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Research Paper

Applications of Artificial Intelligence in the Nigerian Transport System

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Abstract
The rapid advancement of Artificial Intelligence (AI) presents significant opportunities to transform various sectors, including transportation. In Nigeria, where the transport system faces challenges such as increasing travel demand, traffic congestion, safety concerns, and environmental impact, AI offers innovative solutions to enhance efficiency and sustainability. AI methodologies, including Artificial Neural Networks (ANNs), Genetic Algorithms (GAs), Simulated Annealing (SA), Artificial Immune Systems (AIS), Ant Colony Optimization (ACO), Bee Colony Optimization (BCO), and Fuzzy Logic Models (FLMs), have demonstrated their potential in addressing these issues. This paper provides an overview of how AI techniques can be applied to Nigerian transport challenges, examining their role in traffic management, public transportation, and urban mobility. The discussion includes successful case studies, potential benefits, and limitations, concluding with recommendations for future research and implementation in Nigeria's transport sector.
Keywords*: Artificial Intelligence; Genetic Algorithms; Simulated Annealing; Artificial Immune System; Ant Colony Optimization; Bee Colony Optimization; Public Transport; Urban Mobility; Traffic Management*

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I. Introduction

Artificial Intelligence (AI) is a dynamic field within computer science that aims to replicate human cognitive functions in machines. AI's roots trace back to 1956, when John McCarthy coined the term, but early developments faced significant limitations due to technological constraints [1]. The initial focus was on Knowledge-Based Systems (KBS) and Artificial Neural Networks (ANNs) during the 1960s and 1970s, with KBS providing rule-based advice and ANNs mimicking neural connections in the human brain [1,2,3]. Despite initial enthusiasm, progress stagnated until the 1980s, when advancements in gradient descent and Backpropagation algorithms reignited interest in AI [4,5,6].

The evolution of AI into machine learning has enabled systems to learn from large datasets rather than being explicitly programmed. Techniques such as Feedforward Neural Networks, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) have advanced AI's capabilities, particularly in image processing and sequence analysis [7,8,9,10,11,12,13,14]. These developments have paved the way for AI applications in complex domains like transportation.

In Nigeria, AI has the potential to address numerous transport-related challenges, including traffic congestion, safety issues, and environmental degradation. The rapid urbanization and population growth in Nigerian cities exacerbate these problems, making AI solutions increasingly relevant [15,16]. This paper explores the applications of AI in Nigeria's transport system, focusing on traffic management, public transportation, and urban mobility.

II. Applications of AI in Nigerian Transport System

2.1 Traffic Management

In Nigerian cities, traffic congestion is a significant issue, impacting economic productivity and quality of life. AI technologies such as ANN and GA have been applied to traffic management systems to optimize signal timings, predict traffic volumes, and manage congestion. For instance, ANNs can analyze traffic patterns and adjust signal timings in real-time to reduce bottlenecks [17]. GA and SA can be used for optimizing traffic light schedules and routing strategies, improving overall traffic flow [18].

2.2 Public Transportation

Public transport in Nigeria faces challenges related to reliability, coverage, and efficiency. AI applications, such as predictive modeling using ANN and FLM, can enhance the planning and operation of public transport systems. For example, predictive models can forecast passenger demand and optimize bus schedules, reducing wait times and improving service reliability [19]. AIS and ACO can also be utilized to optimize route planning and vehicle dispatching, leading to more efficient public transport networks [20].

2.3 Urban Mobility

Urban mobility in Nigeria is affected by rapid urbanization and inadequate infrastructure. AI technologies like CNNs and RNNs can be leveraged to analyze and predict mobility patterns, facilitating better urban planning and infrastructure development. CNNs can process satellite images and other spatial data to assess land use and identify areas requiring infrastructure improvements [21]. RNNs can model and predict traffic flows and mobility patterns, aiding in the development of more effective urban transportation strategies [22].

2.4 Intelligent Self-Driving Vehicles

The development of autonomous vehicles presents a promising opportunity for Nigeria's transport sector. AI-driven self-driving cars and buses have the potential to improve road safety and reduce traffic accidents. Although trials and implementations are still in early stages globally, AI research and development in Nigeria could benefit from exploring partnerships and pilot projects involving autonomous vehicles [23].

3. Future Directions

The future of AI in Nigerian transport systems is likely to be shaped by advancements in Deep Learning and other emerging AI technologies. Deep Learning techniques, with their ability to handle large datasets and complex patterns, are expected to play a crucial role in improving traffic management, public transport, and urban mobility [24]. Future research should focus on adapting these technologies to the unique challenges of Nigeria's transport system and addressing issues related to data quality, infrastructure, and public acceptance.

AI has the potential to revolutionize Nigeria's transport system by addressing key challenges such as traffic congestion, safety, and environmental impact. The application of various AI techniques, including ANN, GA, SA, AIS, ACO, and FLM, offers promising solutions for improving traffic management, public transportation, and urban mobility. However, successful implementation requires overcoming challenges related to data quality, infrastructure, and integration. Future research should focus on leveraging Deep Learning and other advanced AI technologies to further enhance Nigeria's transport system.

2. Applications of AI in Transport

In many cases, it is hard to fully understand the relationships between the characteristics of the transportation system; therefore, AI methods can be presented as a smart solution for such complex systems that can’t be managed using traditional methods. Many researchers have demonstrated the advantages of AI in transport. For example, AI can transform traffic sensors on the road into smart agents that detect accidents automatically and predict future traffic conditions [18]. Various AI methods are used in transport, such as Artificial Neural Networks (ANNs). ANNs can be applied in road planning [19], public transport [20,21], traffic incident detection [22–25], and predicting traffic conditions [26–33]. ANNs are classified into supervised and unsupervised learning methods. Supervised methods include Support Vector Machines (SVM), Probabilistic Neural Networks (PNN), Radial Basis Networks (RBN), K-Nearest Neighbors (KNN), and Decision Trees, among others. Unsupervised ANNs include greedy layer-wise and cluster analysis methods.

Many transportation problems lead to optimization challenges that require bespoke algorithms for computational analytics. Advanced computational algorithms, known as raster algorithms, are used for these problems. The Genetic Algorithm (GA) is an example of such algorithms. Based on the evolutionary biological concept, GA solves complex optimization problems through the "survival of the fittest" concept and is a useful tool in urban design networks [34–37]. Another optimization algorithm is Simulated Annealing (SA), which simulates the process of annealing in metals [34,38–40]. The Ant Colony Optimizer (ACO) is an AI algorithm inspired by the behavior of ants following their path from the nest to a food source [41,42]. The Artificial Immune System (AIS), modeled after the human immune system, [34,43,44], and Bee Colony Optimization (BCO), which addresses hybrid complex optimization problems [44–47], are also notable. ACO and BCO are part of swarm intelligence systems, inspired by ants and bees working together to reach an optimized solution. These systems can handle uncertainty, imprecision, and vague concepts, making them suitable for route optimization problems in transport [48–51]. Another optimization technique is the Fuzzy Logic Model (FLM), applied to shortest path optimization [52]. The performance of FLM is often compared with Logistic Regression Models (LRM), where FLM has shown superior performance [53]. Intelligent techniques such as FLM, GA, ANN, and ACO are well-suited for prediction, reasoning, and adaptability, addressing optimization problems involving dynamic traffic situations and events. A novel software paradigm based on AI theories, called Agent-Based Software Engineering (ABSE), allows for dynamic identification of shortest paths through multi-criteria and multi-scenario analysis [54].

Furthermore, ANNs have been integrated with the aforementioned algorithms to enhance results [22,49,55]. For instance, other tools using AI include software and hardware implementations for automated vehicles and trip planning [50,51]. Transport authorities must determine when and how to use these technologies to rapidly improve congestion relief, travel time reliability, and the economics and productivity of transportation assets.

2.1. AI in Planning, Designing, and Controlling Transportation Network Structures

The objective of planning is to identify community needs and decide on the best approach to meet this demand while considering the social, environmental, and economic impacts on transportation. Designing an optimal road method for transport planning is part of the Network Design Problem (NDP) [56]. NDP can be continuous when the capacity of existing infrastructure changes (e.g., extending lane width), discrete when adding more infrastructure, or a mix of both. Research in the 1990s focused on NNs for road planning, designing, and modeling. For example, a parallel neural network system was used to model the spatial relationship between transportation and land-use planning [57]. Subsequently, research shifted towards raster algorithms, which are preferred for urban planning due to their ability to find optimal paths without relying on existing links and nodes [58]. Today, the vast amount of data and advanced algorithms have become the focus of most research, using machine learning to identify patterns among data. For instance, a study addressed the continuous NDP problem as a bi-non-linear model assignment with two levels, using GA and SA algorithms and comparing their efficiency on a simulated network. The results indicated that SA finds optimal values with less computational effort when demand is low, whereas GA can reach better optimal solutions with more computations [34]. This result contrasts with [37], which argued that GA provides better results than SA with less computational time, although the model considered was a single-level linear model for a Continuous NDP problem.

Another study modeled the safety management plan for Ankara city using ANN and GA, showing that the ANN model outperformed GA with less error involved [21]. In contrast, [59] used the ant colony algorithm for optimal vehicle path design. Additionally, [58] combined Cellular Automata (CA), a spatial simulation method, with ACO, showing improved urban development planning based on simulated industrial land use patterns in China. [19] focused on a transportation system management and safety plan using ANN for accident and injury prediction on a congested route from Istanbul to Ankara. Lastly, [33] compared GA, SA, and AIS algorithms to find the best modification for an existing network structure, considering it as a Mixed NDP problem in Poland. The results demonstrated that SA performed worse than GA and AIS for this class of problem.

Planning routes for vehicles is crucial to avoid congestion and delays. Many authors concluded that ACO is a promising solution for vehicle routing problems [57,60–62]. [63] addressed a routing and wavelength problem using BCO, which involves choosing a path within a network and assigning a wavelength to maximize connections between nodes. Recent research has also focused on utilizing microscopic traffic data for modeling and identifying security breaches, and for traffic control and management plans [64]. For public transport users, [65] suggested learning and updating real-time path generation systems based on traveler preferences and using a utility-based approach focusing on different attributes of paths and parameters for each user.

An area of rapid AI development is Intelligent Transport Systems (ITS), which aim to alleviate congestion and enhance the driving experience through various technologies and communication systems. These systems capture important data that can be integrated with machine learning technology. For example, deep reinforcement learning has been used for real-time optimization of traffic control policies in large-scale ITS systems [66]. Similarly, a deep learning system has been proposed to empower ITS devices with signal processing and fast computing analytics [67]. As ITS develops and data complexity increases, deep learning techniques will be crucial for finding patterns and features to create more connected transportation systems. Another example is [68], which used genetic algorithms and fuzzy methods to control traffic signal systems automatically at intersections. The system, 'NeverStop,' utilized RFID sensors and effectively reduced average vehicle waiting times. Additionally, [69] developed two NN systems for managing roads based on microscopic simulated data: one for traffic signal control and another for predicting future traffic congestion. [70] demonstrated the feasibility of using NNs for traffic control by proposing a multi-layer NN system evaluated in three intersection networks.

ANNs are also effective in traffic signal control. [71] developed two NN systems for road management based on microscopic simulated data: one for traffic signal control and another for predicting future congestion. [72] demonstrated the feasibility of using NNs for traffic control by proposing a multi-layer NN system evaluated across three intersections.

Moreover, reinforcement learning NNs are used to update system parameters and cycle lengths as traffic flow changes periodically [64,65]. AI is a dynamic research area, continually evolving with new methods and applications that leverage its strengths to improve road planning, decision-making, and management.

2.1.1. Incident Detection

Various attempts have been made to identify the time, location, and severity of incidents to assist traffic managers in mitigating congestion. These attempts range from manual reports to automated algorithms and neural networks. Manual reports, written by humans, can be delayed and costly. In contrast, algorithms measure flow characteristics before and after incidents through data collected from road sensors. Initially, statistical techniques like the California Algorithm were used for incident detection, but these were challenging to apply to arterial roads due to street parking and traffic signals. Therefore, neural network approaches have been developed. A classification neural network algorithm was evaluated to detect incidents on freeways [22]. Other research explored using AdaBoost software for accurate image detection of vehicles [73]. The IMM ENKF algorithm was proposed for detecting incidents in hybrid state problems, and the Efficient Multiple Model Particle Filter (EMMPF) was developed for accurate incident detection on highways using both simulated and field data [23]. Real-time incident detection from social media, such as Twitter, has also been discussed as a cost-effective technique for acknowledging incidents on freeways and arterial roads [74].

2.1.2. Predictive Models

The rapid development of Intelligent Transport Systems (ITS) has increased the need for advanced methods to predict traffic information. These methods play a crucial role in ITS subsystems such as advanced traveler information systems, advanced traffic management systems, advanced public transportation systems, and commercial vehicle operations. Intelligent predictive systems are developed using historical data from road sensors, which is input into machine learning and AI algorithms for real-time, short-term, and long-term predictions [75].

Historically, short-term flow prediction was achieved using simple feedforward neural networks. For example, [28] integrated a neural network system with one hidden layer into the urban traffic control system, demonstrating the ability to predict traffic flow up to 1 minute into the future using simulated data. [25] used field data from a 1.5 km section of a highway in Queensland, Australia, developing an object-oriented neural network model with a time-lag recurrent network (TLRN) that predicted speed for 5 minutes into the future with 90–94% accuracy. The model also predicted travel time with accuracy. Additionally, [76] compared feedforward NNs with statistical models such as autoregressive integrated moving average (ARIMA) and found that NNs performed better in traffic flow predictions.

Long-term prediction methods include deep neural networks (DNN) and convolutional neural networks (CNN), which provide accurate predictions for future traffic conditions by analyzing historical traffic patterns. These models have been evaluated using various techniques. [77] proposed a real-time deep learning system for predicting traffic congestion, achieving high accuracy. [78] introduced a short-term prediction model using Jordan’s Neural Network, demonstrating better performance compared to ARIMA in predicting short-term traffic flow. [79] found that using CNN for modeling improves accuracy compared to traditional methods, though Jordan’s Neural Network performed better under certain conditions. [80] confirmed that DNNs and CNNs offer effective solutions for short-term traffic forecasting.

AI's rapid advancements will likely enhance ITS subsystems' performance and accuracy, providing better tools for traffic management and prediction. In order to build a robust predictive model, it is important to acknowledge three phases as seen in Figure 1.

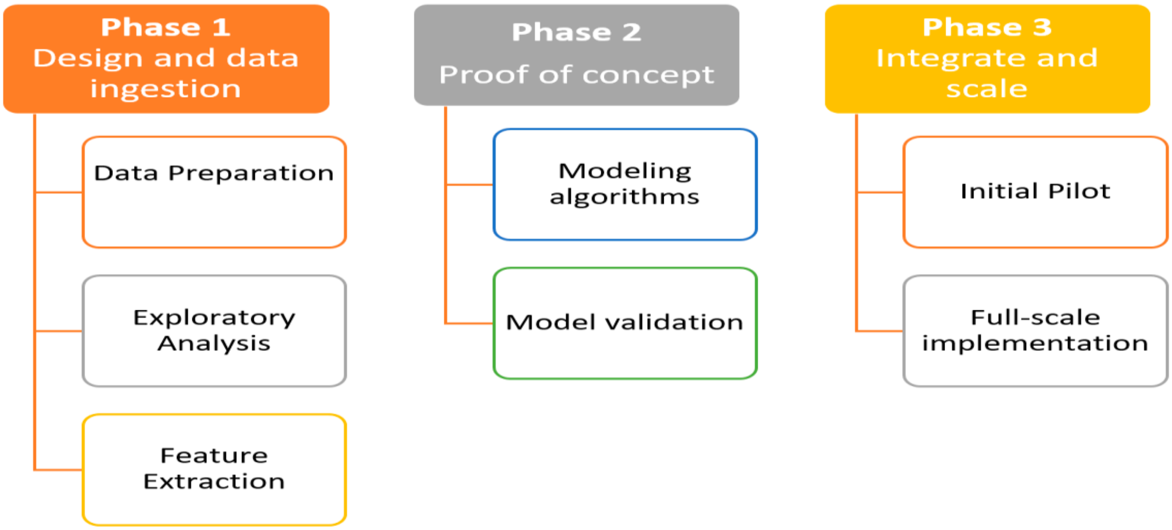

Figure 1. Three-Phases Approach to develop advanced predictive model – adapted from [79].

In Phase 1, it is crucial to evaluate all data sources and integrate the advanced model into the industry. This phase focuses on the initial assessment of asset performance. In the **Proof of Concept** phase, multiple models are assessed more critically to identify failure modes and estimate the time required for the project's overall life cycle. The final phase involves real-time prediction of asset performance, necessitating constant updates and scaling of the model to ensure optimal results.

In [80], the authors utilized demographic and geographic data to forecast future mobility demand in Switzerland. This demand estimation is vital for effective planning and future techniques necessary for managing a more efficient transportation system. They initially clustered population data based on daily route choices. A decision tree and support vector machine (SVM), both supervised neural networks, were then employed to classify data and extract significant features. The decision tree method uses numerous de-correlated decision trees to form a forest, achieving higher accuracy with an increasing number of trees by classifying each tree's attributes and selecting the majority vote for classification. SVM classifies inputs by maximizing the margins between data points. They subsequently applied machine learning algorithms to daily distance traveled by vehicles for future demand estimation.

Another study [65] explored real-time short-term prediction methods for public transport users waiting at bus stops and on-board passengers. This information aids operators in better controlling transit trips and assists travelers in choosing optimal routes during peak hours. Effective communication of this information requires integration between public transport systems and Intelligent Transportation Systems (ITS), enhancing forecasting tools for advanced traveler information systems and operational controls.

The rise of ridesharing services like Uber and Didi Chuxing has increased data collection opportunities, which AI can leverage to predict passenger demand more effectively, thereby reducing congestion and energy consumption [81]. [81] proposed a deep learning model incorporating Multi-View, Spatial, and Temporal (DMVST) Network. They analyzed large-scale ridesharing demand data from DiDiChuxing in Guangzhou, China, combining Local CNN for capturing local regions relative to their surroundings and Long Short-Term Memory (LSTM) networks for modeling temporal features. This model demonstrated superior performance. Similarly, [82] predicted taxi demand in Tokyo using a Multi-Layer Perceptron Neural Network (MLP). Data from the Taxi Probe system, which records taxi locations, was utilized. The results indicated that historical demand data with 50 neurons in the hidden layers provided better prediction accuracy. [83] evaluated taxi performance by selecting key features from a taxi pattern using L1-Norm SVM, while [84] used deep learning techniques with taxi datasets from New York City, finding that deep neural networks (DNN) outperformed other methods, though proper architecture selection is crucial for accurate results.

AI also plays a significant role in preventing urban road accidents and mitigating their impacts. The reasons for vehicle accidents vary by space and time, and AI can capture spatial-temporal patterns in accident databases to design mitigation strategies. For instance, [85] used a deep recurrent neural network to predict traffic accident risk by analyzing spatial and temporal patterns from a traffic accident database in Beijing, China, demonstrating effective warning capabilities for hazardous locations. [86] developed a Stack Denoise Autoencoder Simulation model to predict traffic accident risk levels. [87] identified valuable hidden patterns from a vehicle crash dataset using machine learning techniques like k-Clusters and the apriori algorithm. Additionally, [88] found that factors associated with fatal accidents in the United Arab Emirates included gender (males), age (18–30 years old), collision type (car-pedestrian), and accident location (right angles), determined using Decision Tree and MLP algorithms.

2.3. Intelligent Urban Mobility

The future vision for intelligent urban mobility involves enhancing decision-making with real-time data and optimizing transportation networks through efficient infrastructure use. This aims to create a smarter, safer, and healthier transportation system that fosters intelligent connectivity, promoting sustainability and environmental friendliness. Recent advancements in autonomous vehicle (AV) technology exemplify this vision, with vehicles designed to operate without human intervention [123].

Autonomous Vehicles

Autonomous Vehicles (AVs) leverage artificial intelligence (AI) and deep learning techniques to navigate safely, maintaining proper headways, lane discipline, and vehicle control. Forecasts suggest that AVs will significantly transform global transportation systems, impacting traffic safety and congestion, and potentially altering travel behaviors [124]. They are anticipated to change travel patterns, influence social structures, and reshape urban forms, facilitating car and ride-sharing through innovative business models that address accessibility and reliability challenges [125].The evolution of AVs began in the late 1950s, with significant milestones such as the introduction of the "urbmobile" electric vehicle by The Cornell Aeronautical Laboratory in 1968. Although early technology did not support widespread adoption, recent advancements in sensors and cameras have driven the push toward fully automated vehicles [126]. However, challenges remain, including the need for extensive data to recognize traffic signals, vehicles, and road signs, and address various environmental conditions such as weather and lighting [127]. Additionally, ensuring software security and system integrity remains a critical challenge [62].

AVs consist of hardware and software components. The hardware includes actuators, sensors, and computer systems, while the software encompasses navigation modules, localization algorithms, and perception systems for detecting moving objects [128]. The advancement towards fully automated vehicles involves overcoming challenges related to safe navigation amidst other vehicles, obstacles, and pedestrians, utilizing AI, pattern recognition algorithms, sensors, and 3D cameras [129].Google's introduction of the automated Toyota Prius in 2010 marked a significant step forward, with projections indicating a potential reduction of over 30,000 lives lost annually and a $270 billion decrease in road accident-related costs in the USA. Google's subsequent developments, including the Lexus RX450h and the Firefly vehicle in 2015, further advanced the field, with the project now evolving under the independent company Waymo [130]. Social acceptance of AVs remains a challenge, with research indicating that attributes such as self-healing, self-socializing, self-learning, self-driving, self-configuring, and self-integrating are of particular interest to passengers [131].

Despite these advancements, AV technology faces several challenges and limitations. Benefits include enhanced road safety [108,111], reduced congestion, shorter travel times [132–134], decreased car ownership [135], and lower emissions [62,136]. However, AI techniques in transportation face criticism for being "black boxes," limiting understanding of internal computations [137]. Integrating neural networks with traditional methods may address some limitations, but hybrid approaches still face challenges in performance and generalization [138–140]. AI applications in transportation are currently limited to specific intelligent transportation system (ITS) applications, highlighting the need for more comprehensive AI solutions in traffic analysis, data collection, decision-making, and optimization [142]. The transition from classical data collection methods to novel AI-based technologies is crucial for improving prediction accuracy and reliability.

Furthermore, AI techniques, particularly in deep learning, often face computational complexity issues due to large datasets and noisy data [143]. Solutions such as the MapReduce framework, which distributes computations across multiple computers, can help manage these complexities [149]. Research shows that MapReduce approaches improve the efficiency of various applications, including traffic anomaly detection [149], bus arrival time prediction [152], and traffic flow prediction [153].Overall, while the future of intelligent urban mobility is promising with AVs and advanced AI techniques, addressing these challenges is essential for achieving a fully integrated and efficient transportation system.

III. Future of AI in Vegetation Analysis and Monitoring

Deep learning continues to revolutionize how vast amounts of data are analyzed across various fields, including environmental science and forestry [155]. As of 2016, the market for deep learning technologies was valued at $272 million USD, reflecting its growing importance in managing complex data from diverse sources [156]. This growth is driven by deep learning's superior data storage capacity, computational accuracy, and ability to handle high-volume datasets. By 2025, the value of deep learning is projected to reach $10.2 billion USD, propelled by its applications in sectors like healthcare, automotive, financial services, and data mining [120].

In the context of vegetation monitoring and biomass estimation, AI and deep learning offer transformative potential. As highlighted by [127], the integration of modern deep learning neural networks can significantly enhance the precision of predictive models used in environmental analysis. For example, deep learning techniques can optimize the analysis of terrestrial lidar data to accurately estimate vegetation biomass and cover. This capability is crucial for understanding and managing forest ecosystems and grassland environments.

Deep learning can also improve operational efficiency in vegetation monitoring. For instance, AI algorithms can analyze remote sensing data to detect changes in vegetation cover, predict biomass growth, and assess the impact of environmental changes. This has practical implications for resource management and conservation efforts. In the automotive and transport sectors, similar advancements have led to improvements in route optimization and real-time performance monitoring, which have been applied to environmental data analysis to enhance precision and efficiency [127].

The future of AI in vegetation analysis is promising. If deep learning technologies continue to advance, they are expected to significantly reduce the cost of environmental monitoring and increase the accuracy of vegetation assessments. For instance, the application of AI in analyzing large datasets of lidar scans could lead to more accurate estimates of biomass and vegetation cover, ultimately supporting better forest management practices. If 30% of vegetation monitoring efforts by 2030 incorporate deep learning technologies, significant improvements in data accuracy and cost efficiency are anticipated [157]

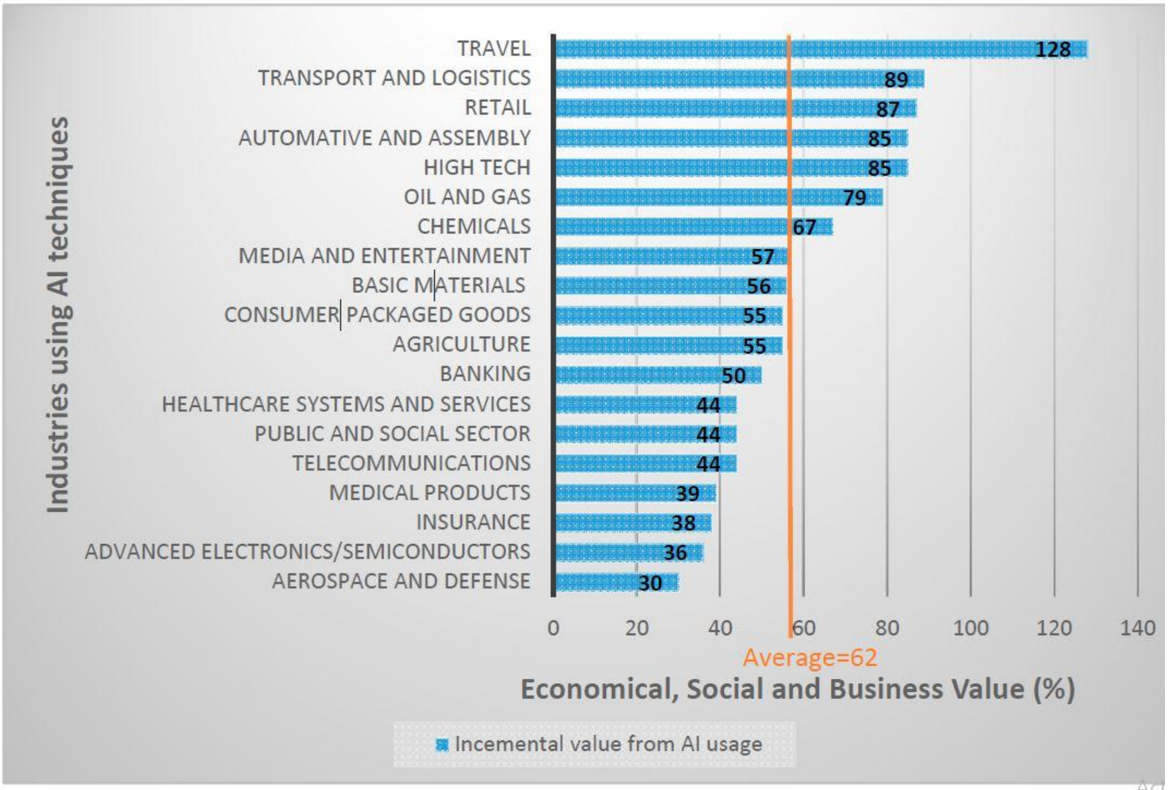

Figure 2. The performance improvement from AI—adapted from [127].

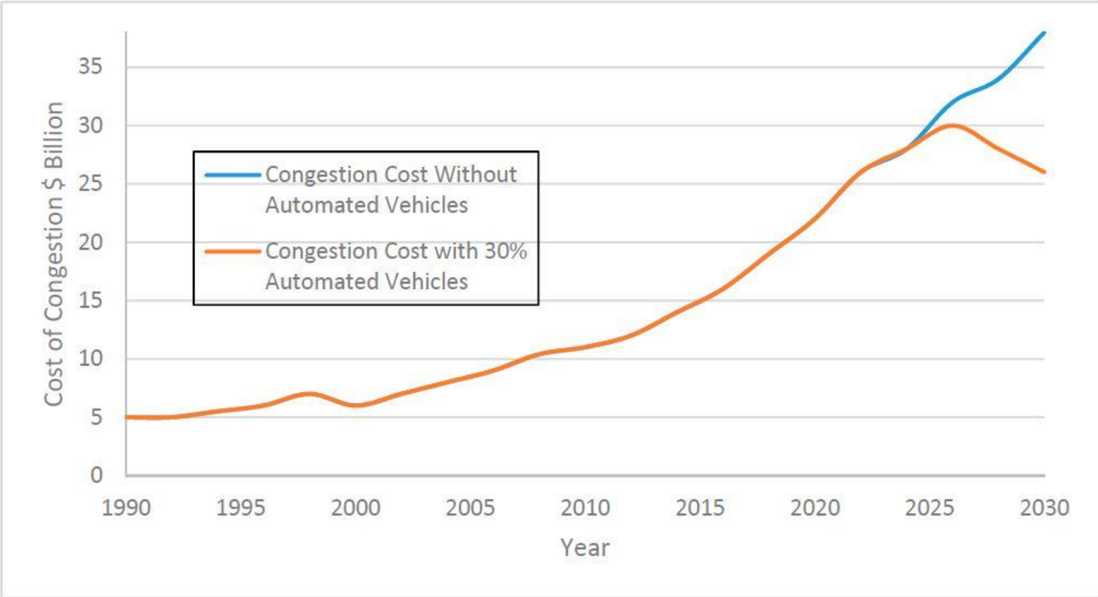

Figure 3. The effect of using 30% autonomous vehicles on road on congestion cost in Australia—adapted from [157].

IV. Future Research Work

Artificial Neural Networks (ANNs) are robust models that excel in handling multiple AI tasks without needing a deep understanding of the targeted process [155]. Their advantages include effective pattern recognition, the ability to manage large datasets, and resilience to noisy data. ANNs are fast and perform well across various tasks and structures. However, there is limited research on long-term traffic state prediction using deep learning architectures. Existing studies often focus on only one or two traffic parameters to develop models. Future research should aim to enhance predictive capabilities by incorporating multiple features and employing more than one hidden layer in the model structure.

The goal is to estimate future traffic conditions based on historical and real-time data collected from detector stations and cameras on freeways. A freeway in Melbourne, Australia, will be used as a test bed to demonstrate the feasibility of this research, with specific locations and data collection methods to be determined in collaboration with freeway authorities. Successful implementation of ANNs relies on selecting the appropriate network architecture, such as the number of neurons and hidden layers [156]. A deep learning system can detect increasingly subtle features in the input data, such as combinations of on-ramp and mainline traffic flows, geometric bottlenecks, and weather conditions, which together might create unique traffic situations [120].

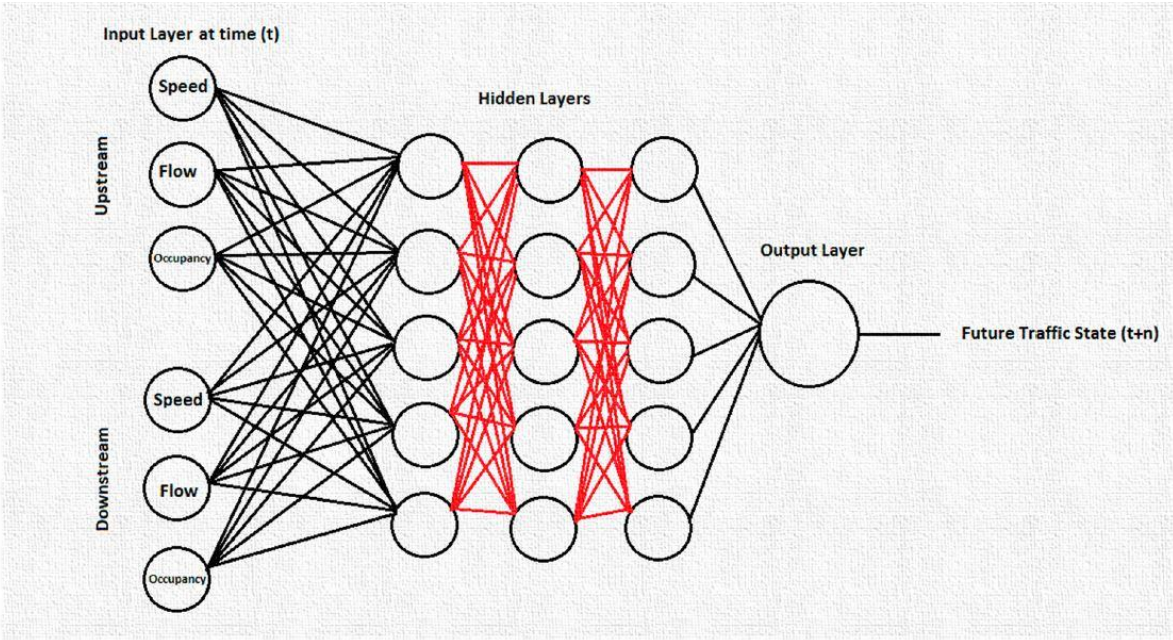

Figure 4. Deep learning system representation. Source: Authors.

One suggestion is to use Recurrent Neural Networks (RNNs) or a combination of Convolutional Neural Networks (CNNs) and RNNs to model sensory and video data. This approach leverages the spatial-temporal nature of sensory data and the distinct properties of sensor and camera data [127]. Such a system could enhance traffic management by predicting network disruptions, allowing road authorities to implement interventions and strategies to mitigate adverse impacts before they occur.

V. Conclusions

This paper reviews the applications of AI across various transport-related problems. The expansion of AI applications is expected as cities and transport systems become more instrumented, providing valuable data for AI development. The review focuses on key areas such as autonomous vehicles, public transport, disruptive urban mobility, automated incident detection, future traffic status prediction, and traffic management and control. AI has demonstrated its potential in addressing challenges like increasing travel demand, CO2 emissions, safety concerns, and fuel waste.Numerous case studies show AI's effectiveness in designing optimal networks, scheduling public transport, enhancing traffic signal timings, and optimizing routes for drivers. AI is also applied in automated incident detection, anomaly detection during flights, and image processing for road data. Recent advancements include AI's use in traffic demand and weather condition prediction, as well as future traffic state management to alleviate congestion and improve decision-making during hazardous situations. AI assists authorities in decisions related to infrastructure expansion, route selection during incidents, and maintenance budgeting. Automated vehicles and public transport systems increasingly benefit from AI to avoid disruptions, accidents, and congestion. Key limitations, such as the "black box" nature of neural networks and potential bias in training data, are also discussed.

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