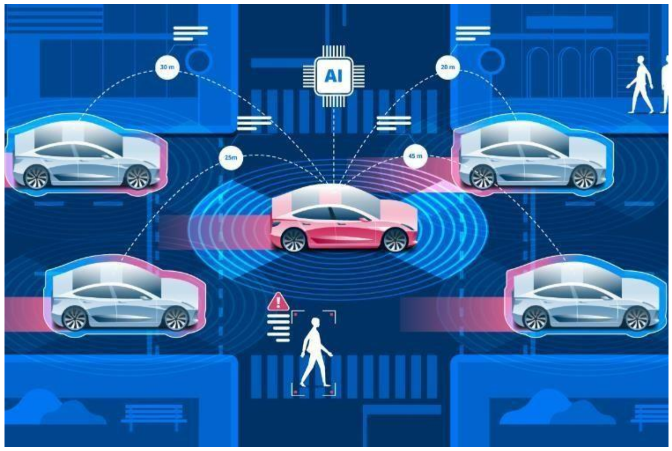
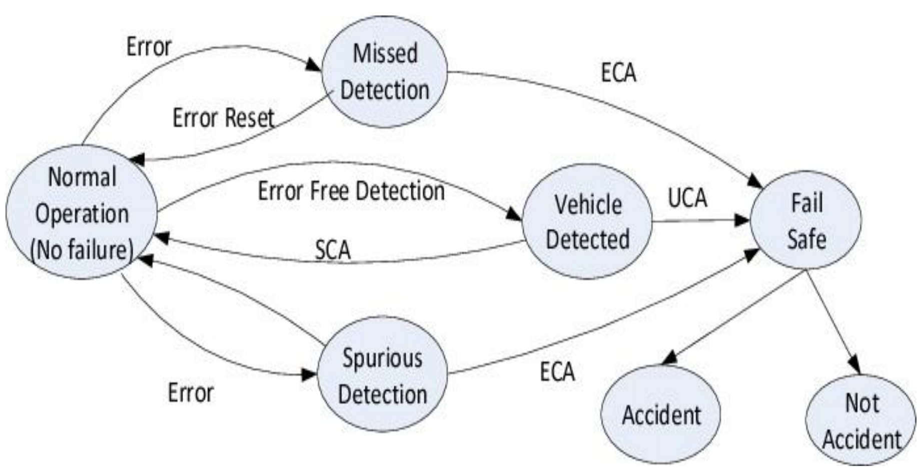


Fig 2.1 Showing an example of an Autonomous Vehicle

A neuron is said to be 'trainable' if its threshold and input weights are modifiable. Inputs are presented to the neurons. If the neurons do not give the desired output (determined by us), then it had made a mistake. Then some weights and thresholds must be changed to compensate for the error. The rules which govern how exactly these changes are to take place are called learning (or training) algorithms. Learning algorithms differ from each other in a way in which the adjustment to synaptic weights of a neuron is formulated. The weights of the network are incrementally adjusted to improve a predefined performance measure over time. The learning process is best viewed as "search" in a multidimensional weight space for a solution, which gradually optimizes a pre- specified objective function. The NN becomes more knowledgeable about its environment after each iteration of the learning process. In order for the net to teach one needs to present a number of examples to the net whose attributes are known or are representatives for the unknown model [2]. The set of given examples is called the training set or training.



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[3] CONCLUSION AND FUTURE WORK

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Each type of NN has been designed to tackle a certain class of problems. Hopefully, at some stage we will be able to combine all the types of NNs into a uniform framework. Hopefully, we will reach our goal of combining brains and computers. Basically, ANN is a part of Artificial Intelligence (AI). The success so far has been in the simulation of intelligence- not the creation of true intelligence. Therefore, ANN may become the foundation for more intelligent systems. Since ANN can be viewed as “low level” data processing tool, hybrid approaches, that are a combination of ANN with other techniques like Expert Systems, Fuzzy Logic, and Genetic Algorithms (GA), are promising areas to be investigated.

Presently, integration of Fuzzy logic with ANN is a major area of research as it combines the advantage of both these fields [18]. GA have been increasingly applied in ANN design such as topology and parameter optimization

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