Journal of Civil, Construction and Environmental Engineering
2024; Vol. 9, No. 3, pp. 72-83
https://doi.org/10.11648/j.jccee.20240903.13

Research Article

A Review of the Advances in Artificial Intelligence in Transportation System Development

Derrick Mirindi*

School of Architecture and Planning, Morgan State University, Baltimore, Maryland, United States

Abstract

In modern times, the rapid expansion of urban populations has intensified the urgency to optimize transportation systems, which has become an alarming issue in the face of urbanization and traffic congestion. This paper reviews the latest applications of Artificial Intelligence (AI) in the transport sector. It explores various AI methodologies, including Artificial Neural Networks (ANN), Genetic Algorithms (GA), Simulated Annealing (SA), Ant Colony Optimizer (ACO), Bee Colony Optimization (BCO), disruptive urban mobility, Fuzzy Logic Models (FLM), automated incident detection systems, and drones, which improve dynamic traffic management and route optimization. The study reveals that integrating these AI techniques with real-time data analytics improves traffic flow, automated incident management, and overall transportation efficiency. The results demonstrate that AI-driven systems, such as drones equipped with advanced sensors and AI algorithms, are increasingly capable of autonomous navigation, real-time monitoring, and predictive traffic management. These advancements in technologies, such as electric Vertical Take-off and Landing (eVTOL) aircraft, Hyperloop Transportation Technologies (HTT), Mobility-as-a-Service (MaaS) and autonomous delivery robots, contribute to smarter urban mobility solutions. However, it is important to focus on refining AI models for better performance, addressing challenges such as computational complexity and privacy concerns, and continuing to innovate in AI to improve the economic efficiency and reliability of transportation systems. Furthermore, to promote sustainability development in this sector, ethical considerations such as the protection of user information and the integration of the concepts of informed consent and human autonomy with community engagement programs should also be considered.

Keywords

Artificial Intelligence, Traffic Management, Urban Mobility, Real-Time Data Analytics, Machine Learning, Deep Learning

1. Introduction

Artificial intelligence (AI) is a field of computer science that aims to make machines function like the human brain, addressing complex issues that traditional computational techniques struggle with. The history of AI dates to 1956 when it was first discovered by John McCarthy [1]. Over the years, AI has evolved through various systems such as Knowledge-based systems (KBS) and Artificial Neural Networks (ANN) [2]. ANN, designed after the human brain, has found applications in diverse fields like medicine, biology, and language translation [3].

The development of AI faced challenges due to limited applications of ANNs until the 1980s when research focused

*Corresponding author: demir1@morgan.edu (Derrick Mirindi)

Received: 7 May 2024; **Accepted:** 4 June 2024; **Published:** 6 June 2024

Copyright: © The Author(s), 2024. Published by Science Publishing Group. This is an **Open Access** article, distributed under the terms of the Creative Commons Attribution 4.0 License (http://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution and reproduction in any medium, provided the original work is properly cited.

on minimizing prediction errors through methods like gradient descent and Backpropagation algorithms [4-6]. With the vast amounts of data availability, Machine Learning (ML) emerged as a subcategory of AI, enabling computers to learn from data and solve complex problems efficiently.

In the context of transportation, AI plays an important role in addressing challenges like increasing travel demand, carbon dioxide emissions, safety concerns, and environmental degradation [7, 8]. The application of AI in transportation systems aims to model and predict travel patterns accurately, especially in the face of growing urban traffic [9]. Researchers are exploring AI applications in corporate decision-making, public transport improvement, and connected autonomous vehicles to enhance productivity and safety on highways [2]. In planning, designing, and controlling transportation networks, Intelligent Transport Systems (ITS), an advance applications which aim to provide innovative services relating to different modes of transport and traffic management and enable various users to be better informed and make safer, more coordinated, and “smarter” use of transport networks, leverage AI technologies like Deep Reinforcement Learning (deep RL) and Genetic Algorithms (GA) to optimize traffic control policies and reduce congestion [10]. Incident detection in transportation systems has also seen advancements through automated algorithms and Neural Networks for real-time detection and mitigation of incidents [11].

Several studies offer a comprehensive examination of AI methods utilized in transportation on a global scale. It focuses on how AI can be used to improve safety, traffic control, public transportation, and mobility around cities [4]. They explore the application of many artificial intelligence techniques, including Artificial Neural Networks (ANN), Genetic Algorithms (GA), Simulated Annealing (SA) to enhance the efficiency of transportation systems. These advanced computational algorithms help address optimization problems in dynamic traffic scenarios effectively [12]. In addition, the integration of AI in transportation still faces unexplored challenges, particularly in ensuring equitable access and addressing privacy concerns [13]. While AI's potential to transform traffic systems is evident, its societal impacts, especially on marginalized communities, and the ethical use of data for traffic predictions, remain underexamined [14]. This paper offers an in-depth review of the ways in which important transportation domains, such as traffic management, safety, public transit operations, and urban mobility planning, are being affected by the application of the evolution of AI techniques. It demonstrates how these computational methods may be used to handle challenging optimization issues in a variety of dynamic transportation settings. This research recommends a balanced approach that considers both technological advancements and their broader implications.

2. Applications of AI on Traffic Management

Artificial Intelligence (AI) plays an important role in revolutionizing traffic management because it addresses challenges such as increasing travel demand, CO_2 emissions, safety concerns, and wasted fuels. The application of AI in traffic management encompasses various areas that are expected to shape future cities and transport systems. These areas include:

2.1. Autonomous Vehicles

Autonomous vehicles, also known as self-driving cars, represent a significant application of AI in traffic management. These vehicles utilize advanced AI algorithms to navigate roads, interpret traffic signals, and make real-time decisions without human intervention. The integration of AI technologies such as Deep Learning (DL), a class of Machine Learning (ML) algorithms that use multiple layers to progressively extract higher-level features from the raw input, and computer vision enables autonomous vehicles to perceive their surroundings accurately and react swiftly to changing road conditions [15]. Recent studies have shown that AI-powered autonomous vehicles can significantly reduce traffic congestion by optimizing routes and minimizing delays, leading to improved travel efficiency and reduced CO_2 emissions [16].

Autonomous vehicles use a combination of AI algorithms, including neural networks and reinforcement learning, to make optimal decisions and navigate complex scenarios. Specifically, Deep Neural Networks (DNN), an artificial neural network with multiple layers between the input and output layers which can model complex non-linear relationships, are extensively used for perception tasks, decision-making, and control systems in autonomous vehicles. Reinforcement learning algorithms play an important role in training autonomous vehicles to optimize their driving behavior by receiving rewards or penalties based on their actions. Additionally, Convolutional Neural Network (CNN) is a primary algorithm used for recognizing and classifying different parts of the road and making appropriate decisions in self-driving cars. Indeed, self-driving cars are autonomous decision-making systems. They can process streams of data from different sensors such as cameras, LiDAR, RADAR, Global Positioning System (GPS), or inertia sensors. This data is then modeled using DL algorithms, while driving decisions are made via a modular perception-planning-action pipeline (Figure 1a) or an End2End learning approach (Figure 1b), where sensory data is immediately transferred to control outputs [17].

Other ML algorithms such as decision forest regression, neural network regression, and Bayesian regression are also utilized for tasks like object detection, identification, classification, localization, and prediction of movement in autonomous vehicles.

Furthermore, the development of autonomous vehicles has the potential to improve road safety, reduce human errors and accidents caused by factors like distracted driving or fatigue. AI algorithms continuously analyze data from sensors and cameras to predict and prevent potential collisions, making transportation systems safer for both passengers and pedestrians. The implementation of AI in autonomous vehicles is not only reshaping the future of transportation but also changing urban mobility by offering convenient, sustainable, and efficient travel options.

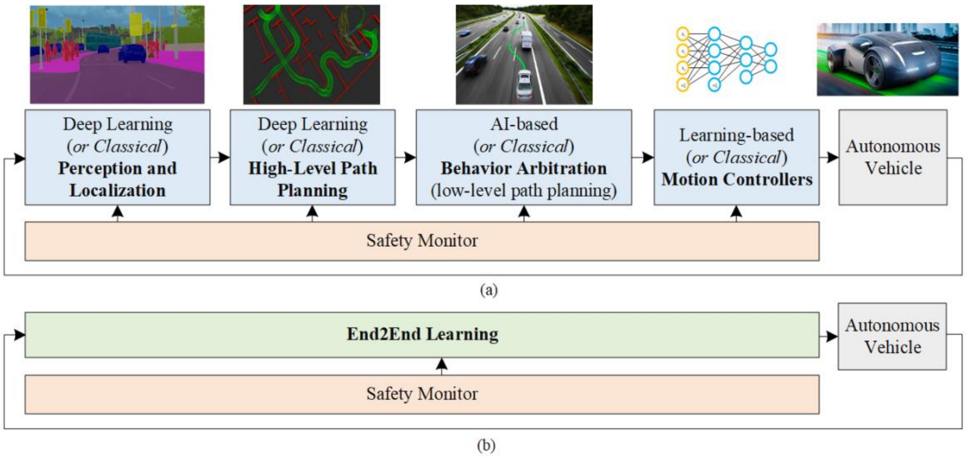

Figure 1. *(a) Deep learning block diagrams for AI-powered autonomous cars, (b) End2End Learning [17].*

2.2. Public Transport

Public transport systems worldwide are undergoing a transformation with the integration of Artificial Intelligence (AI) technologies. AI is transforming public transport by optimizing operations, improving service reliability, and enhancing passenger experience. The application of AI in public transport encompasses various innovative solutions that are reshaping the way people commute and interact with urban transportation networks. These solutions include:

1. Intelligent Scheduling and Routing AI algorithms are being used to optimize public transport schedules and routes based on real-time data analysis and passenger demand patterns. Indeed, with the evolution of ML techniques, public transport authorities can adjust service frequencies, predict peak travel times, and minimize waiting times for passengers. ML algorithms such as reinforcement learning allow us to adjust service frequencies based on demand patterns and predict peak travel times by analyzing historical data and real-time information [18].
2. Smart Fare Collection: AI-powered fare collection systems are enhancing the efficiency and security of public transport payment processes. Through technologies like computer vision and ML, public transport operators can automate fare validation, detect fare evasion, and personalize fare options for passengers, leading to improved revenue management and passenger satisfaction [19]. Smart cards, which is an AI-powered fare collection system can streamline payment processes by enabling passengers to use smart cards for contactless payments. On the other hand, mobile phones also facilitate fare payments through mobile phones, allowing passengers to pay using mobile applications or digital wallets.
3. Passenger Safety and Security: AI-based surveillance systems are being deployed in public transport facilities to enhance passenger safety and security [20]. These systems use facial recognition, anomaly detection, and predictive analytics to identify potential threats, monitor crowd behavior, and respond to emergencies promptly. This can help the authorities to create safer environments for passengers and staff. This includes facial recognition algorithms which are employed to identify individuals and potential threats in public transport facilities, while anomaly detection algorithms help to identify unusual behaviors or events that may pose security risks. Furthermore, predictive analytics algorithms analyze data to forecast potential security threats, monitor crowd behavior, and respond promptly to emergencies.

2.3. Disruptive Urban Mobility

Disruptive urban mobility solutions are reshaping traditional transportation systems through technologies and sustainable practices. These advancements are revolutionizing how people move within cities, promoting efficiency, accessibility, and environmental sustainability. Some of the key innovations in disruptive urban mobility nowadays include:

1. Electric Vertical Take-off and Landing (eVTOL): eVTOL vehicles are emerging as a futuristic mode of urban transportation, offering vertical take-off and landing capabilities for efficient short-distance travel within cities. Companies like XYZ Aviation have introduced

eVTOL prototypes that aim to alleviate traffic congestion and provide eco-friendly mobility options in urban areas (Figure 2) [21].

Figure 2. *eVTOL aircraft [21].*

2. Hyperloop Technology: Hyperloop systems are high-speed transportation solutions that use vacuum tubes to propel pods at near-supersonic speeds, remodeling intercity travel (Figure 3). Companies like Hyperloop Transportation Technologies (HTT) have made significant strides in developing Hyperloop networks that promise to reduce travel times and carbon emissions between major cities [22].

Figure 3. *Hyperloop super speed transportation system [22].*

3. Mobility-as-a-Service (MaaS) Platforms: MaaS platforms integrate various modes of transportation, including public transit, ridesharing, and bike-sharing services, into a single digital platform for seamless urban mobility experiences. Innovations in MaaS platforms by companies like UrbanGo have transformed how people plan and pay for their journeys, promoting multimodal transportation options and reducing reliance on private vehicles [23].
4. Autonomous Delivery Robots: Autonomous delivery robots are changing last-mile logistics by autonomously transporting goods within urban environments. Companies like RoboDeliver have deployed AI-powered robots that navigate sidewalks and pedestrian areas to deliver packages efficiently, reducing traffic congestion and carbon emissions associated with traditional delivery methods (Figure 4) [24].

Figure 4. *Autonomous Delivery Robots [24].*

2.4. Automated Incident Detection

Automated Incident Detection systems powered by AI have revolutionized the way traffic incidents are identified and managed, leading to enhanced safety, reduced response times, and improved traffic flow management. These systems leverage advanced AI algorithms and real-time data analysis to detect incidents promptly and accurately, enabling authorities to respond swiftly and effectively. Key aspects of Automated Incident Detection systems include [10].

1. Sensor Integration: Automated Incident Detection systems integrate various sensors such as cameras, radar, and Internet of Things (IoT) devices along roadways to monitor traffic conditions continuously. These sensors capture real-time data on vehicle speeds, densities, and behaviors, enabling AI algorithms to detect anomalies that indicate potential incidents. Sensors such as radar or LiDAR devices measure the speed of vehicles passing through their detection zones. Sensors also collect data on the density of vehicles in specific areas of the road network. The analysis of how closely vehicles is spaced and how these changes over time allows the system to identify congestion or unusual traffic patterns that may suggest an incident to occur or about to happen. In addition to speed and density, sensors can capture behavioral data such as lane changes, sudden stops, or erratic driving patterns. These behavioral are essential for detecting anomalies that deviate from normal driving behavior and could be indicative of accidents, breakdowns, or other incidents. Figure 5 depicts a schematic representation of a camera sensor simulation system used in the development and testing of vehicle perception systems. It illustrates the process of simulating a camera sensor within a virtual road environment and scenario simulation, where the camera's characteristics such as lens model, color filter, image sensor, circuit board, and noise model are considered [25].
2. Camera Sensor Simulation: This module simulates the input from a camera sensor, considering factors such as the lens model, color filter, image sensor, circuit board, and noise model. It generates synthetic images that

replicate what a real camera would capture in various driving scenarios.

3. Image Injection Adapter: The simulated camera images are adapted through this interface, which ensures compatibility with real-time camera control systems. This allows for the testing of camera-based perception algorithms under controlled conditions.
4. Multithread Electronic Control Unit (ECU): The ECU processes the adapted camera images, performing tasks similar to those in an actual vehicle's ECU, such as object detection and decision-making.
5. ECU Client and Bus Interface: These components facilitate communication between the ECU and the rest of the vehicle's systems, using standard protocols like the Controller Area Network (CAN) bus. Indeed, CAN is a vehicle bus standard designed to allow microcontrollers and devices to communicate with each other's applications without a host computer.
6. Road Environment & Scenario Simulation: This part of the framework provides a virtual environment where different driving scenarios can be simulated, offering a diverse range of conditions for testing the perception system.
7. Vehicle Dynamics Simulation: It models the vehicle's behavior based on dynamics data, which is crucial for understanding how the vehicle will react in different situations.
8. Rest-of-bus Simulation: This simulates the other communication systems within the vehicle, ensuring that the perception system can operate in conjunction with the vehicle's other electronic systems.
9. Machine Learning (ML) Algorithms: AI-powered ML algorithms play a crucial role in analyzing sensor data and identifying patterns associated with different types of incidents. Algorithms like Convolutional Neural Networks (CNN) are used to process visual data from cameras, while Recurrent Neural Networks (RNN) analyze sequential data to predict incident probabilities based on historical patterns. CNN is a class of DNN, most applied to analyzing visual imagery while RNN is a class of ANN where connections between nodes form a directed graph along a temporal sequence, allowing it to exhibit temporal dynamic behavior.
10. Anomaly Detection: AI algorithms in Automated Incident Detection systems employ anomaly detection techniques to identify irregularities in traffic flow that may signify incidents such as accidents, breakdowns, or road hazards. By comparing current data with established patterns, these systems can trigger alerts for authorities to investigate and respond promptly.
11. Integration with Traffic Management Systems: Automated Incident Detection systems are often integrated with Traffic Management Systems to automate responses to detected incidents. This integration enables dynamic rerouting of traffic, adjustment of signal timings, and coordination of emergency services based on real-time incident information provided by AI algorithms.

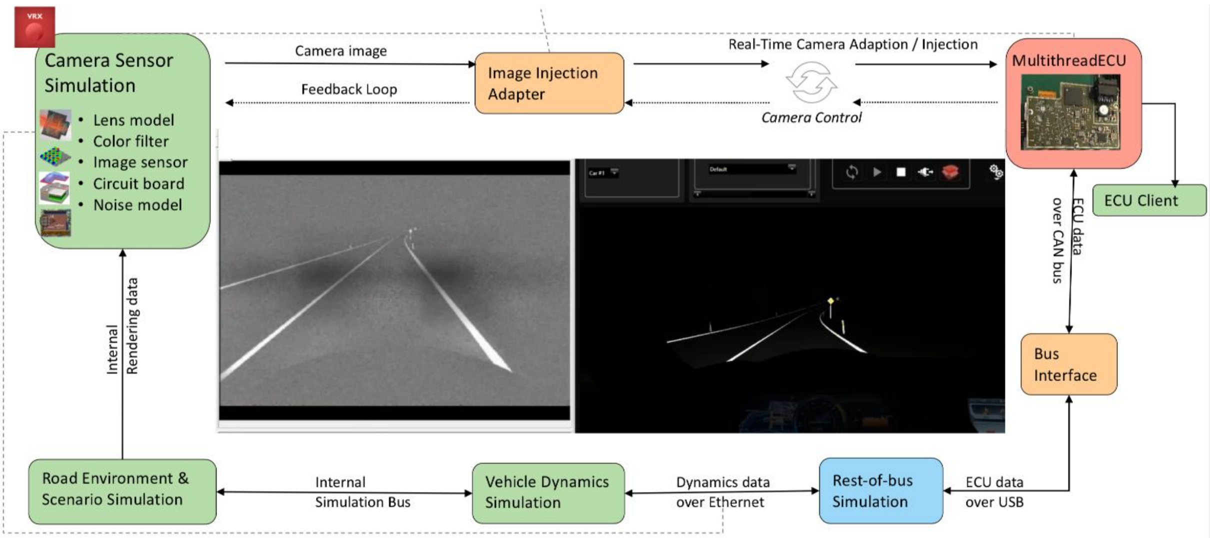

Figure 5. Pipeline for simulating a camera sensor virtually and utilizing the data feed to inform Perception SW and subsequent software layers in the stack [25].

3. Future Traffic Status Prediction

The ability to accurately predict future traffic conditions is crucial for proactive traffic management strategies, and AI plays a key role in achieving this goal. Among the various AI algorithms, Artificial Neural Networks (ANN) are at the forefront, providing the computational power needed to analyze large datasets and identify complex patterns within traffic systems [26]. The design of these ANN models mimics the neural processing of the human brain, allowing them to learn from historical and real-time traffic data, which includes variables like vehicle counts, speeds, weather conditions, and time of day.

These algorithms can generalize and predict future traffic states by recognizing the intricate relationships between various influencing factors by training ANN on diverse traffic scenarios. This predictive capability allows traffic management systems to anticipate congestion, adjust traffic signal timing, and suggest alternative routes to drivers before bottlenecks occur. Additionally, the integration of ANN with other emerging technologies, such as connected vehicle data and edge computing, enhances the granularity and responsiveness of traffic predictions.

The future of traffic status prediction also involves combining ANN with other ML techniques, such as DL and reinforcement learning, to further refine the accuracy of predictions. AI-driven traffic prediction advancements not only improve transportation network efficiency, but they also facilitate the creation of smart cities. These cities optimize traffic flows in real-time, resulting in decreased emissions, energy conservation, and enhanced urban mobility [27].

ANNs are a class of ML models inspired by the biological neural networks of animal brains. ANNs consist of interconnected processing nodes, or "neurons," which work together to solve complex problems like pattern recognition, classification, and prediction. To effectively train and deploy ANN, especially for tasks like future traffic status prediction, a variety of techniques and software tools are utilized.

Two ways to train ANN are backpropagation and gradient descent. Backpropagation sends errors backwards through the network to change connection weights, and gradient descent lowers the cost function of the network's predictions. Recurrent neural networks (RNN) and their more complex variants, such as Long Short-Term Memory (LSTM) networks, capable of learning long-term dependencies, often process sequential data over time for traffic prediction.

The Google Brain team's TensorFlow and Facebook's AI Research Lab's PyTorch are popular software frameworks for developing ANN. These frameworks provide extensive libraries and tools that facilitate the design, training, and validation of neural network models. They also support GPU acceleration, which is crucial for handling the high computational and memory demands of ANN, particularly when dealing with large datasets and complex network architectures.

ANN's computational intensity stems from the need to process large volumes of data and perform numerous calculations during the training phase. This often requires high-performance computing resources with powerful CPUs and GPUs, as well as substantial memory to store the weights, biases, and intermediate calculations for each neuron in the network. However, as traffic prediction models become more sophisticated, the computational and memory requirements for ANNs will continue to grow, necessitating the use of advanced hardware and optimized software algorithms to ensure efficient processing [28].

4. Traffic Management and Control

In the realm of traffic management and control, AI methods are instrumental in optimizing traffic flow, improving route planning, and improving incident management. With the evolution of time, these methods have grown, and their applications have become more widespread and effective. Below are the subsections detailing the latest advancements and applications of each AI method:

4.1. Genetic Algorithms

Genetic Algorithms (GA) have made significant progress in handling complex traffic optimization problems. By simulating the process of natural selection, GA now efficiently evolves solutions for dynamic route planning. They adapt to real-time traffic data to suggest optimal paths for vehicles. Recent developments have even enabled GA to work in conjunction with real-time traffic prediction models, further enhancing their decision-making capabilities [29].

GA can be utilized to optimize traffic signal timing. This is achieved by creating a population of different signal timing plans and iteratively selecting, crossing over, and mutating these plans to improve traffic flow. For instance, a GA could begin with a set of random traffic signal timings at an intersection and measure their effectiveness based on average vehicle wait time. The most effective timings would then be “selected” to create a new generation of signal plans. These plans would subsequently be "crossed over" and "mutated" to produce variations. Over successive generations, the GA would converge on a set of signal timings that minimize wait times [30].

Another application of GA in traffic management is in dynamic route planning for vehicles. A GA could be used to find the most efficient routes for a fleet of delivery trucks by considering factors such as current traffic conditions, road closures, and delivery windows. The algorithm would generate a population of possible routes for each vehicle and evolve these routes over time to find the most time- and fuel-efficient paths.

4.2. Simulated Annealing

Simulated Annealing (SA) is an optimization technique that is particularly well-suited for finding global optima in complex and stochastic systems, such as traffic networks. It is inspired by the physical process of annealing in metallurgy, where controlled cooling is used to reduce defects in materials. In the context of traffic management, SA can be applied to optimize traffic light timing and network flow distribution to improve overall traffic conditions [31].

For example, consider a network of interconnected traffic signals in a busy urban area. The goal is to adjust the timing of each traffic light to minimize congestion and ensure smooth traffic flow (Figure 6) [33]. Using SA, traffic engineers can create a simulation model of the network that includes variables such as traffic volumes, signal timings, and intersection layouts. The SA would start with a random or heuristic-based solution for the signal timings and then iteratively make small changes to the timings (akin to the "mutations" in the annealing process). After each change, the algorithm evaluates the new solution based on a fitness function, such as the average delay per vehicle or the total number of vehicles that pass through the intersections in each time frame.

The "temperature" parameter in SA controls the likelihood of accepting worse solutions as the algorithm progresses. Initially, the temperature is set high, allowing the algorithm to explore a wide range of solutions, including those that may not be immediately promising. This helps to avoid getting stuck in local optima. As the temperature gradually decreases, the algorithm becomes more selective, homing in on the best solutions and fine-tuning the signal timings to achieve the global optimum [32].

At the end of the process, the SA algorithm would have explored a vast solution space and converged on a set of traffic signal timings that optimally balance the traffic flow across the network, reducing congestion and improving throughput. This approach can be particularly effective in dynamic traffic systems where traffic patterns change throughout the day, as the algorithm can be run periodically to update the timings based on the latest traffic data [33].

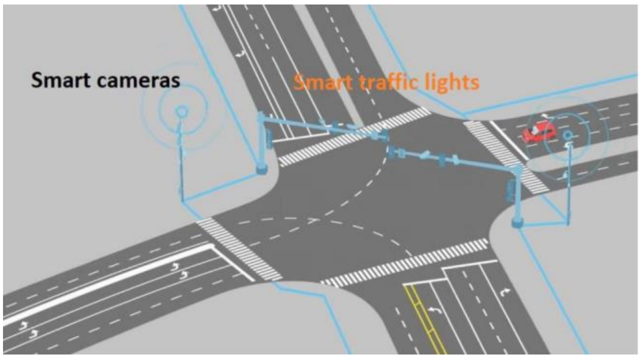

Figure 6. *AI application in traffic transportation [33].*

4.3. Ant Colony Optimizer

The Ant Colony Optimizer (ACO) is an optimization algorithm inspired by the foraging behavior of ants, particularly their ability to find the shortest paths between their colony and food sources. In the context of traffic management, ACO can be applied to optimize traffic patterns and route planning by simulating the pheromone-laying and following behavior of ants [34].

For example, in an urban traffic network, each intersection and road segment can be considered as nodes and paths like an ant colony's environment. Vehicles can be thought of as ants searching for the most efficient routes from their origins to their destinations. As vehicles traverse the network, they leave behind a virtual "pheromone trail" that represents the quality of the route, which in this case could be determined by travel time, congestion levels, or other traffic conditions.

Real-time traffic sensor data, such as vehicle counts, speeds, and queue lengths, are integrated into the ACO algorithm to update the pheromone trails dynamically. This allows the algorithm to adapt to changing traffic conditions. For instance, if a particular road segment becomes congested, the strength of the pheromone trail on that segment would decrease, leading future "ants" (vehicles) to explore alternative routes. Conversely, if a road is clear, the pheromone strength would increase, attracting more vehicles to that route.

Over time, the ACO algorithm converges on an optimal set of routes that balance the traffic load across the network, reducing overall travel times and improving navigation efficiency. This approach can be particularly beneficial during peak traffic hours or in response to traffic incidents, where the ability to quickly adapt route planning can significantly alleviate congestion [35].

4.4. Bee Colony Optimization

Bee Colony Optimization (BCO) is an AI technique inspired by the foraging behavior of honeybees, which is used to solve complex optimization problems. In the context of traffic management, BCO has been augmented with ML to enhance its predictive capabilities and responsiveness to fluctuating traffic conditions [36].

For example, BCO can be applied to optimize traffic signal timings across a network of intersections. Each “bee” in the algorithm represents a potential solution, exploring different combinations of signal timings. The bees communicate with one another through a virtual “dance”, like the waggle dance of real bees, to share information about the quality of their solutions, measured by criteria such as average vehicle delay or intersection throughput.

ML techniques, such as reinforcement learning, can be integrated with BCO to allow the system to learn from past performance and adapt to new data. This enables the BCO algorithm to predict traffic patterns and adjust signal timings proactively. For example, if the algorithm learns that traffic volume increases on certain roads at specific times of the day, it can adjust the signal timings in advance to accommodate the expected increase in vehicles, thereby preventing congestion.

BCO algorithms can also be used for dynamic route planning, where they help manage the distribution of traffic across an entire urban network. BCO can suggest alternative routes to drivers, distribute traffic loads more evenly, and reduce the likelihood of traffic jams by analyzing real-time traffic data. The integration of BCO with ML results in a smart traffic management system that not only reacts to current conditions but also anticipates future traffic states, leading to a more resilient and efficient transportation network [37].

4.5. Fuzzy Logic Model

Fuzzy Logic Models (FLM), a form of many-valued logic or probabilistic logic, are very good at handling the uncertainties and errors that come up in traffic systems. FLM is a type of many-valued logic or probabilistic logic that deals with reasoning that is approximate rather than fixed and exact. Unlike traditional binary logic that operates on true or false values, FLM allows for reasoning with degrees of truth, which can represent the complex and often ambiguous nature of real-world traffic scenarios.

For example, consider the problem of adjusting traffic signal timings at an intersection with fluctuating traffic volumes. A FLM can take input variables such as vehicle density, queue length, and time of day, which are not precise but rather fuzzy in nature. The FLM processes these inputs using a set of fuzzy rules, which are formulated based on expert knowledge and can handle linguistic variables like “high traffic” or “low traffic”.

The output of the FLM is a set of fuzzy conclusions, which are then defuzzied to produce a clear output that can be used to adjust the traffic signal timings. For instance, if the FLM determines that the traffic volume is "moderately high" and increasing, it might extend the green light duration for that direction to alleviate congestion [38, 39].

5. Drones in Traffic Management and Control

Drones, or Unmanned Aerial Vehicles (UAV), an aircraft without a human pilot aboard, controlled either autonomously by onboard computers or by the remote control of a pilot on the ground or in another vehicle, have become increasingly sophisticated with the integration of AI, Machine Learning (ML), and Deep Learning (DL) technologies, significantly enhancing their capabilities in traffic management and control [33]. Sensors and cameras equip these advanced drones to perform complex tasks autonomously, including navigation, mapping, and real-time obstacle detection. DL algorithms have been used in teaching drones to autonomously navigate by processing massive quantities of data from their onboard sensors, allowing them to detect and avoid obstacles and make intelligent decisions during flight. The applications of AI, ML, and DL in advanced drones extend beyond traffic management to a variety of fields, demonstrating their versatility and potential for innovation. In search and rescue missions, drones can quickly cover vast areas, using AI and ML algorithms to detect and recognize objects or individuals in need of assistance. This rapid scanning capability is crucial for locating people, vehicles, or buildings in large-scale emergency situations [40, 41].

DL algorithms enable drones to navigate autonomously, without human intervention. This is particularly valuable in complex manufacturing environments, where drones can safely and efficiently navigate around obstacles and building components. In precision agriculture, drones equipped with AI and ML are used to collect and analyze data on crop health, moisture levels, and soil conditions (Figure 7). This allows farmers to make more informed decisions about managing their crops and optimizing agricultural yield. Drones with AI and ML capabilities are also employed in surveillance and security operations to monitor vulnerable areas, identify instances of unauthorized access, and detect potential threats [42]. This deployment ensures heightened alertness and enables quick response to any detected dangers. Additionally, drones play an important role in improving disaster response operations, as they can rapidly assess the extent of damage, locate survivors, and facilitate efficient distribution of resources during crises.

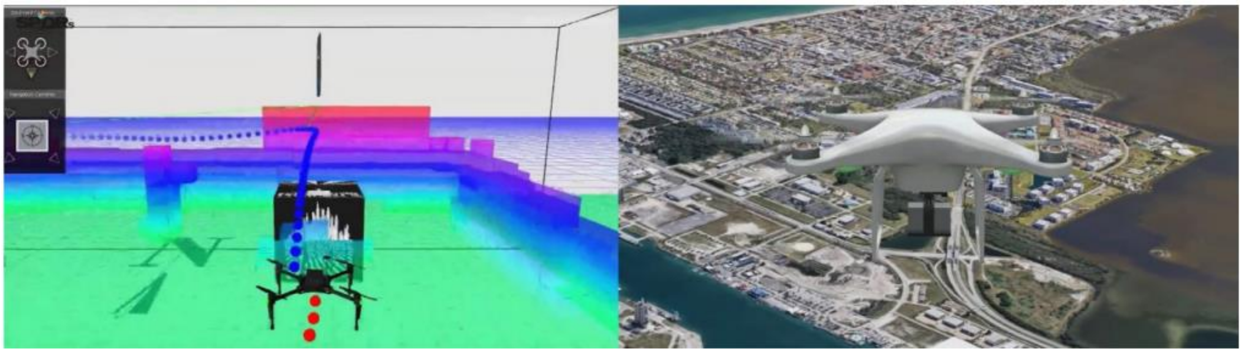

Figure 7. *Application of ML in autonomous navigation of drones [33].*

The integration of drones into traffic management systems has marked a significant advancement in urban mobility. Drones can autonomously patrol routes, analyze traffic patterns, and communicate with traffic management centers to alleviate congestion and optimize traffic flow. They work in tandem with other AI-driven tools, such as GA and SA, to provide comprehensive data that improves traffic predictions and route planning.

6. Responsible and Sustainable Approaches

The use of AI technology has the potential to modify the transportation industry by addressing key challenges such as pollution reduction, improved safety, and alleviating traffic congestion. However, it is important to adopt a responsible and sustainable strategy for integrating AI into transportation systems. This approach should consider factors such as public acceptance, environmental impact, ethical considerations, and community engagement.

6.1. Ethical Implications of AI in Transportation

The integration of automation and AI into transportation systems, such as self-driving cars, presents a significant problem in terms of enabling these AI systems to make ethical decisions [43]. Vehicles need advanced ethical decision-making capabilities integrated into their AI systems and algorithms before achieving full autonomy. Giving AI complete control over moral judgment, however, raises a serious concern.

Automating ethical decision-making in complex moral dilemmas with unclear correct actions presents significant challenges. It will be important to protect significant user input and uphold the concepts of informed consent and human autonomy in these complex issues of ethics. AI cannot be permitted to make all morally difficult decisions on its own without human supervision or the capacity to set ethical boundaries. Suggesting ethical design standards, evaluating the impact of various techniques on autonomy, and developing tools to help engineers and designers balance human autonomy preservation and automated ethical decision-making are possible strategies [44].

6.2. Community Engagement

While implementing ethical design standards and tools may help mitigate some risks, it is unrealistic to expect that AI will always make morally sound decisions without human oversight. Indeed, the integration of AI with transportation systems requires human supervision to implement ethical considerations and preserve human values by monitoring decision-making processes and outcomes. Without active community engagement and input, there is a risk that AI integration in transportation may not align with the values and needs of the people it serves, leading to potential ethical conflicts and societal disconnect. It is important for stakeholders to actively participate in the decision-making process by engaging in regular consultations, conducting impact assessments, and prioritizing ethical considerations such as data privacy, transparency, sharing, and fairness in AI integration with societal values and human needs.

Furthermore, a collaborative approach between communities, governments, and manufacturing companies integrating diverse perspectives is vital for creating a transportation system that meets moral standards and preserves human values through AI integration. For instance, in the development of self-driving cars, community members played an important role by suggesting safety measures that significantly reduced the risk of accidents and enhanced the ethical consideration of AI integration. The absence of community engagement in the development of autonomous vehicles can erode trust among the public, resulting in increased skepticism towards AI technology in transportation and raising resistance to technological advancements. Additionally, incorporating diverse perspectives can help address potential biases in AI algorithms and ensure fair treatment for all individuals. This collaborative approach not only cultivates a sense of ownership and responsibility among community members but also results in increased accountability towards the ethical enhancement of the transportation system, leading to a more transparent and trusted infrastructure [45, 46].

7. Conclusion

The integration of AI in the transportation sector has reformed traffic management and control. Advancements in AI methodologies, such as Genetic Algorithms (GA), Simulated Annealing (SA), Ant Colony Optimizer (ACO), Bee Colony Optimization (BCO), and Fuzzy Logic Models (FLM), have significantly improved dynamic traffic scenarios, route planning, and incident management. These AI techniques have led to the development of adaptive, responsive, and ITS that can effectively meet the growing demands of urban mobility.

The use of drones, or Unmanned Aerial Vehicles (UAV), equipped with AI, ML, and DL technologies, has expanded the capabilities of traffic management systems even further. Drones provide a unique vantage point for real-time traffic monitoring, incident response, and data collection. When combined with AI-driven analytics, they can enable proactive traffic control measures and improve traffic flow. Drones can also be applied in search and rescue, precision agriculture, surveillance, security, disaster response, and delivery services.

Looking ahead, there are several recommendations and areas for further research to continue advancing AI applications in transportation:

1. Enhanced Integration of AI and IoT: Further research into integrating AI with IoT can create more interconnected and automated traffic systems. Real-time data from various sensors and devices can be analyzed and acted upon instantly.
2. Improved Machine Learning (ML) models: Developing sophisticated ML models capable of handling the vast and

complex datasets associated with transportation systems is crucial. These models should focus on improving predictive accuracy and real-time decision-making.
3. Autonomous Vehicle Collaboration: Exploring the collaborative potential of autonomous vehicles, where they communicate and make collective decisions, can lead to smoother traffic flows and reduced congestion.
4. Drone Technology Advancements: Continued innovation in drone technology, including better battery life, more robust AI algorithms for autonomous operation, and improved integration with ground-based traffic management systems, will enhance their usefulness in transportation.
5. Ethical and Privacy Considerations: As AI becomes more prevalent in transportation, addressing ethical and privacy concerns regarding data collection and usage is essential. Research into frameworks and policies that protect individual rights while enabling the benefits of AI is needed.
6. Economic and Environmental Impact Studies: Studies on the economic and environmental impacts of AI in transportation can provide insights into long-term benefits and potential trade-offs. This can guide sustainable and cost-effective investments in technology.

The implementation of these recommendations by focusing on these research areas can continue leveraging the latest AI advancements to reduce congestion, improve travel reliability, and optimize the economic efficiency of important transportation assets.

Abbreviations

ACO	Ant Colony Optimizer
AI	Artificial Intelligence
ANN	Artificial Neural Networks
BCO	Bee Colony Optimization
CAN	Controller Area Network
CNN	Convolutional Neural Networks
DL	Deep Learning
DNN	Deep Neural Networks
ECU	Electronic Control Unit
eVTOL	Electric Vertical Take-off and Landing Aircrafts
FLM	Fuzzy Logic Model
GA	Genetic Algorithms
GPS	Global Positioning System
HTT	Hyperloop Transportation Technologies
IoT	Internet of Things
ITS	Intelligent Transport Systems
KBS	Knowledge-Based Systems
LiDAR	Light Detection and Ranging
LSTM	Long Short-Term Memory
MaaS	Mobility-as-a-Service
ML	Machine Learning
RNN	Recurrent Neural Networks
SA	Simulated Annealing
UAV	Unmanned Aerial Vehicles

Author Contributions

Derrick Mirindi is the sole author. The author read and approved the final manuscript.

Funding

This work is not supported by any external funding.

Data Availability Statement

Not applicable.

Conflicts of Interest

The author declares no conflicts of interest.

References

[1] Shukla Shubhendu, S., & Vijay, J. (2013). Applicability of artificial intelligence in different fields of life. International Journal of Scientific Engineering and Research, 1(1), 28-35.

[2] Sadek, A. W. (2007). Artificial intelligence applications in transportation. Transportation research circular, 1-7.

[3] Abraham, A. (2005). Artificial neural networks. Handbook of measuring system design. https://doi.org/10.1002/0471497398.mm421

[4] Abduljabbar, R., Dia, H., Liyanage, S., & Bagloee, S. A. (2019). Applications of artificial intelligence in transport: An overview. Sustainability, 11(1), 189. https://doi.org/10.3390/su11010189

[5] Backpropagation, Available from: https://brilliant.org/wiki/backpropagation/ [Accessed 6 March 2024].

[6] Wolpert, D. H. (1993). Bayesian backpropagation over io functions rather than weights. Advances in neural information processing systems, 6.

[7] Vasudevan, M., Townsend, H., Dang, T. N., O'Hara, A., Burnier, C., & Ozbay, K. (2020). Summary of potential application of ai in transportation (No. FHWA-JPO-20-787).

[8] Vasudevan, M., Townsend, H., Samach, M., Walsh, P. T., Wang, P., Seshadri, A., & McManus, I. (2022). Artificial Intelligence (AI) for Intelligence Transportation Systems (ITS) Challenges and Potential Solutions, Insights, and Lessons Learned (No. FHWA-JPO-22-968). United States. Department of Transportation. Intelligent Transportation Systems Joint Program Office.

[9] Vemuri, N., Tatikonda, V. M., & Thaneeru, N. (2024). Enhancing Public Transit System through AI and IoT. Valley International Journal Digital Library, 1057-1071. https://doi.org/10.18535/ijsrm/v12i02.ec07

[10] Olugbade, S., Ojo, S., Imoize, A. L., Isabona, J., & Alaba, M. O. (2022). A review of artificial intelligence and machine learning for incident detectors in road transport systems. Mathematical and Computational Applications, 27(5), 77. https://doi.org/10.3390/mca27050077

[11] ElSahly, O., & Abdelfatah, A. (2022). A systematic review of traffic incident detection algorithms. Sustainability, 14(22), 14859. https://doi.org/10.3390/su142214859

[12] Jevinger, Å., Zhao, C., Persson, J. A., & Davidsson, P. (2024). Artificial intelligence for improving public transport: a mapping study. Public Transport, 16(1), 99-158. https://doi.org/10.1007/s12469-023-00334-7

[13] Saiwa. Available from: https://saiwa.ai/blog/ai-in-public-transportation/ [Accessed 15 March 2024].

[14] Veritone. Available from: https://www.veritone.com/blog/ai-public-safety-public-transportation/ [Accessed 10 March 2024].

[15] Forbes. Available from: https://www.forbes.com/sites/forbestechcouncil/2023/05/12/how-ai-is-helping-to-improve-transportation-safety-on-a-global-scale/?sh=58d160985436 [Accessed 21 April 2024].

[16] Tselentis, D. I., Papadimitriou, E., & van Gelder, P. (2023). The usefulness of artificial intelligence for safety assessment of different transport modes. Accident Analysis & Prevention, 186, 107034. https://doi.org/10.1016/j.aap.2023.107034

[17] Grigorescu, S., Trasnea, B., Cocias, T., & Macesanu, G. (2020). A survey of deep learning techniques for autonomous driving. Journal of field robotics, 37(3), 362-386. https://doi.org/10.1002/rob.21918

[18] Feng, S., Duan, P., Ke, J., & Yang, H. (2022). Coordinating ride-sourcing and public transport services with a reinforcement learning approach. Transportation Research Part C: Emerging Technologies, 138, 103611. https://doi.org/10.1016/j.trc.2022.103611

[19] Dhamodhiran, R. P., Saravanan, K., Rangasamy, P. J., Kannappan, V. V., & Dhandapani, S. (2024, March). Automatic fare collection system for public transport with high level security. In AIP Conference Proceedings (Vol. 3035, No. 1). AIP Publishing. https://doi.org/10.1063/5.0194815

[20] Iyer, L. S. (2021). AI enabled applications towards intelligent transportation. Transportation Engineering, 5, 100083. https://doi.org/10.1016/j.treng.2021.100083

[21] Aviator. Available from: https://www.theaviatorme.com/news/report/advanced-air-mobility-middle-east [Accessed 19 March 2024].

[22] TimeofIndia. Available from: https://timesofindia.indiatimes.com/auto/news/allow-foreign-firms-to-demonstrate-hyperloop-tech-for-ultra-high-speed-travel-niti-aayog-member/articleshow/87709189.cms [Accessed 19 March 2024].

[23] Jutila, M., Matinmikko-Blue, M., Saarakkala, S., & Salonurmi, T. (2022). Infotech Oulu Focus Institute: periodic report 2018–2021.

[24] Baltimoresun. Available from: https://www.baltimoresun.com/2023/12/28/morgan-state-robot-food-delivery-service/ [Accessed 19 March 2024].

[25] Fadaie, J. (2019). The state of modeling, simulation, and data utilization within industry: An autonomous vehicles perspective. arXiv preprint arXiv: 1910.06075. https://doi.org/10.48550/arXiv.1910.06075

[26] Sadeghi-Niaraki, A., Mirshafiei, P., Shakeri, M., & Choi, S. M. (2020). Short-term traffic flow prediction using the modified elman recurrent neural network optimized through a genetic algorithm. IEEE Access, 8, 217526-217540. https://doi.org/10.1109/ACCESS.2020.3039410

[27] Fouladgar, M., Parchami, M., Elmasri, R., & Ghaderi, A. (2017, May). Scalable deep traffic flow neural networks for urban traffic congestion prediction. 2017 international joint conference on neural networks (IJCNN) (pp. 2251-2258). https://doi.org/10.1109/IJCNN.2017.7966128

[28] Alkheder, S., Taamneh, M., & Taamneh, S. (2017). Severity prediction of traffic accident using an artificial neural network. Journal of Forecasting, 36(1), 100-108. https://doi.org/10.1002/for.2425

[29] Baker, B. M., & Ayechew, M. (2003). A genetic algorithm for the vehicle routing problem. Computers & Operations Research, 30(5), 787-800. https://doi.org/10.1016/S0305-0548(02)00051-5

[30] Du, X., Htet, K. K. K., & Tan, K. K. (2016). Development of a genetic-algorithm-based nonlinear model predictive control scheme on velocity and steering of autonomous vehicles. IEEE Transactions on Industrial Electronics, 63(11), 6970-6977. https://doi.org/10.1109/TIE.2016.2585079

[31] Osman, I. H. (1993). Metastrategy simulated annealing and tabu search algorithms for the vehicle routing problem. Annals of operations research, 41, 421-451. https://doi.org/10.1007/BF02023004

[32] Chiang, W. C., & Russell, R. A. (1996). Simulated annealing metaheuristics for the vehicle routing problem with time windows. Annals of Operations Research, 63, 3-27. https://doi.org/10.1007/BF02601637

[33] Soori, M., Arezoo, B., & Dastres, R. (2023). Artificial intelligence, machine learning and deep learning in advanced robotics, a review. Cognitive Robotics. https://doi.org/10.1016/j.cogr.2023.04.001

[34] Blum, C. (2005). Ant colony optimization: Introduction and recent trends. Physics of Life reviews, 2(4), 353-373. https://doi.org/10.1016/j.plrev.2005.10.001

[35] Xia, D., Shen, B., Zheng, Y., Zhang, W., Bai, D., Hu, Y., & Li, H. (2024). A bidirectional-a-star-based ant colony optimization algorithm for big-data-driven taxi route recommendation. Multimedia Tools and Applications, 83(6), 16313-16335. https://doi.org/10.1007/s11042-023-15498-4

[36] Jacob, I. J., & Darney, P. E. (2021). Artificial bee colony optimization algorithm for enhancing routing in wireless networks. Journal of Artificial Intelligence, 3(01), 62-71.

[37] Jovanović, A., Nikolić, M., & Teodorović, D. (2017). Area-wide urban traffic control: A Bee Colony Optimization approach. Transportation Research Part C: Emerging Technologies, 77, 329-350. https://doi.org/10.1016/j.trc.2017.02.006

[38] Prontri, S., Wuttidittachotti, P., & Thajchayapong, S. (2015, June). Traffic signal control using fuzzy logic. In 2015 12th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON) (pp. 1-6). https://doi.org/10.1109/ECTICon.2015.7207110

[39] Murat, Y. S., & Gedizlioglu, E. (2005). A fuzzy logic multi-phased signal control model for isolated junctions. Transportation Research Part C: Emerging Technologies, 13(1), 19-36. https://doi.org/10.1016/j.trc.2004.12.004

[40] Thiels, C. A., Aho, J. M., Zietlow, S. P., & Jenkins, D. H. (2015). Use of unmanned aerial vehicles for medical product transport. Air medical journal, 34(2), 104-108. https://doi.org/10.1016/j.amj.2014.10.011

[41] Surman, K., & Lockey, D. (2024). Unmanned aerial vehicles and pre-hospital emergency medicine. Scandinavian journal of trauma, resuscitation and emergency medicine, 32(1), 9. https://doi.org/10.1186/s13049-024-01180-7

[42] Mirindi, D. Mirindi, F. & Oluwakemi, O. (2024). Navigating Construction Project Outcomes: Synergy through the Evolution of Digital Innovation and Strategic Management. International Journal of Latest Research in Engineering and Technology, 10(3), 17-25. https://doi.org/10.56581/IJLRET.10.3.17-25

[43] Kumar, A. (2024). Exploring Ethical Considerations in AI-driven Autonomous Vehicles: Balancing Safety and Privacy. Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023, 2(1), 125-138.

[44] Bijalwan, J. G., Singh, J., Ravi, V., Bijalwan, A., Alahmadi, T. J., Singh, P., & Diwakar, M. (2024). Navigating the Future of Secure and Efficient Intelligent Transportation Systems using AI and Blockchain. The Open Transportation Journal, 18(1). https://doi.org/10.2174/0126671212291400240315084722

[45] Cooper, A. (2023). Having a Say: Analyzing Community Engagement Efforts for Sacramento Transportation Plans Using Arnstein's Ladder of Citizen Participation and the Goals of Mobility Justice. University of California, Davis.

[46] Englund, C., Aksoy, E. E., Alonso-Fernandez, F., Cooney, M. D., Pashami, S., & Åstrand, B. (2021). AI perspectives in Smart Cities and Communities to enable road vehicle automation and smart traffic control. Smart Cities, 4(2), 783-802. https://doi.org/10.3390/smartcities4020040

Biography

Derrick Mirindi, a civil engineer, both structural and hydroinformatician specialist, and member of the American Institute of Architecture Students (AIAS), American Society of Civil Engineers (ASCE), Construction Management Association of America (CMAA), and Deep Foundations Institute (DFI), is a doctoral candidate in Architecture, Urbanism, and Built Environments with a strong foundation in civil engineering and hydroinformatics. His research interests lie in the intersections of infrastructure, artificial intelligence (AI), machine learning (ML), and remote sensing, with a focus on analyzing urban nexus analysis through remote sensing and nexus assessment and modeling, as well as combining structural materials for construction in Building Information Technology (BIM). Derrick is committed to advancing knowledge in sustainable infrastructure solutions using waste materials and is seeking opportunities to collaborate, teach, and further his research. He has a diverse educational background, including a Master of Science in Water Science and Engineering with a specialization in hydroinformatics from the Netherlands, a Master of Science in Civil Engineering with a focus on structures from Kenya, and a Bachelor of Science in Civil Engineering from Burundi. Derrick's research experience includes roles as a research assistant at Morgan State University, where he conducts literature reviews, designs research studies, and collaborates with other researchers. He has published various articles focusing on waste materials for construction, artificial intelligence, transportation system and building information technology.

Research Field

Derrick Mirindi: Building Information Technology, Artificial Intelligence, Machine Learning, Materials for Construction, Transportation Systems Management and Architecture.