Artificial Intelligence Applications For Efficient Road Asset Management Practices

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ARTIFICIAL INTELLIGENCE APPLICATIONS FOR EFFICIENT ROAD ASSET MANAGEMENT PRACTICES

Artificial Intelligence Applications for Efficient Road Asset Management Practices

Introduction to Road Asset Management

Asset management is defined by the Organisation for Economic Co-operation and Development (OECD) as "a systematic process of maintaining, upgrading and operating assets, combining engineering principles with sound business practice and economic rationale, and providing tools to facilitate a more organized and flexible approach to making the decisions necessary to achieve the public's expectations"(Organisation for Economic Co-operation and Development., 2001). The road asset management process requires, but is not limited to, an asset inventory and condition assessments of the road assets to identify maintenance and rehabilitation treatment needs and formulate a budget. Data collection involve field inspections of bridges, pavements, and non-pavement assets (e.g., signs, guardrails) that requires analysis and interpretation to assess road infrastructure performance. Data silos with lack of information about the cause of road infrastructure deterioration can slow down the road asset management process.

The foundation of asset management practices is the strategy as shown in Figure 1. The strategy should establish the type of physical treatments and defines management of use. Data are collected to register asset features, asset condition, and asset use. This information is useful to monitor and manage the road system performance. If the road asset management process is efficient, there should be community benefits.

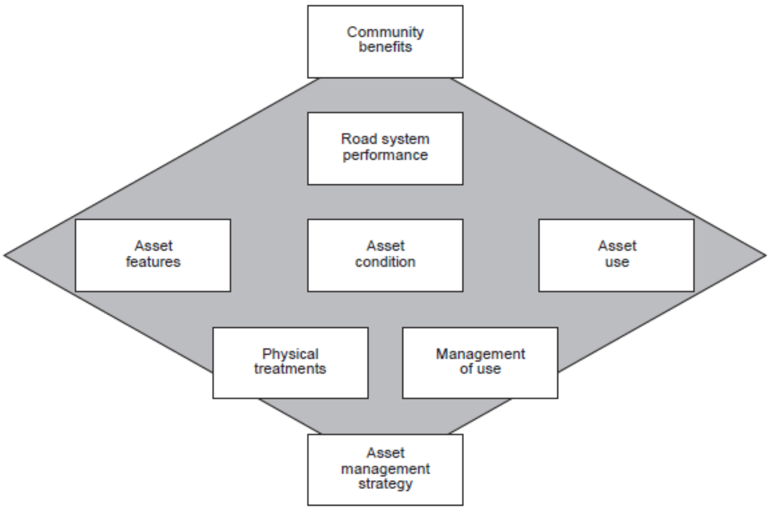


Figure 1. Major Elements of Road Asset Management (OECD, 2001).

The main goal of asset management practices is to preserve road infrastructure in a "State of Good Repair" (SGR). SGR is defined by the American Association of Highway and Transportation Officials as "a condition in which existing physical assets, both individually and as a system, are functioning as designed within their useful service life and are kept functional through regular maintenance and replacement programs" (AASHTO, 2019). It is essential to preserve road infrastructure in SGR to address the needs of society. If efficient road management practices are implemented, communities will benefit from the usage of road infrastructure. This is humongous challenge that has many factors to deal with including budget limitations, increase of public service demands, higher society expectations, impact of climate change, and human development concerns to mention some examples.

The responsibility of preserving assets belongs to road administrations. Each organization encounters a unique the decision-making context (e.g., political, economic, environmental, condition of road network) that influence how road administrations address the challenges. Road administrations should consider all types of assets involved in the management process. Even though road administrations may have their own definitions to classify their assets, OECD includes the following asset category as a reference:

- Physical infrastructure (e.g., pavements, bridges).
- Human resources (personnel and knowledge).
- Equipment and materials.
- Other assets of value (e.g., right-of-way, computer systems)

This paper focuses on physical infrastructure assets and how to integrate artificial intelligence (AI) applications for data collection, analysis, and interpretation. Data collection methods are the backbone of road asset management practices. Technical knowledge is required to analyse and interpret the data to determine the causes of the damage and their impact on road performance. In the practice, large data sets can experience an inconsistent and impractical exchange of data due to manual handling for formatting and manipulation of data to maintain consistency. On the other hand, ad hoc data collection method to gather information on a case-by-case basis results in smaller data sets, however, potential data problems of inconsistency, variability, and lack of standardization could also be found.

In this paper, the authors describe AI applications to assist in collecting, assembling, processing, and interpreting asset data towards the implementation of effective asset management practices. The paper presents AI initiatives to maintain assets in SGR and provide examples of cutting-edge methods to analyse, interpret data, and predict deterioration. The paper is organized into six sections (a) this introduction, (b) an overview of artificial intelligent, (c) AI applications for bridge management, (d) AI applications for pavement management, (e) challenges of AI applications for road asset management practice, and (f) final conclusion.

Artificial Intelligence

With the rapid increase of computer power, applications of Artificial Intelligence (AI) are growing exponentially, potentially transforming industry's practices. AI is used in various disciplines to process, analyse, model, and predict data trends within time frames that would otherwise be very expensive, time consuming, and subjective to human interpretation. Moreover, AI can connect up-to-date big data repositories to access asset records from multiple sources.

At present, asset management systems are still limited to existing methods of data analysis, and the limitations of experts and human-led data analysis techniques. Visual records of road recordings (captured in annual surveys or through ad hoc video collection) can be combined with available data sets for interpretation, however the complexity and size of data sets make this task time-consuming, costly, outdated, and at high risk of human error.

The practical reality of using AI for road asset management is still in progress, nevertheless, there are research efforts towards the use of trained data pool methods to predict road infrastructure performance using a combination of interactive and coloured images (2D image frame).

As AI assisted software models of road infrastructure detection emerge, there is a need to standardize acceptable limits of AI assisted detection. With several road maintenance operators considering or already adopting those methodologies, this is the appropriate time to establish the parameters required in the standards for the following purposes:

1) Standard for comparison between vendors.
2) Standards for qualifying vendors.
3) Standards for service level agreements / service level objectives
4) Standards for accuracy of defects and assets reporting
5) Standards for privacy
6) Standards for multi-tenancy for SaaS based operators
7) Standards for windshield or vehicle mounts
8) Standards for re-use of data for AI modelling
9) Open-Source standards

Examples of standards implemented by IRIS R&D Group Inc.; a Canadian based AI company are:

- Definitions for types of assets: Right of Way, Pavement Inventory, Road Defect classes, PCI standards.
- Definitions for demonstratable proof of accuracy – 85% for poor light conditions, 90% for standard conditions and 95% for excellent conditions.
- SLA/SLO's: Turnaround time from collection of data to availability of reports within accuracy boundaries.
- Privacy: At source reduction of private information such as license plates and human faces.
- Multi-tenancy: Standards to ensure SaaS based operators have data segregation for multiple customers on same platform.
- Vehicle mounts: Standards to ensure driver and passenger safety in placement of mounts, power supply, touch free operation of devices.
- Data re-use: Policies governing re-use of data across customers or across vendors for improving AI model accuracy.
- Open Source: Standards for usage of open-source software and
- AI components: SLAs for upgrades.

Moreover, standardization of AI and computer vision in asset management and the collection of asset condition data offers several significant benefits to the asset management industry such as:

1) Consistency and Comparability: Standardized AI methods and data collection processes ensure consistency and comparability across different asset management practices. This allows for fair and accurate assessments of asset conditions, performance, and maintenance strategies, regardless of the specific organization or location.

2) Interoperability: Standardization enables different AI systems and data sources to work seamlessly together. This facilitates the integration of diverse data sets, tools, and technologies, leading to more comprehensive insights and better decision-making.

3) Efficiency and Cost-Effectiveness: Standardized processes streamline data collection, analysis, and reporting. This reduces duplication of efforts, minimizes errors, and saves time and resources, making asset management practices more efficient and cost-effective.

4) Benchmarking and Performance Measurement: With standardized AI methods and data collection standards, organizations can establish benchmarks and performance indicators for asset conditions and maintenance strategies. This allows for better tracking of progress and improvements over time.

5) Quality Assurance: Standardization ensures that AI models and data collection methods meet predefined quality and accuracy standards. This helps build trust in the results and recommendations generated by AI systems, leading to more informed decision-making.

6) Innovation and Advancement: Standardized practices provide a solid foundation for further innovation in AI technologies. As the industry adopts common standards, it creates a collaborative environment that encourages the development of new AI algorithms, techniques, and applications tailored to asset management needs.

7) Data Sharing and Collaboration: Standardization promotes data sharing and collaboration among different stakeholders in the asset management ecosystem. This includes government agencies, industry partners, researchers, and technology developers, leading to a richer pool of data and expertise.

8) Scalability: Standardized AI methods and data collection practices make it easier to scale asset management initiatives across different regions, jurisdictions, or countries. This scalability enhances the impact and reach of AI-driven asset management solutions.

9) Risk Management: Standardized AI approaches help mitigate risks associated with biased or unreliable results. By adhering to well-defined standards, organizations can reduce the likelihood of making incorrect decisions based on flawed data or models.

10) Public Trust and Accountability: Standardization enhances transparency and accountability in asset management practices. When stakeholders can understand and validate the methods used to assess and maintain assets, it builds public trust and confidence in the outcomes.

11) Regulatory Compliance: Standardized AI practices can align with existing regulatory frameworks and requirements. This ensures that asset management activities adhere to legal and ethical standards, avoiding potential legal or compliance issues.

12) Long-Term Sustainability: Standardized AI and data collection practices contribute to the long-term sustainability of asset management efforts. As technologies evolve and personnel change, adherence to standards helps ensure the continued effectiveness and relevance of asset management practices.

The next sections describe AI applications for bridge and pavement management practices.

AI Applications for Bridge Management

In 2021, the American Society of Civil Engineers (ASCE) released the "Report Card for America's Infrastructure", with a comprehensive assessment of the infrastructure condition in the U.S. Bridges registered a C grade (mediocre). The ASCE report states that 42 percent of all bridges (617,000 bridges) in the United States are at least 50 years old, and the number of bridges in fair condition (291,339 bridges) has surpassed the number of bridges in good condition (279,582 bridges) as shown in Figure 2 (ASCE, 2021a).

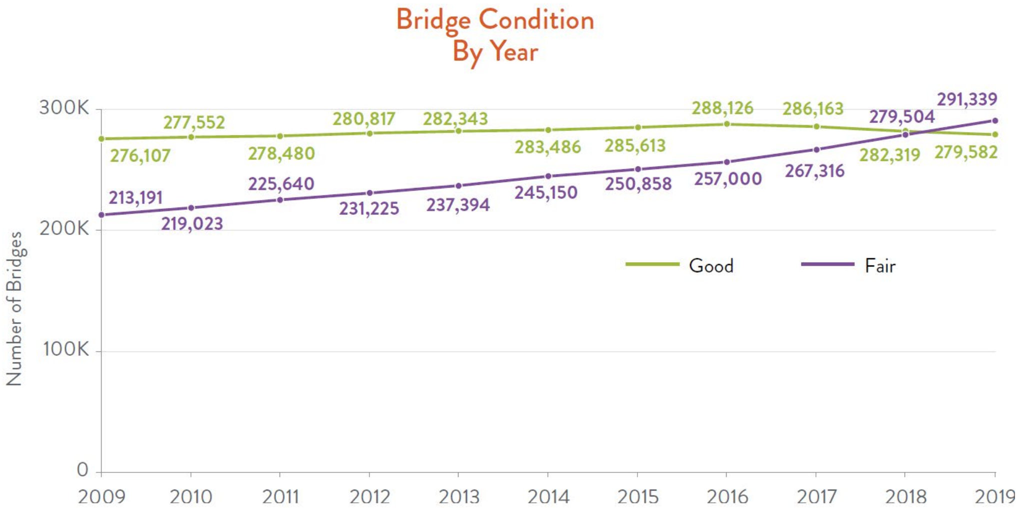


Figure 2. Bridges in Good and Fair Condition, 2009-2019 (ASCE, 2021).

This is a situation of major concern because most of the bridges were designed for a service life of 50 years. According to the ASCE report, the backlog to recover the SGR of the bridge network is estimated at $125 billion (ASCE, 2021a). Japan also faces a similar situation, half of its bridges will turn 50 years old by 2027(Chun et al., 2020; Road Bureau Ministry of Land, 2018).

A bridge management strategy to repair deteriorated aging bridge infrastructure is needed. At the network level, this involves the development of policies, standards, procedures, and specifications with the support of data management systems for their implementation. There have been AI efforts to improve the analysis of bridge data collected from visual inspections and predict bridge performance.

<u>Bridge Visual Inspections</u>

To assess the bridge condition (overall structural condition), visual inspections are conducted by transportation agencies. The bridge inspector must register the type and severity of the damage. Inspectors must visit the bridge and perform several tests. This task becomes complicated and risky if the bridge is in a high location; in this case, inspectors must use a rope access or get a high-elevation work platform vehicle with a high exposure to injuries. These inspections inflict costs and require a huge labour force. After recording bridge damages, the next step is usually finding the cause. In some cases, due to the complexity of the task, different types of tools such as advanced image processing techniques can be used in each structure component.

Working with an AI software, damage identification is facilitated. For example, Convolutional Neural Networks (CNNs) is a sophisticated classification method that has been applied for Structural Health Monitoring (SHM) using vision-based surface defect detection (Saleem et al., 2021). An AI algorithm can be trained to detect different types of damage such as:

- cracks,
- spalling,
- exposed reinforcement,
- corrosion of reinforcement,
- rust flags,
- cavities,
- moisture,
- gravel pockets.

Recently, CNNs models have been proposed (e.g. Faster R-CNN, YOLO, and SSD) with promising results in terms of accurate object detection (Saleem et al., 2021). A CNN model can provide damage identification and location to prepare a global bridge damage map. Another example is a deep neural network model called Mask R-CNN. The model can also detect corrosion areas in the steel structure as shown in Figure 3 (Chun et al., 2020).

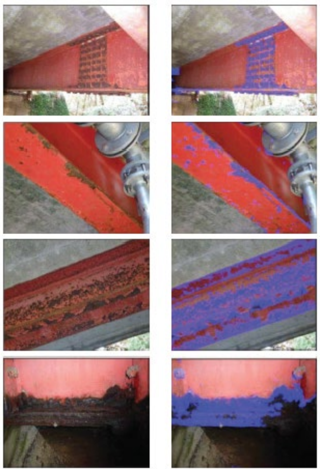


Figure 3. Corrosion detection results (Chun et al., 2020).

Bridge Structural Diagnosis

Another application of AI is when some of the data needed for a complete structural analysis are missing. Examples of missing bridge data are:

- Material characteristics.
- Detail characteristics (reinforcement quantity and position, cable details, etc.
- Geometry characteristics.
- Load characteristics.

In this case, AI assists to complete missing data as plausible as possible, and it is essential to integrate information from past inspection reports to assess the bridge performance. In fact, knowledge of the state of construction of the bridge and mathematical simulation of the deterioration is often not enough to fully determine the evolution of bridge performance over time.

The integration of information provided by inspectors is useful to refine the model considering the existence of exogenous and random events in the deterioration model. However, inspection data are normally received in the form of qualitative classifications and class breakdowns, which are difficult to translate in terms of structural safety. Therefore, AI tools are used to interpret automatically, or semi-automatically, bridge data to extract quantitative information from the inspection records (e.g., pictures, schemes, comments).

The same information extraction tools are useful for the analysis of printed drawings of existing bridges (e.g., original design drawings). AI tools could extract geometry, details, and materials from drawings and input them into a Building Information Model (BIM) of the structure itself, that could be built automatically or semi-automatically from existing records.

AI Applications for Pavement Management

Pavement field data collection is a big challenge to transportation agencies due to the size of the pavement networks and the limited inspection resources. Inspections performed at the right time are crucial to formulate preventive maintenance programs. In 2021, ASCE reported that 43% of the pavement network is in poor or mediocre condition (ASCE, 2021b).

Traditional pavement data collection methods are time-consuming, expensive, and subjected to human error. This has led to explore the possibility of using AI applications in pavement management practices including data collection, condition assessment, performance modelling, and funding prioritization.

Pavement management areas that have attracted the most for AI applications are distress detection, interpretation, and prediction model development. For example, deep learning is an AI method that trains a computer algorithm using large data sets populated with existing knowledge. In this method, the AI algorithm continues teaching and correcting itself using training generated data. As new data sets are curated and recursively provided to the algorithm, confidence and knowledge of the results may far exceeds the subjective and limited capacity of a single field human expert (Goodfellow et al., 2016). In pavement management practices, algorithms can be trained using machine learning techniques on existing data sets of pavement condition, crash history, pavement strength, and historical maintenance trends. This AI methods provide the condition fingerprint for a pavement section and predicts its likelihood of failure in the future.

With AI and computational advancements, it is possible to identify pavement distresses including potholes, cracks, and edge breaks. Deep learning techniques are applied to recognize distresses from visual data (e.g., photos and videos). CrackNet is an example of a deep-learning model used to identify cracks on pavements as shown in Figure 4 (Zhang et al., 2017).

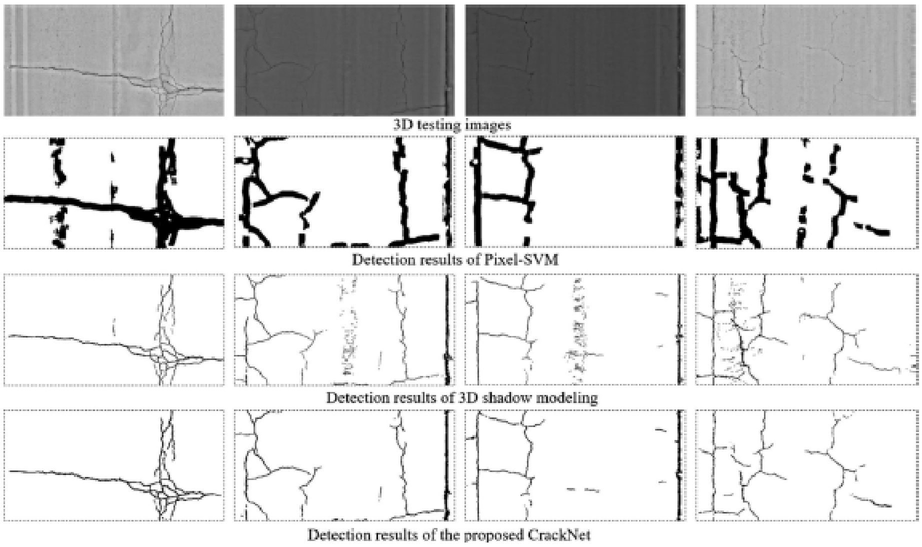


Figure 4. Example of CrackNet pavement distress identification images (Zhang et al., 2017).

U-HDN is another example of an automatic crack detection algorithm (Fan et al., 2020). U-HDN fuses "multi-scale features in encoder-decoder network based on U-net". Figure 5 shows the U-HDN architecture that consists of three components: U-net architecture, multi-dilation module (MDM), and hierarchical feature (HF) learning module. U-net models perform semantic image segmentation The U-net architecture was redesigned to implement end-to-end training with zero-padding during each convolution and up-convolution processes. The MDM module learns crack features of multiple context sizes and the HF learning module performs crack detection.

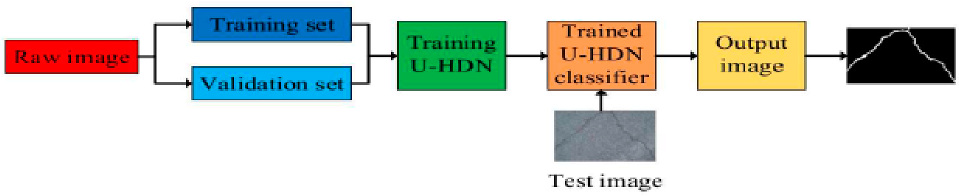


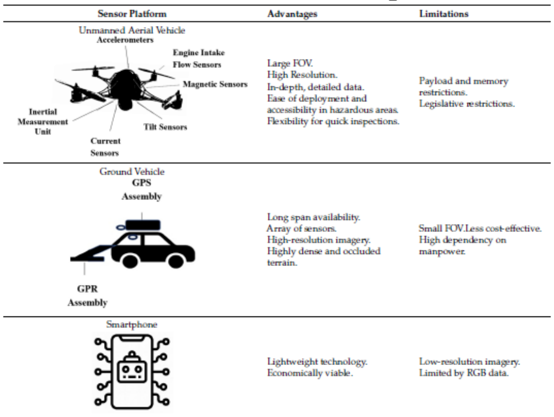
Figure 5. U-HDN methodology for crack detection(Fan et al., 2020).

The usage of thermal images for the automatic detection of cracks has also been investigated since "the surface temperature distribution pattern is directly related to the pavement crack profile, which can be used as an indicator of crack depth"(Chen et al., 2022; J. Golrokh et al., 2021).

The International Roughness Index (IRI) is another measure to evaluate the functional pavement performance. IRI is one of the major parameters used for treatment selection criteria in pavement management practices. An example of AI applications to forecast the IRI is the AdaBoost regression (ABR) model develop by Wang to improve the IRI prediction using records from the Long-Term Pavement Performance (LTPP) database. This AdaBoost algorithm improves ability of AI algorithms through continuous self-training (Wang et al., 2021).

Challenges of AI Applications for Road Asset Management Practice

The major challenge is to integrate AI applications into daily asset management practice. For asset inventories, there are several AI platforms for data collection ranging from remote sensing techniques (e.g., Unmanned Aerial Vehicle) to ground vehicles, and smartphones; each platform has their own advantages and limitations as shown in Figure 6.



Sensor Platform	Advantages	Limitations
Unmanned Aerial Vehicle Accelerometers Engine Intake Flow Sensors Magnetic Sensors Inertial Measurement Unit Tilt Sensors Current Sensors	Large FOV. High Resolution. In-depth, detailed data. Ease of deployment and accessibility in hazardous areas. Flexibility for quick inspections.	Payload and memory restrictions. Legislative restrictions.
Ground Vehicle GPS Assembly GPR Assembly	Long span availability. Array of sensors. High-resolution imagery. Highly dense and occluded terrain.	Small FOV.Less cost-effective. High dependency on manpower.
Smartphone	Lightweight technology. Economically viable.	Low-resolution imagery. Limited by RGB data.

Figure 6. AI platforms for asset data collection (Ranyal et al., 2022)

AI techniques are relatively new for road asset management, and they have not been fully implemented to support the entire process. AI applications can be integrated to existing condition assessment and performance modelling methods as described in the examples presented in this paper. However, the integration of AI techniques for maintenance and rehabilitation treatment selection to support short- and long-term planning and management of road assets requires further development.

AI applications might also assist to identify vulnerable road infrastructure assets due climate change scenarios. Chang proposed an asset management framework to assess the risk of infrastructure failure as result of extreme climate events. The asset management framework blends performance models with risk assessment and climate models (Chang et al., 2021). AI can enhance data collection, condition, and risk assessment methods described in this framework as shown in Figure 7.

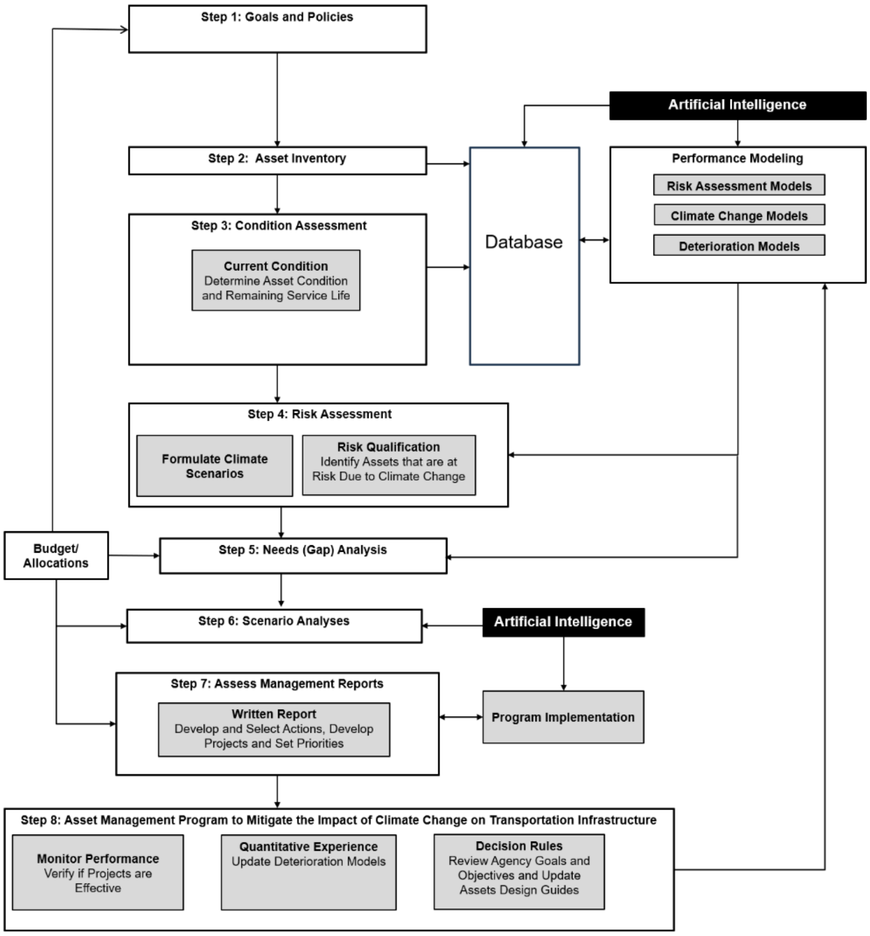


Figure 7. Transportation Asset Management Risk-based framework (Adapted from Chang et al., 2021).

Final Summary

In combination with existing expert knowledge, AI leads to a deeper understanding of the asset network performance. Therefore, AI applications can regulate, assimilate, and centralize asset data to provide a holistic assessment of road network conditions. At present, many AI applications are available for data collection, analysis, and interpretation but their full integration into road asset management practices is still in progress.

The standardization of AI applications for road asset management is required to provide a framework for consistent, efficient, and effective practices that drive innovation. AI can be used to develop and sustain strategic and operational asset management programs. The proper use of AI applications aims to improve current practices to preserve road infrastructure in a SGR by contributing to optimize time and resources through the entire road asset management process.

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