Real-Time AI-Enhanced Systems for Road Condition Monitoring

By Dr. Chen Wang

Associate Professor of Information Technology, National Chung Cheng University, Taiwan

1. Introduction

The growing number of traffic vehicles, the complexity of road construction and maintenance, and the intensity of use increase the need for road reinforcement and subsequent monitoring. This task becomes essential in larger cities, where the length of pipes and roads makes it difficult to effectively inspect the safety of the entire infrastructure. One solution is to use advanced data analysis tools that can be used to quickly and safely diagnose traffic safety. Therefore, the main goal of the developed system is to ensure road traffic safety and minimum congestion so that driving is as efficient as possible.

Artificial intelligence is becoming increasingly integrated into virtually every industry. However, it is doing particularly well in the field of transportation. The practical introduction of AI has expanded in recent years thanks to the development of more powerful computers and the rapid analysis of very large data sets. It is difficult to overestimate the benefits of integrating various sensors with data analysis. In many cases, this concept is the next step, solving a broad problem that has not been solved before. The real-life applications involving the use of intelligent technologies can produce clear benefits to society. This is especially true for practical applications related to road traffic safety and efficiency.

Real-time monitoring of road conditions offers several benefits. First, the time required to process the response is practically negligible, leading to a significant reduction in the time required for intervention, which would not be feasible with purely human resources. In addition, continuous monitoring will allow the systems to increase the quality and quantity of the data available, creating opportunities that were previously impossible. Despite the clear benefits, there are several technical challenges associated with traditional monitoring methods. Solutions to these problems are then suggested, indicating possible innovative system solutions that may in the future serve as a basis for real-time monitoring.

1.1. Background and Significance

The topic of road condition monitoring has been of interest for a century. The evolution has moved slowly, and most road condition observations, mainly about surfaces, have been constructed based on physical surveys, which are not dynamic in terms of road safety monitoring. Various aspects of transportation issues have been studied by researchers in different geographic locations to understand the driving environment, the effects of weather conditions, and road geometry on traffic operations and safety. Timely available real-time data are used in different ways to enhance the existing knowledge of transportation networks to improve decision-making, such as arranging storage routes, controlling access of automobiles to highways, scheduling transportation services between railway companies, targeting safety inspections, evaluating and anticipating transportation risks, and forecasting injury risks to the human body.

With the innovative use of transportation technologies and increased deployment of intelligent transportation systems, there is vigorous and accelerated interest in automated road assessment. The technologies have overcome the limitations of traditional methods by providing increased levels of accuracy in road surface, subsurface, and structure measurements, and are being improved to measure environmental contaminants, among others. This is particularly relevant in terms of sustained and increased traffic flows on the roads and adverse weather impacts on traffic safety, especially for specific groups of road users such as motorcyclists. A number of studies have shown that poor road conditions impact not just congestion, but also drivers' health and stress. The problem draws intensified concern because of its significant impacts on the planning of sustainable and livable cities through understanding needs and presenting data to the public. Poorly maintained roads cost city motorists a total of $29 billion annually in additional vehicle repairs, including $336 per year in additional operating costs per motorist. A figure of 14% of fatalities in Europe is also attributed to traffic-related pollution, mainly in the cities.

1.2. Research Objectives

The primary objectives of the proposed research are to explore advances in machine learning to develop AI-enhanced assessment techniques for road condition monitoring. This technique will allow the absence of human intervention and manual data collection, updating road conditions and traffic flow automatically in real-time. Furthermore, the research will be carried out from two perspectives: road traffic management systems and road quality assessment. This study will serve to identify gaps and explore key avenues for contributing to state-of-the-art trends in this field.

This research seeks to explore up-to-date machine learning algorithms for effective classification using integrated input data from road monitoring to optimize road assessment techniques. The objectives can be summarized as follows: to analyze recent machine learning techniques and intelligent image processing in the assessment of road conditions; to critically identify the limitations of the current machine learning and analytical real-time-based road assessment systems in TMS; to focus on improving Transportation Quality Assessment Theories, specifically the service quality of road infrastructure; to adapt machine learning techniques to improve real-time-based road assessment techniques for the early prevention of road accidents; to segment the individual parts of the transportation management system and create a range of AI methods in various applications. The results should facilitate the identification of performance in the enhancement of infrastructure used. Create a traffic management system tool that will be used nationally, thus promoting research. This project directly follows up on a recently completed project. This project was successful, and thus we have identified a topic area for potential investigation that would enable another exciting addition to real-time quality monitoring.

2. Road Condition Monitoring Technologies

Road maintenance is essential in maintaining comfortable vehicle operation and reducing accidents. Extensive efforts have been invested in developing road condition monitoring systems, and a variety of traditional inspection methods and innovative technologies for road conditions have been proposed. Traditional road inspection methods are mainly manual inspections, data monitoring vehicles, and remote sensing data, which are time-consuming, laborious, high risk, and periodic. Although these methods can truly reflect the condition of the road or the site, the road section inspection lacks timeliness and the site inspection cost is high. The combination of different effective technologies and sensors based on artificial intelligence optimization, identification, and analysis can build a data acquisition and analysis system for different environments and improve work efficiency and quality. In recent years, due to technological advancement and growing demand, many significant advances have been made. In many cases, sensors and measurement instruments have been used for automatic measurements, and data analytics have been used to extract useful information. Innovations in various technologies that range from mechanical and electronic sensors to sound and image processing have significantly improved the accuracy and reliability of measurements. The advantages of these new technologies, mainly cost and flexibility, have extended the range of road condition monitoring applications. Response times to analyze the available data and recommend an appropriate follow-up action can also be shorter than before. Artificial intelligence and machine learning engines make it easy for all of the massive sensor data to be automatically analyzed as it is collected and integrated with other factors. The AI-enhanced system is generating actionable information from it in real time.

2.1. Traditional Methods

Traditionally, road condition assessment is carried out by manual inspection. Visual assessment of road conditions has been employed since the early days of road construction but requires increased human resources and does not satisfy current requirements for real-time traffic estimates and early warning systems. Physical surveys, which mainly focus on pavement conditions, were introduced in the 1990s. The traditional survey methods of road surface condition employed by some traffic and road departments generally rated road surface conditions from good to those requiring maintenance, but they were not repeated often enough to assess the dynamic road surface condition. Road surface condition is one of the most important parameters in determining the safety and comfort of road users. A comprehensive understanding of road surface conditions is increasingly in demand for monitoring and management of long-term road infrastructures.

The current methods for the detection of road infrastructure needs are still based on assessments made by qualified experts, i.e., civil engineers, who, on the basis of their experience and through the check of particular parameters, assign to each road infrastructure a state of overall operation and provide the necessary maintenance that needs to be applied. Despite the fact that those traditional methods have played an important role in providing valuable information for the understanding of road infrastructural behavior, the necessity to understand the behavior of these road systems in real time has shown the weaknesses of these traditional data in monitoring these structures. Governorates, together with regional and local staff, used these previous assessment data to determine which roads should receive maintenance action. In addition, the public also had access to this data to help determine the choices they make affecting their daily lives, directly linked to road safety announcements. However, governmental, municipal, and jurisdictional authorities, as well as private companies, are inherently concerned about road safety and compliance with road safety laws.

2.2. AI-Enhanced Systems

Compared to traditional monitoring systems, the novel data-driven monitoring systems adopt AI-enhanced techniques for road condition and safety control. The data-driven algorithm enhances the monitoring accuracy based on real-time data concerning the status of the infrastructure and road users. The sensors collect field data while AI techniques handle data mining and knowledge discovery. Consequently, real-time monitoring systems have shown great potential to improve state-of-the-art monitoring and predicting models. AI-enhanced monitoring mainly resorts to probability theory and big data analysis to operate and handle a large number of data effectively. Enhancing the accuracy of real-world AI-enhanced systems is not an end in itself, but a vehicle to achieve informed decision-making from the platform, thanks to the AI algorithm. The decision-making, for instance, may be related to answering what, when, why, where, and how the road infrastructure is operating in the downstream sections. Indeed, AI can support predictive analysis, but also offer the possibility of a dashboard that aggregates all data collected in order to automatically draw conclusions or offer insights by means of natural language.

In this sense, an AI-enhanced monitoring system should be capable of reporting the road status and combining data collected from multiple sources of information. One important question to answer is who is considered the current 'state-of-practice' receivers of the systems. In general, systems may be proposed as tools of support to road management authorities, in which different layers of the system are handling the information and data available, all different analyses, and providing the results in terms of a comprehensive report. AI can also serve as an automated process of classifying, ranking, and identifying the 'abnormal situations' or those events that require the attention of the road operators. These AI models have shown to be effective in classifying the current status of the road; several case studies exist in the entire work, in which innovative algorithms are capable of supporting a wider classification of the road infrastructure in a potentially given shape. For instance, AI was employed to investigate the safety of road infrastructure, providing big data on the usage of existing infrastructure spread over different geographical areas. It was clearly beneficial to relate to the classification of the infrastructure based on the quality and morphology of the network or to prioritize among the existing competing infrastructure and their retrofit. The same principle can be extended to live monitoring of the road infrastructure, considering that the traffic users over a given infrastructure bring a new shape and line up, which can generate new events of interest for the road operators. Alternatively, the response of AI scenarios may propose a better usage of the safety status or the commissioning information.

3. Machine Learning for Road Condition Assessment

Algorithms based on machine learning have been proposed and successfully used as a means to assess road conditions. Their advantage lies in the simplicity of their integration within the information systems dedicated to road network administration and in the fact that they allow real-time data analysis. Many machine learning techniques have been employed in autonomous vehicle management in other projects, including supervised and unsupervised learning algorithms, reinforcement learning, and deep neural networks. They may be used in various stages of road condition forecasting, including traffic, environmental events, context awareness, and replacing the classical data processing algorithms used in the literature.

These algorithms are designed to determine patterns in inhomogeneous datasets and predict future outputs. This allows for exploiting their potential in predicting future measures of road segments and assessing road conditions. Road condition monitoring based on data collected from various sources present in a road environment, which are continuously exposed to harmful traffic and weather conditions, represents a current research topic. Weather stations are already available with updated data about multiple meteorological elements, air quality, wind strength, visibility, etc., while traffic environment scanners provide real-time data about vehicles, vehicular speeds, vehicle lengths, waiting times for vehicles to enter a road or a road segment, waiting times at traffic lights, and energy consumed/refueled via an energy scanner, etc. Such a system needs to assess/analyze real-time data in order to speed up traffic and contribute to efficient road network administration through optimal congestion alert management based on compressed data.

3.1. Types of Machine Learning Algorithms

This paper is focused on developing real-time AI-enhanced road condition assessment and prediction systems that can enhance the performance and usability of the information systems for the maintenance of road pavements. The monitoring of road and traffic characteristics is a very demanding task. The advances in information and communication technologies have made it possible to classify existing solutions into three main categories: (1) non-hierarchical systems, (2) hierarchical systems, and (3) prediction systems.

Machine learning may be a solution that will affect the improvement in the usability of the decision support systems. Generally, machine learning algorithms can be categorized into three groups according to their functionalities, namely supervised, unsupervised, and reinforcement learning. Supervised learning methods are either used to classify data or to predict the value of the function. Unsupervised learning techniques can be used to find patterns in the data and for evaluating the data into a structure. Clustering techniques are the main example of unsupervised learning. Reinforcement learning can be the best approach if there is no data available or if data is useful and expensive. Decision trees are examples of the algorithms based on this technique. Each algorithm has its strengths and weaknesses; therefore, the choice of the most suitable one for a particular application should be investigated in depth since the choice of the correct algorithm is highly dependent on the objectives of the research and the set of data.

3.2. Data Collection and Preprocessing

For road condition monitoring purposes, it is necessary to access data for the road of interest. Data collection methodologies have been split into three areas which include: sensor networks, mobile applications, and citizen reports. It is important to note that in any of the possible methodologies, high-quality raw data is a necessity; data must be clean and proficiently cover the fundamental data categories. A standard first step in machine learning is data collection and must be performed cautiously as this step determines the success of the output classification model. Data quality issues are common since many data sources can lead to noise, missing values, and inconsistencies within the acquired datasets. Missing values are common and can be addressed with techniques aimed at approximating missing data and transforming data to remove such errors. Moreover, the challenge exists when different data sources have different categories.

Mapping categories to a standard classification is a potential technique to tackle this issue. This can relate all diverse collected data categories to a single standard classification for effective road condition prediction. Road condition monitoring requires the assessment of road conditions to coincide with the present time. In this regard, features in use with computation will be focused on streaming real-time data rather than historical data. This is important as mapping present road conditions can only be effective using the accuracy of the latest reports and mobile sensor data arriving at the application server. In this present work, a methodology is presented for developing a data processing technique that can be used to normalize data prior to training. Finally, data preprocessing is common and helps prepare the raw data for analysis. Raw data is always the start of any machine learning model and should be recently collected due to the periodic changing rate of road conditions. It is important to note this section as these will critically lead into the next section that we will discuss.

4. Real-Time Response Mechanisms

Real-time response mechanisms facilitate quick actions based on monitoring results. Presently, automated systems process incoming data and data products, often using AI augmentation, to provide insights for decision-making as quickly as possible, considering the input data's refresh rate, monitoring objectives, and decision-making time. The timely response of monitoring systems is especially important in the context of road condition monitoring. Immediate warnings and/or road traffic management measures, triggered by road weather conditions preventing safe driving, can prevent road accidents.

The integration of AI-augmented response mechanisms with existing traffic management systems can allow for investment in upgrades to existing infrastructure and greatly enhance the efficiency of system-wide management. At the basic level, the algorithmic response mechanisms automate the decision-making process, bypassing human decision-making delays. Many systems have been successfully automated, such as smart homes, utility distribution systems, power consumption, and industrial processes. The integration of developed systems with traffic management in various countries has proven beneficial in improving the overall efficiency of transportation by better matching pedestrian and vehicle flows to available infrastructure.

Some of the main barriers to effectuating quick decisions include system latency, access to information, insufficient expert knowledge, and computational complexity. Algorithms that can decisively act or produce quickly restartable outputs that depend on bad data can bypass latency. In addition, the adaptation of refresh rates allows for quick updates based on critical data.

In summary, it is crucial to have AI-augmented response mechanisms for real-time action to prevent road traffic congestion when possible because it takes a very long time to recover from a road traffic incident. Some of the key elements for successful deployment have been spelled out.

4.1. Automated Decision-Making

Automation in the context of intelligent systems represents the process of replacing decision-making, performance of physical actions, or learning by an automated actor, otherwise performed by a human operator. Automatic processing, unlike human operation, can be implemented at a speed and scale out of reach of human operation, which is where significant gains in efficiency are expected to come from. In today's environment, several AI insights are immediately relevant. Historically, AI research has described four primary types or levels of AI-based decision-making: reactive, restricted, sub-human, and human-level. In this typology, automated decision-making (ADM) functionally refers to independent action selection based on real-time data. Recent rapid advancements in AI and machine learning, deep learning in particular, have greatly enhanced the capabilities of algorithms to make real-time decisions based on streams of data. Their applications are vast. Traffic management, such as adaptive traffic lights that adjust to current congestion levels, is an oft-cited example of AI algorithms making decisions affecting the physical world in real time. Most impacts from automated decisions can be observed in terms of operational effectiveness and safety.

Traffic light adaptive schemes have been shown to improve capacity for road users and minimize queuing at junctions. Dynamic speed advisory systems are known to lower vehicle speeds and subsequently vehicle accident rates as well as severity. An adaptive traffic signal system containing road monitoring sensors and computing algorithms was used to predict future conditions and develop plans that would specifically keep emergency response vehicles moving through intersections. Further evaluation of this project showed that the system kept 95% of intersections clear 90% of the time. The accuracy of the flaws in the above systems is limited by the accuracy of the inputs to these systems, and in the case of the system, it was estimated that emergency vehicle travel times could improve by up to 50% if the system could differentiate between emergency and normal users beyond the engine sensing system currently in place. Further, these automatic systems need to be calibrated and adjusted to the models developed to ensure optimal decisions. The consequences of machine learning algorithms with uncalibrated outputs have recently come under much scrutiny, in particular for scenarios where algorithm bias may have significant social consequences. However, automated decision-making promises to reshape the management of transportation systems when effective.

4.2. Integration with Traffic Management Systems

Interoperability between new technologies and legacy traffic systems is a crucial aspect that ensures cities and infrastructure providers optimize existing investments and resources while integrating innovations. System integration represents the blending of these technologies that function together within an environment to improve operations and increase functionality. System integration between AGD detectors and the Regional Traffic Management Centre (RTMC) for monitoring variables of interest like real-time traffic congestion assists in effective traffic management. Similar potential can be practiced within the case of road condition monitoring to a Traffic Management System (TMS).

The driving aspect behind the aforementioned system design and integration benefits is to ensure timely and effective responses to varying and deteriorating traffic conditions. Therefore, engaging real-time AI-enhanced systems for road condition monitoring will add an extra advantage to the TMS, which can further streamline the adaptation of the TMS. It would be of particular interest to operators if the AI assistant system could automatically reroute traffic and update Variable Message Signs (VMS). The key for TMS to integrate data products from AI-based RCM is the data sharing protocol. If the TMS and RCM providers use a common or compatible data sharing protocol, it is up to the transport authority to facilitate smooth data exchange. A real-world example of TMS integrating a road surface data product comes from the collaboration between authorities that have expressed a willingness to share data and integrate systems should the systems prove compatible. This is another example of system integration based on interoperability. Note that an alternative method of integration relies on pre-existing relationships between the TMS and the RCM system provider where the data produced by the RCM system does not necessarily have to adhere to a fixed data sharing protocol but can be understood by the systems it feeds. System integrators act as intermediaries. They not only identify interoperabilities but offer customized solutions, including providing on-the-ground support and additional technical support. Hence, alignment of policy and regulatory frameworks is essential to both support and mandate such partnerships to ensure the development of coherently integrated systems that enhance urban mobility and safety. Such system integrations further act as the precursors to advances in urban traffic management design and decision-making systems.

5. Case Studies and Applications

5.1 Urban Road Networks 5.1.1 Traffic Control and Energy Consumption. An AI-enhanced road condition monitoring system is proposed for an urban road network. Once the road conditions are defined (free-flow, normal traffic, or road congestion), several adaptive actions can be taken, such as traffic light regulation, variable message signs, route guidance information for drivers, and public transport vehicles, to increase the energy efficiency of vehicles and, therefore, reduce fuel consumption and $CO2$ emissions. The whole system is evaluated in a microsimulation environment for three traffic scenarios (free-flow, normal, and congestion) with promising results. 5.2 Rural Highways System 5.2.1 Crash Prediction. An AI-enhanced road condition monitoring system based on a five-stage framework that consists of: initial data acquisition, pre-processing and feature computation, feature selection, model training, and online deployment is proposed. The AI component comprises a multilayer perceptron and a modified cost-sensitive AdaBoost algorithm for training. The AI-enhanced monitoring system was implemented at two diverse highway sites. One of the main conclusions of this case study is that real-time crash prediction is feasible using this kind of road condition monitoring system. The performance of these predictions is, however, serviceable, and a significant amount of data is required for a proper estimation.

5.1. Urban Road Networks

As sensors and AI-based systems become mature, they have started being broadly applied in specific scenarios related to road and transport management. They focus on urban environments, where the majority of vehicles are moving, and highlight the pathway for developing Intelligent Transportation Systems and smart cities, allowing them to unite various functions, such as mobility, monitoring, energy efficiency, and others. Urban road networks are usually characterized by intense traffic and major traffic jams and are more complicated to regulate in comparison to those roads in sparsely populated areas. The specifics of these urban road networks lead to the diversity of vehicles, vehicle counts, and densities changing swiftly. Congestion, as a result of accidents, vehicle breakdowns, or traffic jams, can become even more intense since it is similar to a digital tangle of information that does not move in urban environments.

The necessity of monitoring cities goes beyond these federations of roads where limitations in terms of speed, increased urban land use, and lively environments are more likely to be in place. Sensor technologies have been upgraded, not only providing real-time views of the roads at specific points of the network depending on the domain of sensing but also the capability to give predictions and analytics of the roads in their entirety. Sensors and the AI incorporated within them have observed increases in demand since they began working in spray pattern monitoring applications. Road condition applications in many engineering fields and smart cities are well known for operating the majority of public transport and traffic signals. These become more complicated to measure in urban and city-like settings where improved densities and continual traffic occur either on a twenty-four-hour pattern or have a greater magnitude caused by interruptions in currently operating traffic. Road performance in urban or city-like environments can be a better predictor than normal or lighter traffic patterns because of the increased flow of vehicles on both minor and major roads. Previous research has found that machine learning within urban settings can provide a more accurate predictor of incidents occurring, and the best predictive model is also the simplest. This suggests that the increased data and observation possibilities would not necessarily lead to a more complex model that outperformed the others used. Machine learning, especially deep learning methods that have shown capability within more technical models, may now be adopted for increased computational power as a broader application. This would then allow monitoring techniques, information, and future forecasting abilities to transcend city barriers. It is possible now and in the future to see how effective sensors could be embedded within cities for wider observations. These applications may have broader city implications in the future.

5.2. Highways and Rural Areas

Highways and rural environments have different operational needs compared to urban settings. In a highway, an average traffic density of about 14 vehicles/km is estimated, which might lead to traffic congestion only during rush hour. Moreover, along the highway, sections could often be subject to overpasses, with these free-flow configurations of motorways having few equilibrium zones. In this limit, highways may de facto operate as a trunk, and FEV can be considered, without loss of generality, uncontrolled. These aspects make the control of a stretch of highway quite easier compared to urban scenarios, and it may also justify the assumption of using a non-urban FEV. Weather conditions are the main factor to be taken into account in rural area monitoring, especially if they are characterized by frequent and sudden weather changes. Ice patches or the presence of snow, combined with very low temperatures, can lead to the appearance of icing on the road surface at an unexpected moment. Most of the icy spots are not detected, and treatments with spread salt only occur near the area closer to the boundary with the urban area. Road managers generally experience great difficulties in programming and organizing treatments, and constant cost-profit enhancement has led to a reduction of reserved resources and, further, to the reduction of road treatments, especially in the most peripheral areas. For such reasons, there is a need for signage systems that can adequately inform the driver of the state of streets and roads in advance. Especially on highways, special sections run along the worst winter weather areas. Therefore, real-time monitoring systems in rural areas, specifically on roads, must have a low cost and minimal control and maintenance requirements, possibly being self-sufficient. Case studies also confirmed the potential to adapt AI-enhanced monitoring systems in rural areas for use on roads going through valleys in a mountainous region, which are characterized by rapid changes in weather, or in the industrial areas at the outskirts of towns and urban centers, for use during nighttime. The monitoring solutions focus on or have limited operational requirements and interesting performance in rural situations such as poorly populated areas with few resources, being capable of providing useful information to help manage these areas and reduce the risk of vehicle incidents that self-driving cars cannot control without human supervision. It can be used in different operational settings considering empty highways with few resources and non-urban areas concerning solutions to be used during nighttime. Affordability of IoT technology is also important to be confirmed. AI-enhanced systems provide essential real-time monitoring of driver and passenger safety, especially in remote and/or contested areas where providing extra police and emergency response coverage is infeasible. It is possible to furnish key on-road assessment services without an operational presence at continuous low or no additional cost for initial deployment. Lessons learned can be seen in terms of rural roads that often cross multi-country areas as an integration of very different technologies and smart systems with low-cost solutions in contrast to routing roads in a city of 1 million inhabitants. This can lead to the enlargement of the current local fleet of smart street lighting for 'no error two-way safe communication' IoT networks, giving complete coverage of peripheries and adjacent countryside.

6. Challenges and Future Directions

Challenges in developing real-time, AI-enhanced road condition monitoring systems are complex. They include considerations of data privacy, security, and other ethical implications specific to AI usage. Dealing with extensive big data and ensuring compliance with regulatory and legal requirements while capitalizing on value creation is a compounded challenge. At the same time, the scalability and generalization of AI models to account for diverse road condition monitoring regions and associated operational conditions are critical. Vehicles, traffic, and road infrastructures could exhibit a high level of heterogeneity, and monitoring should address these variations. Confronting these challenges envisions future research, conversing evolution to revolution in dealing with them. The ongoing innovation to tackle these challenges preemptively will be far more beneficial than a reactive approach in dealing with them in the future.

Future directions will involve collaboratively working with stakeholders in the transportation ecosystem. Best practices before a large-scale deployment could be facilitated to provide recommendations for AI design and data use standards and ethical guidelines as part of the infrastructure and operational policy. The best practice can involve standardized experimentation platforms aiding the development of explainable AI models for road condition monitoring applications. The development of technical guidelines across transversal points can link related impact areas. Collaborating across organizations such as national and regional government bodies, road operators, automobile manufacturers, software and database providers, social scientists, and researchers could provide a firm bedrock for constructive interchange and dissemination of AI-enhanced road monitoring information. To summarize, the roadmap includes the development of pragmatic solutions to be used in perpetuating collaborative cross-sectional communities. Future technological advancements are pivotal in alleviating the highlighted challenges. Vehicle-to-thing and infrastructure-to-vehicle communication could advance the state of the art in real-time monitoring. Contemplating robust communication architectures would alleviate the threats arising from cyber imposts and phishing attacks. Future research on decentralized monitoring, control, and event-driven systems could provide another exciting direction of exploration. Through practical updates and scenarios of AI implementation and upskilling, researchers and practitioners will be able to prepare for the future through proactive measures.

6.1. Data Privacy and Security

Road condition monitoring systems require a large amount of anonymized and aggregated data to provide meaningful insights and services. There are many regulatory data protection requirements for the transportation sector. As vehicles and smartphones are frequently used in a transportation setting, there is an extensive need for understanding the challenges of using this data. Based on the legal basis for processing, access to this data could require the receiving organizations to inform controllers who have asserted these uses of the data. These rights could stem from local, regional, and/or national regulations and/or laws, such as for processing an individual's data via public authorities.

Another consideration is consent issues. Do individuals provide informed consent when gathering data? There is also ownership of data to consider. Whose data is it? Transportation data comes from various sources, and there may be commercial issues regarding who can use it for what purpose. There are also data security vulnerabilities—such as theft, hacking, and lawsuits. Even in anonymized data, information could potentially be traced back to an individual. Hardware deficiencies shield testers from access to their results. The only way to be certain that the data security is appropriate is to ensure that the systems are custom-built to contain the software without the possibility of shadowing. Data availability includes how the storing of the data in a particular system also gives rise to back-end access to the data. It is best to ensure that access to this data is not accessible and to ultimately delete it at the end of the evaluation. There are multiple efforts to develop various privacy-preserving tools such as data anonymization and data encryption. It is of paramount importance to continue to develop and implement AI tools that still offer privacy to data protection.

In the case of Los Angeles, the release of data led to a lawsuit by passengers who were accidentally exposed in a data release. This lawsuit was coupled with a breach-of-contract lawsuit. An unknown individual or entity broke into a contractor's computer server and gained access to personal information that was stored on the server. The incident revealed the basic details of individuals in the Los Angeles area, and many lawsuits were filed as a result. Incidents such as these have economic and financial consequences in the transportation sector. Furthermore, technologies for accessing and marketing towards these customers involve AI systems that analyze large amounts of sensitive individual data. The field is plagued with data protection scandals that have large economic consequences. All of these considerations for legal and ethical standards need to be taken into account for the future development of AI in C-ITS systems.

6.2. Scalability and Generalization

One of the major challenges in AI development is the "scaling difficulty": the good performance generated in one context does not necessarily result in delivering the same amount of goodness in a different situation. This is especially noticeable in road condition monitoring, as the road environment can be extremely varied over different geographical spaces and climate conditions. The most common root of the generalization problem in machine learning models is their inadequate ability to change and adjust the acquired knowledge. As a result, the data needs to be made diverse. This issue is universal to machine learning processes because robustness in real-life models depends on their massive and diversified knowledge.

A possible solution is presented in the innovative research area of the stability-plasticity dilemma of artificial intelligence models, which promotes creating AI models that are able to "learn when to learn." On the other hand, transfer learning data states that one of the important paths to good generalization of models is the intensification of their "skills" to adapt to different target tasks and data. While the model may not work in the geographic setting it was not trained for, a correctly trained AI model can transcribe into an adaptive general learning model suitable for a wide array of other algorithms and situations. Currently, different research-based models focus on hyper-specialization and learning robustness for concrete and specific applications; hence, their scalability and organization are of high concern. This is also the core of real-world AI-based systems, as they need to possess cost-effectiveness and scalability as part of their internal requisites. Future outputs of this work will be centered on improving generalization and decreasing overfitting in these networks.

To address these issues and also make the literature closer to real-world business big data, some immediate research concerns about scaling procedures are suggested. The primary goal of these procedures could include iterative learning frameworks or even modular or object-oriented AI networks. This allows networks to develop or "plug in" some parts of data and neglect others, reassuring the ideal result or performance in terms of time and business analysis. Moreover, diverse and increasingly huge datasets simulating most of the world's possible issues and particular conditions about road surfaces, pedestrian behavior, vehicle behavior, and so on are needed. Rather than yearly or semi-yearly benchmarks only, these cumbersome datasets to train should need massive validation and cross-validation recordings; hence, one critical aspect would change the above-mentioned more traditional KPIs to triple semi-supervised cross-validation maintained for the average percent error, thereby obtaining the standard deviation regarding each feature. In this way, the researcher would know the most unwanted connections and focus primarily on the residuals. This very costly validation process gives businesses a better chance to implement AI-based solutions in a business environment.

7. Conclusion

7. Conclusions It is clear that there is a lot of interest in the area of AI-enhanced road condition monitoring and management. Improved road monitoring may improve public safety while facilitating economic activity and traffic management. While the applications of traditional road condition monitoring systems have not changed with the introduction and integration

of AI technologies, the way services are provided and the potential level of integration across the system components is enhanced with the real potential offered by AI. This could lead not only to an increased capacity to monitor networks but also to integrate signals from multiple sources. The AI analytics could integrate and interpolate signals, allowing better urban and rural applications. The overarching conclusion from the case studies is that advances can be made through the inclusion of AI analytics over pre-existing schemes. The traditional sensing schemes may still be required to collect data for the analytics to work; however, new systems are in development that are AI-only with remote external monitoring and could offer more insight into the way AI may revolutionize road condition assessment.

Working on situational awareness of a road includes monitoring the road measurement through calibration and hence maintenance of assets across the network, to the safety warnings to the road user in the vehicle. Processing the raw measurement in speed of road networks has never been available as it is today. There are challenges to applying AI to Intelligent Transportation Systems and networks in practice, which require researchers to address real-life challenges such as data privacy and scalability. Moving forward, the main thrust will be the integration of the key roadside traditional monitoring such as traffic signals, crossings, and traffic flow detection in roundabouts and highways, with a comprehensive analysis and insight into how vehicles behave through the network, what this means for the road asset condition, and how to address these impacts. Further data sources and the in-vehicle situation can be studied for the future autonomous vehicle and the vast potential that early fault detection can bring for smart road infrastructures. This success can only be achieved through joined-up research with many different researchers and other people from all areas brought together.

Reference:

1. Tamanampudi, Venkata Mohit. "Automating CI/CD Pipelines with Machine Learning Algorithms: Optimizing Build and Deployment Processes in DevOps

Ecosystems." *Distributed Learning and Broad Applications in Scientific Research* 5 (2019): 810-849.

2. Pal, Dheeraj Kumar Dukhiram, et al. "AIOps: Integrating AI and Machine Learning into IT Operations." Australian Journal of Machine Learning Research & Applications 4.1 (2024): 288-311.

3. Kodete, Chandra Shikhi, et al. "Determining the efficacy of machine learning strategies in quelling cyber security threats: Evidence from selected literatures." Asian Journal of Research in Computer Science 17.8 (2024): 24-33.

4. Singh, Jaswinder. "Sensor-Based Personal Data Collection in the Digital Age: Exploring Privacy Implications, AI-Driven Analytics, and Security Challenges in IoT and Wearable Devices." Distributed Learning and Broad Applications in Scientific Research 5 (2019): 785-809.

5. Alluri, Venkat Rama Raju, et al. "Serverless Computing for DevOps: Practical Use Cases and Performance Analysis." Distributed Learning and Broad Applications in Scientific Research 4 (2018): 158-180.

6. Machireddy, Jeshwanth Reddy. "Revolutionizing Claims Processing in the Healthcare Industry: The Expanding Role of Automation and AI." Hong Kong Journal of AI and Medicine 2.1 (2022): 10-36.

7. Tamanampudi, Venkata Mohit. "AI-Powered NLP Agents in DevOps: Automating Log Analysis, Event Correlation, and Incident Response in Large-Scale Enterprise Systems." Journal of Artificial Intelligence Research and Applications 4.1 (2024): 646-689.

8. Singh, Jaswinder. "Social Data Engineering: Leveraging User-Generated Content for Advanced Decision-Making and Predictive Analytics in Business and Public Policy." Distributed Learning and Broad Applications in Scientific Research 6 (2020): 392-418.

9. S. Kumari, "Real-Time AI-Driven Cybersecurity for Cloud Transformation: Automating Compliance and Threat Mitigation in a Multi-Cloud Ecosystem ", IoT and Edge Comp. J, vol. 4, no. 1, pp. 49–74, Jun. 2024

10. Tamanampudi, Venkata Mohit. "Leveraging Machine Learning for Dynamic Resource Allocation in DevOps: A Scalable Approach to Managing Microservices Architectures." Journal of Science & Technology 1.1 (2020): 709-748.