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The Role of Artificial Intelligence in Safety Assessment Across Various Transport Modes

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Abstract: Recent studies in transportation safety put emphasis on the usage of extensive data through intelligent systems to scale down the accidents among users. Numerous applications of Machine Learning (ML) and Artificial Intelligence (AI) have been created to tackle safety challenges and enhance the efficiency of transportation systems. Despite some limitations in knowledge exchange across different transport modes, this paper explores the application of machine learning (ML) and artificial intelligence (AI) techniques in road, rail, maritime, and aviation transport to enhance safety. The study aims to identify best practices and experiences that can be adapted across these sectors. The methodologies examined include statistical and econometric techniques, algorithmic strategies, classification and clustering methods, artificial neural networks (ANN), as well as optimization and dimensionality reduction approaches. Findings reveal a growing interest among transportation researchers and practitioners in leveraging AI for crash prediction, incident and failure detection, pattern recognition, driver/operator assistance, route optimization, and problem-solving. Among the most used and effective techniques across all transport modes are ANN, Support Vector Machines (SVM), Hidden Markov Models, and Bayesian models. The selection of analytical methods largely depends on the specific safety assessment objectives. Notably, the road transport sector exhibits the broadest range of AI and ML applications and a significantly higher and continuously growing volume of research compared to other transport modes.

Key Words: Artificial Intelligence, Transportation, Safety.

1. INTRODUCTION

Artificial Intelligence (AI) is a branch of computer science emphases on enabling computers to perform rationally and operate effectively across a broad range of domains (Nilsson, 1982). It entails the design and advancement of computer systems has the potential to perform tasks that typically require human intelligence, such as reasoning, visual identification, speech processing, automated learning, scheduling, decision-making, and language translation. AI utilizes computational power to simulating human cognition, including problem-solving and decision-making. A subset of AI, Machine Learning (ML), develops algorithms that imitate human learning patterns by analysing data and progressively boost the accuracy of a model.

In recent decades, technological breakthroughs have progressed considerably, particularly in areas such as telematics, the Internet of Things (IoT), the Internet of Vehicles (IoV), and Big Data (BD) analytics, including their applications in transportation. Alongside the expanding implementation of information technologies by drivers—such as smartphones—progress in sensor technologies, including autonomous vehicles (AV), vessel telematics, and cameras, has created new prospects, new horizons for monitoring driver and operator behaviour, facilitating vehicle communication, intensifying surveillance, and detecting incidents across various transport modes (aviation, maritime, rail, and road).

The extensive acceptance of these innovations is driven by a wealth of positives, and countless pros, high market penetration, and the interconnected nature of IoT and IoV. This marks the beginning of a modern times distinguished by the storage, collection, and management of vast amounts of data, commonly referred to as the BD era. A key example is the growing number of connected vehicles, which continues to increase annually. Predictions indicated that by 2020, one in five vehicles on the road would be internet-connected, with global vehicular data traffic expected to reach 300,000 exabytes (Xu et al., 2017). Initial findings from related studies (Theofilatos et al., 2017; Tselentis et al., 2017) have demonstrated the effectiveness and value of BD collection frameworks for assessing transportation safety.

A formidable problem in this new era is efficaciously supervising and utilizing vast amounts of data. To extricate meaningful insights, data must be methodically examined. Without AI, elucidating this information would be staggering. AI plays a crucial role in data analytics, making it an indispensable element of Big Data (BD) (Kibria et al., 2018). Through AI and deep learning, systems can process data inputs, derive patterns, and formulate new analytical rules for future use. In this way, BD fuels the "AI machine," transfiguring raw data into Intellectual process. One of AI's most significant advantages across industries is its ability to learn, detect patterns, and adapt to shifts in data trends. By recognizing anomalies, making predictions, and refining its understanding based on new information, AI generates valuable insights. Although AI as a concept has existence for decades, its accelerated development in past few years is due to improvements in computer performance, and processing capability, cloud storage, and processing throughput. These advancements have made it possible to leverage AI for BD applications. By amalgamating AI techniques such as natural language processing, pattern recognition, and machine learning with IoT- and IoV- networked devices, and sensing elements. We can now unlock the greatest extent, and highest capability of BD across various fields (Xu et al., 2021).

Transportation systems are intricate, requiring multiple components and different stakeholders, each with perceptible and sometimes contrasting objectives. When hold forth to safety concerns across different conveyances, and transit systems —such as road, aviation, , rail, and maritime —the focus is on intelligent systems designed for lessening the impact of potential negative outcomes, and hazard control, statistical analysis of occurrences, accident causation modelling, severity reduction, root cause investigations, accident evaluations, human factors analysis, identification of risky driver or operator behaviours, automated incident detection and monitoring, and obstacle detection. The goal is to reduce the number of accidents and amplify safety for transportation users (Machin et al., 2018).

To attain this, it is decisive to process all available data and identify critical information. In the recent past, numerous Machine Learning (ML) and AI applications have been formulated to get grips with these challenges and optimize the safety of transportation systems. Interest in ML and AI has been advancing consistently among transportation researchers and professionals, driven by advancements in computational power compared to earlier decades (Abduljabbar et al., 2019). While AI methods are progressively being solicit across various transportation safety domains, there is still a ignorance and unknowledgeability exchange between them.

Conventionally, safety models were created using collision records stow in databases. However, recent perspective to collision modelling and safety analysis focus on directly observing indicators that something is about to happen, such as conflicts and near-misses, and analysing their interconnection through video recordings or sensor data. AI and advanced approaches used in computer science and information technology are especially apt, and congenial for extracting insights from these data, discerning patterns, and training predictive models. This represents a significant improvement over past methods, which primarily relied on statistical techniques that often-produced suboptimal results.

1.1 Indian Context

India's road safety situation stands at a pivotal moment. With one of the widest-spanning road infrastructure globally, spanning over 5.89 million kilometres covering both urban and rural areas, the country supports a proliferating, and exponentially growing vehicle population, which reached approximately 295 million in 2021. Additionally, over 230 million driving licenses have been issued, accentuate the nation's subservience, and vulnerability on road transportation. Despite continuous efforts to improve infrastructure and law enforcement, India still accounts for a shocking 12% of global road fatalities, with 155,000 lives lost in 2022 alone.

The economic impact of road accidents is equally referring to, with estimates suggesting that these incidents cost the country around 4% of its GDP, causing substantial financial losses and obstructing national progress. Both rural and urban road networks face individual hurdles, and specific difficulties. In rural regions, poor road conditions and inadequate enforcement increase accident risks, while urban areas grapple with congestion, high vehicle density, and the complexities of managing diverse traffic, including motorbikes and heavy commercial vehicles.

Despite these challenges, integrating Artificial Intelligence (AI) into road safety enforcement presents a disruptive solution. AI can enhance existing systems, offering a much-needed upgrade to traditional enforcement and data analysis methods. AI-powered technologies can address the shortcomings of non-automated enforcement, which is often labour-intensive and susceptible to human error.

Predictive analytics can help identify high-risk zones and anticipate potential accidents, enabling anticipatory actions. AI-driven traffic management systems can facilitate, and expedite traffic flow, mitigate, and improve flow, and minimize accident risks. Automated license plate conceding and violation detection can improve enforcement efficiency, ensuring without deviation, and maintaining a steady and faithful commitment to traffic regulations. Additionally, intelligent emergency management systems can facilitate rapid and effective assistance, potentially saving countless lives.

Now is the time for policymakers and enforcement agencies to adopt AI-driven solutions. By leveraging AI, India can revolutionize its road safety framework, reducing accidents and fatalities while making more efficient use of resources. This technological shift holds the potential to save lives, reduce economic losses, and create a safer, more effective transportation system. Embracing AI in road safety enforcement is not merely an option—it is an urgent necessity for the future of India’s roads.

2. REVIEW OF LITERATURE

Derrick Mirindi, (2024) examines recent advancements in the application of Artificial Intelligence (AI) within the transportation sector. It highlights various AI techniques, including Artificial Neural Networks (ANN), Genetic Algorithms (GA), Simulated Annealing (SA), Ant Colony Optimization (ACO), Bee Colony Optimization (BCO), and Fuzzy Logic Models (FLM), alongside innovations such as disruptive urban mobility, automated incident detection systems, and drone technology. These approaches contribute to enhancing real-time traffic management and optimizing route planning. The study recommended ethical design principles, assessing the influence of different methods on autonomy, and creating tools to assist engineers and designers in balancing human autonomy with automated ethical decision-making are potential approaches.

Rusul et al., (2024), examined the usage of AI in transportation to eradicate challenges that occurred during transportation management worldwide. The study is divided into four sections. Section 1 identifies the application of AI for planning, designing, and decision-making, section 2 detects real-time road incidents and predicts the future state of traffic, section 3 reveals future scope of study, and section 4 provides the conclusion. The study presented a three-phase robust predictive model.

The transportation sector is essential in shaping integrated scenarios for developing strategies to achieve decarbonization and carbon neutrality. This research (Huma Rauf and Muhammad Umer, 2023) seeks to define quantitative emission reduction targets for the transport sector, enabling it to support a country's nationally determined goals. Currently, only 10% of UNFCCC signatory countries have included transport sector emission targets in their mitigation plans. As a result, alternative emission reduction strategies and techniques are necessary to make these abatement plans achievable. Integrating optimization methods with an AI-driven climate change prediction module provides an effective approach to monitoring and controlling pollutants within specified limit.

This region-specific, scenario-driven approach is applied to North Punjab, a province of Pakistan. It first classifies transportation modes based on their emissions and then utilizes AI modelling with a Deep Neural Network to establish sustainable trade-offs for carbon reduction.

McLean et al., (2023), utilizes Event Analysis of Systemic Teamwork (EAST) broken links approach to estimate the functioning of an AGI system responsible for managing safety at road transport and helps us in identifying potential hazard. EAST is a sociotechnical system integrate with three network-based activities: social, task and information networks. The study analysis considerable gap within AI safety literature, while previous studies did not give clear representation of specific AGI functionality, domain specificity, or formal ex-ante risk modelling (McLean et al. 2021). The reason of potential risk was identified as less understanding about information between tasks and agents regarding cash/injury data, condition of road and road system data, hazard and incident data, vehicle status and maintenance requirements data.

Evolution of 4.0 drastically change the way we live the life. Michal Tonhauser and Jozef Ristvej (2021) focuses on implementation of new technologies and automation on safety of road transport by enhancing efficiency and reduce environmental issues. European Commission funded Thematic Network of various stakeholders of participating EU member states ROSEBUD - Road Safety and Environmental Benefit-Cost and Cost-Effectiveness Analysis for Use in Decision-Making. The projects focus on Seat belt reminder in passenger cars and ignition interlock for seat belts can raise seat belt wearing among front seat occupants up to 97% that results in vast reduction in deaths. Results also shows that us automated camera systems maintain speed limits and supervise road traffic.

Artificial intelligence (AI) explores new opportunities in V2X (Vehicle-to-everything) systems. W. Tong, A. Hussain, W. X. Bo and S. Maharjan (2019), provided inclusive research on V2X paradigm to share the communication in the form of Vehicle-to-Infrastructure (V2I), Vehicle-to-Vehicle (V2V), Vehicle-to-Pedestrian (V2P), Vehicle-to-Self (V2S) and Vehicle-to-Road side units (V2R) .AI-powered algorithms for V2X applications have demonstrated superior performance compared to conventional algorithms.

Ruth et.al (2017), illustrated usage of an adapted version of the Unified Theory of Acceptance and Use of Technology (UTAUT) to analysis the factors that affect adoption of automated road transport systems (ARTS). A questionnaire was floated with 315 participants from the CityMobil2 ARTS demonstration in Trikala, Greece. The study concluded that UTAUT framework increasing the public acceptance for these automated vehicles. Hedonic Motivation, or the users' enjoyment of the system, significantly influenced their Behavioural Intentions to use ARTS in the future. Additionally, Performance Expectancy, Social Influence, and Facilitating Conditions also had notable effects.

P. K. Agarwal, Jitendra Gurjar, Ashutosh Kumar Agarwal & Ramkrishna Birla (2015), proposed that the Advancement of Smart Transportation Systems is required for smart cities due to environmental, economic, and social equity issues needed to control its working. The research focuses on understanding various sub-systems of Intelligent Transport Systems i.e. smart public transport systems, intelligent traffic management and control systems, smart traffic information systems, safety management & emergency systems, smart parking management and smart pavement management systems in smart cities. The development of smart cities is a collaboration of transportation experts and computer engineers.

Dalia Streimikiene, Tomas Baležentis and Ligita Baležentienė (2013) examined the road transport technologies in terms of atmospheric emissions a cost to identify the most cost effective and ecofriendly technology. The technologies are evaluated based on private costs and life cycle emissions of the main pollutants (GHG; particulates, NO_x, CO, HCs). his paper examines the impact of transportation infrastructure on greenhouse gas emissions from road vehicles and explores the policy implications of the assessment conducted. The Study utilizes multi-criteria assessment of energy technologies for road transport.

3. OBJECTIVE

AI techniques are exercise across various domains of transportation safety and security, including road safety, maritime safety, autonomous vehicles (AV), rail safety, traveller safety, transportation infrastructure security, transit safety, freight and commercial vehicle safety, disaster response and evacuation, wide-area alert systems, and hazardous material (hazmat) safety (Tselentis et al., 2019; Xue et al., 2019). Each sector presents unique collision risks that depend on distinct users —such as vehicle drivers or airplane pilots—and peculiar attributes, and special characteristics. For instance, in aviation, risks increase during take-off and landing, whereas in road transportation, collision risks are by and large proportional to the traveling distance.

This research aims to explore three key questions:

1. Which AI-driven techniques in transport safety are the most promising?
2. What challenges do these techniques address across different transportation modes, and how effective are they?
3. What insights and experiences can be shared between transportation sectors to improve safety outcomes?

This paper examines the machine learning (ML) and AI methodologies applied to safe transportation, resolving concern that have typically been difficult to solve using common, and mainstream mathematical methods.

4. METHODOLOGY

The literature review focuses on four major transportation modes: road, rail, maritime, and aviation, with a particular emphasis on road safety. This focus is justified by the high number of casualties in road transport and the rapid development of AI applications in this sector. The significant amount of research dedicated to driving behaviour and AV technologies further supports this focus.

Following a methodology like that of Nascimento et al. (2020), the review process included explore, and examine research questions, determine cast about strands, selecting sources and search engines, determining study required qualifications, and data transformation, and integration.

5. ANALYSIS

Road safety and accident prediction play a crucial role in Intelligent Transportation Systems (ITS), which are designed to prevent or minimize the impact of traffic collisions. These systems aim to enhance driver and passenger survival rates while analysing and understanding the conditions under which accidents occur (Machin et al., 2018).

Traffic crashes are influenced by various factors, including human elements such as driving behaviour, environmental or traffic conditions, and road infrastructure. Preventing these incidents requires the ability to efficiently process data collected from in-vehicle sensors, extracting valuable insights to proactively address safety risks.

In the era of Big Data (BD) and the Internet of Vehicles (IoV), the most utilized data sources for road safety analysis are smartphones and sensors embedded in autonomous vehicles (AVs), connected vehicles, and Advanced Driver Assistance Systems (ADAS). Recent research on intelligent road safety systems and crash prediction highlights various applications, including visual monitoring, accident modelling and analysis, identification of accident causes, driver fatigue detection, recognition of hazardous driving behaviours, automatic incident detection, and automated braking systems (Machin et al., 2018).

AI plays a crucial role in predicting road crashes and reducing their severity by developing crash prediction and pattern recognition models. These models effectively capture spatiotemporal variations in accidents and identify recurring patterns.

Ren et al. (2018) were the first to highlight the significance of spatiotemporal correlations in traffic accidents. They employed a long short-term memory (LSTM) model with high accuracy to predict accident risks. The model was tested on a traffic accident database in Beijing, China, demonstrating its effectiveness and practical applicability. Similarly, deep learning techniques have been leveraged in other studies. For instance, Rezaie Moghaddam et al. (2011) utilized artificial neural networks (ANNs) along with traffic and road geometry data from Iran's capital to estimate crash severity and identify key contributing factors on urban highways. Another example is the application of neural networks (NNs) to predict intersection crashes in Macomb County, Michigan, USA (Darçedil & Büuml, 2010). Their model, which analyzed nonlinear relationships between crash types and factors such as time, weather, lighting, surface conditions, driver attributes, and vehicle characteristics, achieved an impressive 90.9% accuracy in predicting crash types.

Several researchers have integrated machine learning techniques such as K-means and K-medoids clustering, expectation-maximization (EM) algorithms, and a priori algorithms to uncover hidden patterns in historical crash datasets (Vasavi, 2018). Ali and Bakheit (2011) evaluated the predictive accuracy of various AI methods, including ANN, multiple regression, and principal component analysis, in forecasting future vehicle crash casualties.

Furthermore, Wahab et al. (2009) compared statistical models, ANN, and fuzzy NN techniques to identify driving patterns and develop accurate driver profiling models. Their models were trained using data collected from in-vehicle signal recordings. Other studies, such as those by Papadimitriou et al. (2019) and Tselentis et al. (2019), explored AI and mathematical optimization techniques to classify drivers into behavioural groups based on driving patterns.

5.1 Rail

Safety is a crucial element in railway operations. This review found that AI techniques are primarily utilized for rail defect detection and obstacle detection on tracks. However, their applications are not limited to these areas. For instance, Alawad et al. (2019) employed a decision tree (DT) approach for safety classification and accident analysis at railway stations, aiming to predict the characteristics of passengers involved in accidents.

Over the past two decades, research has increasingly focused on developing computer vision (CV) algorithms to automatically detect and identify rail defects. Mandriota et al. (2004) conducted an experimental comparison of three filtering techniques—Gabor filter, Wavelet transform, and Gabor wavelet transform—utilizing texture analysis of rail surfaces to locate rail corrugation. This study used high-resolution images captured by a DALSA line scanner. Similarly, Hajizadeh et al. (2016) addressed the challenge of imbalanced datasets, where non-defective rail samples outnumbered defective ones, and the presence of large amounts of unlabelled data by implementing a semi-supervised rail defect detection model. Data was collected through a high-resolution camera spanning 700 km of railway tracks. Additionally, Shang et al. (2018) introduced a two-step rail defect detection algorithm that integrates conventional object localization with Convolutional Neural Networks (CNNs). Initially, 5,793 cropped training images focusing on rail sections were obtained using traditional image processing techniques. These cropped images were then processed through a CNN to extract part-level features for rail image classification. Furthermore, both Support Vector Machines (SVM) and CNNs have been tested for wheel defect detection, demonstrating promising results (Krummenacher et al., 2017).

5.1.1 Rail Obstacle Detection

Although environment perception and object detection are crucial for both trains and autonomous vehicles, research on railway obstacle detection is less extensive compared to road systems (Ristić-Durrant et al., 2021). According to this study, vision-based obstacle detection methods can be categorized into traditional CV-based and AI-based approaches. Some studies, such as Ukai (2004), applied distinct detection methods for stationary and moving objects on the tracks. Moving objects were detected using an optical flow method within the Region of Interest (ROI), while stationary objects were identified using the Sobel edge detection technique followed by morphological processing. Another effective approach for obstacle detection involves background subtraction, which is particularly useful for moving cameras. Mukojima et al. (2016) employed this method by comparing live onboard camera images with reference images to detect obstacles.

In terms of AI-based methods, Manikandan et al. (2017) developed an early warning system utilizing vision-based techniques, artificial intelligence, and sensors. This research proposed two methodologies: first, the AdaBoost algorithm was applied to data from a single thermal camera to detect obstacles at level crossings and calculate the distance between obstacles and the train; second, an artificial intelligence-based camera setup and image processing techniques were used to identify landslides on railway tracks. Additionally, Yu et al. (2018) trained a Fast Region-based CNN (Fast R-CNN), using images sourced from the internet (e.g., people, trains, animals). This model, optimized using a residual learning network block, achieved an accuracy of 94.85%. Lastly, Pamuła and Pamuła (2021) developed an obstacle detection model for railway level crossings by analysing video footage from monitoring cameras, employing a CNN to assess the condition of the ROI, which is critical for ensuring the safe passage of trains.

5.2 Maritime Industry and AI Applications

Despite the growing significance of Artificial Intelligence (AI) and Big Data (BD) in decision-making across various industries, the maritime sector has traditionally relied on human expertise and experience rather than data-driven approaches. This is largely due to the vast scale and complexity of its networks and planning challenges (Munim et al., 2020). However, AI techniques are increasingly being adopted for digital transformation, particularly in applications involving automatic identification systems (AIS), energy efficiency, and predictive analytics—of which AIS-based applications and predictive analytics are directly related to transportation safety (Xue et al., 2019). Moreover, AI and BD are now being utilized in real-time maritime intelligence platforms, such as Marine Traffic.

5.2.2 Maritime Surveillance

Fontana et al. (2020) employed Convolutional Neural Network (CNN) models to enhance vessel detection, counting, and recognition using super-resolution satellite data for maritime surveillance. The study suggested that this approach could be further specialized to detect untracked ships or monitor critical infrastructure near harbors and restricted areas. Similarly, Solmaz et al. (2018) used a CNN-based framework to classify and identify maritime vessels, training their model on the MARVEL dataset, which led to improved recognition accuracy. Additionally, a review by Soldi et al. (2021) highlighted the emerging opportunities in global maritime surveillance due to advancements in space-based sensor technology. This study demonstrated how synthetic aperture radar (SAR) and high-resolution imaging are utilized in deep learning and machine learning applications for target detection, segmentation, and classification.

5.3 Incident Detection

Several AI-driven approaches have been explored for maritime incident detection. Handayani and Sediono (2015) applied Bayesian networks to detect anomalies in vessel tracking, while Shahir et al. (2015) introduced a two-step method using Hidden Markov Models (HMM) for pattern representation and Support Vector Machines (SVM) for classification. Their approach integrated multiple data sources—including kinematic and geospatial data, contextual information, and maritime domain knowledge—to distinguish suspicious activities from normal behaviour. Similarly, Handayani et al. (2013) used SVMs for pattern classification in anomaly detection, analysing three months of AIS data from Port Klang, which included 9,845 observations covering vessel identity, status, speed, location, heading, and timestamps.

Rhodes et al. (2007) tested a neuro-biologically inspired algorithm for real-time situation awareness in the maritime domain. The algorithm continuously learned motion patterns from tracking data, enabling it to adapt to evolving conditions while maintaining high performance. Bayesian Networks (BN) have also proven effective for identifying abnormal vessel behaviour, as they allow expert knowledge integration and facilitate model interpretation (Johansson & Falkman, 2007). This BN approach, tested on synthetic data, showed strong performance in detecting single-object anomalies like excessive speed.

Lane et al. (2010) developed a method for identifying five types of anomalous ship behaviours based on AIS transmissions. These behaviours included deviations from standard routes, unexpected AIS activity, unexpected port arrivals, close approaches, and unauthorized zone entries. Lastly, Kowalska and Peel (2012) designed a non-parametric Bayesian model using Gaussian Processes to model normal maritime behaviour. Trained on AIS data, this model assessed the normality of each transmission by analysing vessel velocity and location coordinates.

5.4 AI in Aviation

Artificial Intelligence and automation have been integral to the aviation industry for decades, with various applications spanning incident diagnosis and flight assistance. Recent advancements have introduced AI solutions for unmanned aerial system detection, collision prevention, airborne component diagnostics, management automation, combat mission planning, and air traffic control optimization (Kulida & Lebedev, 2020).

5.4.1 Incident Diagnosis

Research suggests that AI can enhance flight journey management more efficiently than human intervention (Abduljabbar et al., 2019). Budalakoti et al. (2008) applied an unsupervised machine learning algorithm to cluster landing phase sequences, utilizing the normalized length of the longest common subsequence as a similarity measure. By analysing around 2,200 flight sequences and conducting detailed outlier analysis, this approach effectively detected landing anomalies, outperforming Hidden Markov Models (HMM).

Aretakis et al. (2015) focused on engine health assessment by analysing on-wing data from a commercial aircraft. They utilized a Probabilistic Neural Network (PNN), which successfully identified subsystem faults with high accuracy.

Williams (2014) tackled real-time turbulence forecasting by integrating data from various sources, including Doppler radar, geostationary satellites, lightning detection networks, and numerical weather prediction models. The study employed a Random Forest-based unsupervised classification approach, enabling more precise turbulence detection. This technique contributed to optimizing flight routes, reducing fuel consumption, and improving air traffic management.

6. DISCUSSION

The methodological approaches utilized in transportation safety include regression analysis, classification, clustering, mathematical optimization, and artificial neural networks (ANN). It was observed that, except for incident detection in maritime transport, all other areas of transportation safety reviewed in this study incorporate ANN-based methods. This widespread adoption is likely due to the high modelling accuracy of ANN, particularly in image processing tasks, though these methods require extensive datasets for training. Additionally, support vector machines (SVM), hidden Markov models (HMM), and Bayesian models are frequently applied across various transport modes, primarily for incident detection. Among these, Bayesian models are the most used for incident detection, followed by SVM, while HMM, despite being less prevalent overall, is utilized across a wider range of transport applications.

6.1 Problem

The literature review highlighted various safety challenges addressed by AI techniques across different transportation modes:

A) Incident detection, crash prediction, and autonomous vehicle (AV) and advanced driver-assistance systems (ADAS) in road transportation.

B) Defect identification and obstacle detection in rail transportation.

C) Maritime surveillance and incident detection in the maritime sector.

D) Flight assistance and incident diagnosis in aviation.

In most cases, the AI-driven models demonstrated high accuracy and performance, effectively solving these complex safety challenges.

6.2 Key Challenges and Future Prospects

While AI offers significant advantages for transportation safety, several challenges and concerns must be addressed before its full implementation. As highlighted by Abduljabbar et al. (2019), these challenges include:

- Managing the vast amount of data required for AI models and ensuring efficient processing.
- Ensuring the representativeness of collected data and establishing proper procedures for data collection.
- Detecting and preventing intentional manipulation of training datasets.
- Addressing cybersecurity risks and regulatory concerns to support policymakers.
- Tackling ethical and societal acceptance issues to facilitate the integration of AI-driven systems.
- Defining safe operational boundaries and identifying potential risks.

The choice of analytical techniques is largely influenced by the specific purpose of safety analysis. For instance, classification models are predominantly used for incident detection in road, maritime, and aviation sectors, distinguishing between various conditions such as free-flowing and congested traffic. Similarly, classification techniques are the primary approach for detecting defects and obstacles in rail systems, relying heavily on image processing.

Dimensionality reduction methods are primarily applied in road transportation, likely due to the vast amount of data collected in this sector. In contrast, crash prediction models encompass a range of analytical techniques, allowing researchers to frame the problem as either a regression task (predicting the number of crashes) or a classification task (categorizing crash types). This flexibility presents opportunities for applying similar methodologies to other areas of transportation safety.

Furthermore, emerging transportation technologies—such as urban air mobility, last-mile delivery drones, and Hyperloop systems—are increasingly integrating AI. Future research should focus on the safety implications of these advanced transportation concepts to ensure their secure and efficient implementation.

7. CONCLUSION

Our research highlights the growing interest among transportation researchers and professionals in leveraging AI applications to enhance transport safety. By utilizing AI-driven tools and methodologies, they are now able to tackle complex transportation challenges that were difficult to address using traditional approaches. AI advancements are proving highly beneficial across all transportation modes—road, rail, maritime, and aviation—particularly in improving the safety of autonomous systems within these domains.

Our findings suggest that knowledge transfer between different safety fields is feasible and could be further enhanced through a more structured mapping of experiences within the transport safety sector.

However, despite the significant advantages AI techniques offer, several challenges and concerns must be overcome before their full integration into transport safety. These include the vast volume of data required, ensuring the representativeness of collected data, preventing intentional manipulation of training datasets, addressing cybersecurity and regulatory issues, considering ethical and societal acceptance, and defining clear safety thresholds (Abduljabbar et al., 2019).

The future adoption of autonomous vehicles (AVs) and advanced driver-assistance systems (ADAS) is anticipated to deliver substantial benefits, including improved traffic flow and reduced accidents. With the increasing reliance on sensor technology and vehicle-to-vehicle communication, as well as advancements in sensor availability and high-speed computing, interest in AV and ADAS research continues to grow. These developments are shaping a vision for a more automated and safer transportation system.

This research has certain limitations. Firstly, not all transportation modes were included in the review. AI applications in urban transportation, such as air urban mobility, last-mile delivery drones, and public transit, were not deliberately excluded but did not appear in the search results. This is likely because existing research primarily emphasizes efficiency and public acceptance rather than the safety aspects of these systems. However, as these AI-driven transportation concepts continue to evolve, their safety considerations should be explored in future studies. Similarly, the Hyperloop, which was not covered in this review, has only been analysed for safety on a theoretical level (Mateu et al., 2021) and warrants further investigation.

Additionally, future reviews should broaden their scope to examine other subcategories within the four transportation modes discussed in this study. Another limitation is the timeframe of the reviewed publications, which was restricted to studies published between 1995 and 2021. Future research should extend this period to include studies from before 1995 and beyond 2021 to provide a more comprehensive analysis.

Lastly, a significant portion of aviation research is absent from academic literature, as much of it falls under industrial research and development. Due to confidentiality concerns, many advancements in this field are not publicly available, limiting the scope of this review.

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