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The Use of Machine Learning, Computational Methods, and Robotics in Bridge Engineering: A Review

Parankush Koul[a,*]

[a] Department of Mechanical and Aerospace Engineering, Illinois Institute of Technology, 3201 South State Street, Chicago, 60616, Illinois, United States of America

ABSTRACT

In this review paper, the applications of machine learning, computational methods, and robotics to bridge design are considered to help improve structure integrity and resilience. It describes a variety of computational methods, including finite element analysis (FEA) and computational fluid dynamics (CFD), that have been used to calculate failure modes and evaluate the dynamic behavior of bridge structures in extreme conditions, such as earthquakes and floods. It also highlights robotics' potential to streamline inspection techniques, showing new robotic systems for effective bridge monitoring. Additionally, it points out issues related to data shortages and implementation difficulty and presents future research priorities, such as the need for powerful machine learning algorithms and the use of Internet of Things (IoT) solutions for real-time monitoring. In summary, the paper highlights the life-changing impact of these technologies on the safety and reliability of bridge systems.

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1. Introduction

Machine learning, computation, and robotics combined have revolutionized so many disciplines that bridge engineering does not have any place. In recent years, these technologies have increasingly been used to design, monitor, service, and inspect bridges. Machine learning is a subset of artificial intelligence (AI), and it uses algorithms that can look at enormous data sets, learn from them, and make inferences or decisions based on them [1]. With this feature, engineers can measure structural health with greater precision and accuracy, which increases the life-cycle safety of bridges.

Computational tools such as numerical simulations and optimization techniques are used to develop and analyze bridge systems. They allow engineers to simulate advanced behaviors with multiple load loads and make better design decisions [2]. Combining computing hardware with machine learning algorithms, engineers can produce predictive maintenance algorithms to increase the service life of bridges at reduced costs and operating times [3].

The history of bridge engineering is shaped by robotics, too. Thanks to the use of robotics, automation has become

* Corresponding author. Tel.: +1 (630) 341-7082; e-mail: pkoul2.iit@gmail.com.

possible for automatic inspection in real time and early detection of any potential problems in bridge structures [4]. These robots could even do something dangerous or challenging for human inspectors, like navigating narrow hallways or performing inspections in severe weather.

The combination of machine learning, robotics, and computation improves the quality of bridge tests as well as reduces administrative work in the engineering industry [5]. Keeping pace with this interdisciplinary process, the new best practice in bridge engineering will be safer, more effective, and more predictive. Thus, an exhaustive review of applications, limitations, and future challenges of these technologies in bridge engineering is needed.

Overall, combining machine learning, computational techniques, and robotics in bridge engineering is a revolutionary step toward better design, repair, and management of bridge infrastructure and is therefore an emerging field of research and application [6].

2. Applications of Machine Learning in Bridge Engineering

Structural Health Assessment: Machine learning algorithms are used to use the real-time data from bridge sensors to monitor the bridge's health and integrity. This way it can be used to catch problems before they become more severe.

Bridge Inspection and Condition Forecast: Machine learning algorithms are used to optimize bridge inspection and condition forecast models. By considering historical inspection data, these algorithms will predict possible future states, saving time on maintenance and money.

Reinforced Concrete (RC) Bridge Design and Inspection: Machine learning technology is applied in RC bridge design and inspection. These procedures help in resilient design decisions and accurate inspections [7].

Wind Engineering: Machine learning models in bridge wind engineering are used to model the impact of wind loads on bridges. It is an application that is very important for keeping bridges safe and stable in the face of changing wind conditions.

Load Capacity Rating: Decision trees and random forests are used to rank bridge populations on their load capacity. This application optimizes the usage by giving reliable estimations of current bridges' load-bearing capacity.

Time Series Prediction: Machine learning is used to implement time series prediction methods in coastal bridge engineering to be proactive based on time-series trends [8].

Bridge Pier Scour Prediction: Machine learning tools can help in scour around bridge piers by going through all models' reviews. This information is essential for keeping bridge foundations in excellent shape and avoiding catastrophic erosion failure [9].

Monitoring Technology Selection: Use case of concrete and steel bridge structural health monitoring (SHM) using machine learning infers monitoring technologies. This technique of tuning gives accurate data collection and analysis for structural evaluation.

3. Applications of Computational Methods in Bridge Engineering

Computational tools like FEA and CFD play an important role in bridge design in terms of design cost, safety, and performance. Below are some of the primary uses of these techniques:

3.1. Applications of FEA in Bridge Engineering

FEA is also very widely used in bridge design as it can simulate sophisticated geometries and behavior of materials under different loads. Key applications include:

- Structural Design: FEA permits you to model bridge structures in detail to determine the response to dead, live, wind, and seismic loads. This facilitates discovering stress points and failure modes.
- Design Optimization: FEA can be used to optimize bridge designs through material and geometry selections in order to obtain the most cost-effective structure meeting safety and performance standards at a minimal material usage and cost [10].
- Preliminary Evaluation of Existing Bridges: FEA plays an important role in evaluating existing bridges for structural integrity. Engineers can mimic the condition and stress and then suggest reinforcement or repair where needed [11].
- Construction Simulation: FEA can simulate the building of the bridge to enable engineers to predict how different ways or sequences of construction might affect its performance [12].

3.2. Applications of CFD in Bridge Engineering

CFD is required to determine the flow behavior around bridges. Key applications include:

- Wind Load Simulation: CFD is used to evaluate the impact of wind on bridge stability and performance. Simulating wind over bridge models will help designers discover aerodynamic properties and design bridges to deal with the heaviest wind [13].

- Hydrodynamic Impact: For bridges over the ocean, CFD helps in modeling the hydrodynamic effects of waves and currents so that the bridge can resist these environmental stresses [14].
- Scour Analysis: The scour around the piers and foundations of bridges, driven by the flow of water, can be calculated using CFD, important for the bridge's stability.
- Thermal Impacts: CFD can also simulate the thermal impacts of materials on bridges based on environmental factors and help determine potential expansion and contraction problems that can weaken the structure.

4. Applications of Robotics in Bridge Engineering

For bridge engineering, robots contribute to the increase of productivity, safety, and precision in many activities. Below are the major robotic applications in this context.

- *Bridge Deck Construction*: Robots are used to automate the construction of bridge decks, with more accuracy and a shorter time to build [15].
- *Testing and Inspection*: The bridges are now increasingly tested and inspected by robots, which provide non-destructive testing methods that can evaluate structural integrity without destroying it [16].
- *SHM*: Intelligent robotic devices perform the continuous SHM and provide instantaneous data and information about the functioning and state of bridges [17].
- *Bridge Automation*: Roadside robots enable bridge automated inspections with much faster and more accurate assessments compared to the manual method [18].
- *Inspection data collection*: Robotic technology is providing better data collection solutions in robot bridge inspections to perform more effective and detailed analysis [19].
- *Robust Robot Selection for Restoration*: Genetic algorithms are employed to choose robotics best suited for restoration of bridges and provide optimal robotic solutions according to requirements [20].
- *Non-destructive Inspection*: Robot platforms armed with the best sensors and algorithms perform non-destructive inspection of bridges that allows thorough inspection without degrading the structure [21].
- *Cable Inspection Robots*: Cable-stayed bridge inspection robots can also monitor the critical elements, such as cables, and lead to an increase in maintenance operations [22].
- *Smart Material Adoption*: Robotics, along with smart materials, are emerging as major parts of construction engineering, enabling new designs and construction of bridges [23].

5. Industrial Case Studies for the Application of Machine Learning, Computational Techniques and Robotics in Bridge Engineering

5.1. Applications of Machine Learning in Bridge Engineering

Machine learning has been used in various ways to improve bridge engineering performance, stability, and safety.

- AMC Bridge: It offers software development solutions like machine learning solutions in bridge design. They use AI to simplify operations and process quality, allowing them to get the most out of data and optimize engineering processes [24].
- Rowan CREATES: They are exploring machine learning methods for structural health assessment of bridge infrastructure in highly seismically active areas. This program seeks to enhance the resilience of bridge constructions through rapid decision support tools that use predictive analytics [25].
- Imetrum and University of Exeter Collaboration: a project that creates a new technology for long-term bridge condition monitoring via machine learning. The technology also has intelligent features that automatically interpret data, report problems, and predict potential issues of condition in the future, thus saving on maintenance expenses and improving safety [26].

5.2. Applications of Computational Techniques like FEA and CFD in Bridge Engineering

The computational methods of FEA and CFD are used to analyze and optimize bridge designs for safety and efficiency.

- *DH Glabe & Associates*: DH Glabe & Associates apply FEA to the structural analysis of bridges. Their engineers compute complicated bridge structures for load-bearing conditions such as wind and earthquakes using sophisticated software such as LUSAS [27].

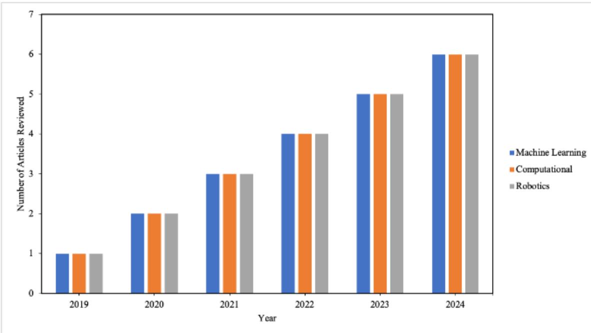

Fig. 1. Articles reviewed (2019-2024) for applications of machine learning, computational techniques and robotics in bridge engineering.

- *Predictive Engineering*: They are quite proficient in using FEA for bridges and other projects. They consider the stress, vibration, and fatigue effects needed to prevent or prolong the life of bridges [28].
- *Resolved Analytics*: This company uses CFD modeling to model scour and erosion at bridges. As they model fluid dynamics, they can predict erosion that could compromise bridge foundations to enhance design and maintenance plans [29].

5.3. Applications of Robotics in Bridge Engineering

This trend of using robots to improve productivity, tackle labor issues, and make bridge construction safer continues.

- *Advanced Construction Robotics*: They've created TyBot, a robot for rebar tiedown in bridge construction. TyBot ties up to 1,000 intersections per hour, which is an impressive savings in labor and keeps workers away from dangerous situations at the site [30, 31].

- *Autodesk and USC Collaboration*: Autodesk collaborated with USC during the Arroyo Pedestrian Bridge Project in Los Angeles, which involved using a robotic arm to raise and install special steel girders for welding. Such cooperation among human and robot hands simplified the manufacturing of this complex design.

- *MX3D*: A Dutch firm that's innovating with 3D printing of bridges. They built a 3D-printed steel bridge by industrial robots, which demonstrates new construction technologies and will contribute to sustainability through reduced material waste [32].

6. Literature Review on Applications of Machine Learning, Computational Techniques and Robotics in Bridge Engineering

The number of articles covered for the applications of machine learning, computational techniques and robotics in bridge engineering in this review are shown in Figure 1 from 2019 through 2024.

6.1. Leveraging Machine Learning for Optimized Bridge Design, Adaptive Smart Infrastructure, and Predictive Maintenance in Dynamic Environmental Conditions

Table 1 below shows a quantitative distribution by publisher of the number of articles related to machine learning advancements in bridge engineering.

Table 1
Number of articles from different publishers reviewed for advancements of machine learning in bridge engineering

Publisher	Number of Articles Reviewed
Springer	5
Elsevier	4
IEEE	2
MDPI	2
SPIE	2
ASCE	1
IOP Publishing	1
Sage Journals	1
Structurae	1
Wiley	1
Zenodo	1
Total	21

Mathern et al. (2019) designed a model using AI and machine learning to design bridges that are sustainable and buildable to accelerate structural decision-making and improve the environmental impacts through fast design evaluation [33]. In contrast, Pan et al. (2020) focused on conditional infrastructure evaluation of massive infrastructure such as high bridges with deep learning and specifically convolutional neural networks (CNNs). This research used satellite images to improve the feature extraction for safety analysis and showed that AI could be applied to continuous spatial and temporal infrastructure health monitoring [34]. Moon et al. (2020) used recurrent neural networks (RNNs) and active learning to extract damage objects from inspection reports for bridges, using Named Entity Recognition (NER) to automated extraction of entities caused by damage. Such automation enabled more reliable and timely maintenance programs that made structural integrity calculations more accurate [35].

Xu et al. (2021) covered all the machine learning use cases in construction, from shallow to deep learning. They showed how site monitoring, automatic structural defect detection, and predictive maintenance can make construction and infrastructure work safer, more efficient, and more structurally sound [36]. Nguyen (2021) was interested in material evaluation on bridge spans by using a data-driven method with a new viscosity resistance coefficient (IC), deep learning, and balancing composite motion optimization (BCMO) to investigate material performance and safety in bridges in Ho Chi Minh City. It was shown that IC values calculated from real-time vibration data could be used as an indicator for long-term structural monitoring [37]. Meanwhile, Moon et al. (2021) used artificial neural networks (ANN) to estimate dynamic displacements in bridges during heavy traffic. They used the correlated measured strains with displacement data to confirm the performance of the ANN model in predicting structural responses to loads in real time, enabling more responsive smart bridges [38].

The paper by Wang et al. (2022) used a gray neural network for designing recycled concrete bridges with sustainability and recycling in mind by making predictions of durability. In this study, we observed that the AI algorithm improved construction control by predicting the longevity of recycled concrete bridges to encourage green bridge design [39]. Meanwhile, Kumar et al. (2022) built a modified CNN for bridge condition measurement using a large dataset from the National Bridge Inventory. Their model with the Firefly algorithm to improve feature selection, predictability of 97.49%, which was a high improvement over the regular CNN model, showed that machine learning can be applied to adaptive infrastructure monitoring without physical inspection [40]. In contrast, Entezami et al. (2022) implemented a three-stage machine learning system for SHM for damage detection in environmental uncertainty with very limited sensor information. Using autoregressive spectra, log-spectral distance, and auto-associative neural networks (AANN), they controlled for environmental perturbations and performed accurate damage quantification on rarely seen structures [41].

The article by Zhou et al. (2022) concerned creating maintenance policies with the best possible policy by modeling bridge component degradation. This method used Q-learning algorithms coupled with matrix updates in real time and was verified by simulating a simple supported beam bridge and a cable-stayed bridge—far superior to the existing methods in making dynamic decisions on larger bridge designs [42]. Dolui et al. (2023) used machine learning classifiers—one such being a decision tree—to compute bridge health from galfenol-based magnetostrictive sensors. With structural vibration converted to electrical signals with an accuracy of 98.72%, this technique showed the effectiveness of connecting sensor data with machine learning to give an accurate, live structural health report [43]. Giglioni et al. (2023) took the lack of labeled data for damage detection and applied domain adaptation within a transfer learning framework. This approach relied on vibration measurements and damage features by domain to pass health-state labels from one structure to the next, proven by testing it on the Z24 and S101 bridges, and was suitable for sparse data [44].

Xie et al. (2023): machine learning applied for severe wind conditions to construction of fast railway bridges over typhoon zones with safety and proactive action via the Back Propagation-Genetic Algorithm model for wind speed prediction. This model was practical as it related actual wind measurements to predefined standards and so supported adaptive building practices [45]. Meanwhile, Ghafoori et al. (2023) leveraged historical bridge condition information using a machine learning framework for bridge maintenance optimization. They modeled degradation through random forests and linear programming to forecast it, prioritize maintenance resources, and deliver maximum infrastructure performance under budget constraints [46]. In contrast, Tai et al. (2023) focused on the economic cost minimization of stochastic optimization algorithms for cable-stayed bridge designs. They proposed two stochastic conjugate gradient algorithms—Modified Armijo and Modified Weak Wolfe-Powell line search algorithms—which improved global convergence and robustness in minimizing construction cost under uncertainty [47].

Zhang et al. (2024) addressed wind-bridge dynamics and applied machine learning for wind field simulation and aerodynamic control to refine insights on wind-induced bridge vibrations and make design responses to changing winds more responsive. Similarly, Nguyen et al. (2024) using ANN and adaptive neuro-fuzzy inference systems (ANFIS) for SHM of Dbica railway bridge produced predictive precision (up to 85%) in diagnosis of dynamic bridge behavior, thus improving maintenance practices and lowering failure probability [48]. Bai et al. (2024), by contrast, focused on the conceptual design of bridges, automating beam type choice with graph neural networks (GNNs) via AutoDis Graph Ontology Attention Matching (AGOAM). This change dramatically accelerated and optimized design choices by mapping attribute interactions to structural demands, a revolution in automated, scalable conceptual design [49].

Yang, Wang, and Nassif (2024) studied the environmental causes of bridge decay by applying XGBoost to condition predictions of RC bridge decks and identified age, freeze-thaw cycles, and rain as major factors contributing to decay. Their result confirmed that feature weighting supports efficient resource allocation for predictive maintenance [50]. In contrast, Gunderia et al. (2024) were focused on sustainable predictive maintenance with different AI-based models such as ANN and CNN. They suggested a combined ANN, CNN and life cycle assessment-based integrated model for maintenance best practices based on sustainability in prediction [51]. Giglioni et al. (2024) adapted transfer learning as a domain adapter to enhance damage classification and generalized machine learning algorithms from well-labeled data to unlabeled data over bridge networks. This was proven to work on prototype bridges, improving damage classification and compute speed of SHM with inadequate labeled data [52].

6.2. Leveraging Computational Techniques like FEA and CFD in Bridge Engineering: Predicting Failure Modes and Enhancing Structural Integrity for Long-Lasting Resilience

Table 2 presents the number of articles reviewed for computational techniques' advancements in bridge engineering, by publisher.

Table 2
Number of articles from different publishers reviewed for advancements of computational techniques in bridge engineering

Publisher	Number of Articles Reviewed
IOP Publishing	4
MDPI	3
ASCE	2
Elsevier	2
Springer	2
Copernicus Meetings	1
IJIREM	1
Sage Journals	1
Sciendo	1
Structurae	1
Taylor & Francis	1
TU Delft Open Publishing	1
University of Toledo	1
Total	21

In the study by El-Ghandour and Foster (2019), FEA and Multibody Systems Dynamics (MSD) were combined to explain the bridge approach problem in railroad systems, that is, the detrimental effects of abrupt stiffness changes at bridge entrances. They found that installing an inclined concrete slab greatly reduced stress and vertical deformations, making railroads safer and more durable [53]. In contrast, Izvekov et al. (2020) focused on a metallurgical crane's girder using FEA to detect the zones of failure at static loads. Their probabilistic model elucidated important risks for the integrity of the girder, which was a precursor to appropriate reinforcement, pointing towards the necessity of continuous maintenance to extend service life [54]. Sharma and Guner (2020) were pioneers of this field when they proposed a nonlinear FEA approach for the strength analysis of deep bridge bent caps that are typically placed under loads beyond their design limits. Their findings showed more accurate prediction of cracking and modes of failure than the older approaches, which gave bridge engineers a strong basis for measuring deep concrete components [55].

Liu et al. (2021) devised a coupled CFD-FEM simulation technique for bridge fire performance and showed how previous tests had often missed the dynamic interactions between heat and structure. Their study showed that the coupled method accurately predicted vulnerability under fire conditions—and hence safety studies and design guidelines for bridges that are vulnerable to fire [56]. Sengsri and Kaewunruen (2021) tested the local failure modes and critical buckling loads of a meta-functional auxetic sandwich core for composite bridge bearings. They used three-dimensional finite element models, which they verified using experimental results, and they showed that the novel auxetic design led to a major increase in crashworthiness and structural strength through local buckling failures that could occur before yielding when compressed [57]. Ko (2021) looked at the seismic behavior of RC single-column bridge bents under near-fault ground movement. By using nonlinear fiber finite element models without bond-slip effect, Ko's study accurately predicted the modes of failure; modeling without it could overestimate the strength of structures [58].

Zhu and Wu Tian (2022) applied CFD to the main girder of cable-stayed bridges to study vortex-induced vibrations (VIV). Their numerical models, derived using a bidirectional fluid-structure coupling process, had shown the importance of wind loads on bridge safety in construction and operation by modeling the vortex vibration behavior of the main girder [59]. Parallax-style, Yoneda et al. (2022) focused on a 3D finite-element modeling generation system with data processing platform (DPP) for fatigue evaluation of reinforced concrete bridges. Their results showed the DPP can be used to improve the structural model's predictive power under various stress conditions, resulting in a more accurate and effective modeling of real bridge structures compared with conventional modeling [60]. Meanwhile, Tang et al. (2022) carried out a reliability-based vulnerability study of bridge piers damaged by debris flow using FEA to simulate fluid-solid effects. Their study—through a finite element model and impact forces using a two-phase flow theory, distilled into an easy-to-understand 2D model—determined critical velocity and failure modes of bridge piers in debris flows and helped provide safer infrastructures [61].

Quan et al. (2022) conducted a comprehensive study of the seismic mitigation of a long-travel high-speed railway continuous beam bridge by using FEA to model the behavior of the bridge under earthquake loads with viscous dampers as an essential design element. They discovered that the dampers acted as good absorbers, with damping rates up to 81% on some seismic waves, which enhanced structural stability and dynamic response [62]. Duan and Tao (2023), meanwhile, considered flood resilience using both CFD and Fluid-Structure Interaction (FSI) modeling to analyze flood damage to bridge piers and came up with the best design for piers in flood areas. Their parametric analysis found that wave height and speed were critical parameters that determined structural integrity, which is important for the infrastructure resilience to floods [63]. Similarly, Fleit et al. (2023) studied flows and local scour in a multiphase hydro- and morpho-dynamic numerical model (REEF3D) of submerged bridge decks. They made it clear that the transport of sediment was a significant factor and backed up their model with experimental evidence, highlighting the challenge of modeling scouring [64].

Kaushal et al. (2023) dynamically simulated bridge geometry with ANSYS FEA and observed natural frequencies and mode forms that highlighted zones at high deformation and potential resonance. Their result called for the development of damping and vibration damping controls for long-term stability [65]. In contrast, Malekghaini et al. (2023) used Bayesian model updating to bridge FEA and data from the real world to identify damage in bridges using a robust model validated on synthetic data and adapted to the real structure. Their findings showed that the framework was useful in determining damage, and so SHM systems became dramatically better [66]. Meanwhile, Dong et al. (2023) focused on the seismic failures of river-spanning girder bridges in the presence of soil liquefaction. Their two-dimensional finite element model revealed that soil liquefaction influenced the response to an earthquake with increased displacements and deformation of important elements, which increased the risk of bridge collapse during a seismic event [67].

Zhu et al. (2024) did a detailed CFD simulation to quantify aerodynamic forces on tall cars crossing the Queensferry Crossing Bridge in different wind loads. The truck's ability to withstand aerodynamic instability, they discovered, was particularly at risk, and hence vehicle dynamics must be taken into account in bridge design to maximize safety [68]. In contrast, Petruccelli et al. (2024) dealt with the hydrodynamic loads acting on bridges in flood events and used CFD to calculate stress conditions and carrying capacity. Their simulations offered important details on drag and lift coefficients for several different submergence scenarios that were used to devise strategies for strengthening bridges against floods [69]. Han and Wang (2024) used FEA to explore failure modes of rock slopes around bridge anchorage foundation pits. They combined limit equilibrium and finite difference techniques to discover major causes of slope failure, such as rain and earthquakes, providing an overview of slope mechanics in vulnerability geological systems [70].

Fusco et al. (2024) were focused on an efficient beam finite element model of the nonlinear structure of existing prestressed RC bridges. They applied a damage-plasticity model on OpenSees, and they showed how their model saves computing time without sacrificing accuracy during inspections [71]. Jia et al. (2024) examined seismic faulting for a simple-supported beam bridge by modeling it using a three-dimensional FEA model in LS-DYNA under real-world conditions. The key variables they found, for example, fault-crossing angle and ground surface permanent rupture displacement, indicated that the position of the bridge in relation to seismic faults had a significant effect on stability [72]. Zhu et al. (2024) investigated the dynamic response of a cable-stayed pipe bridge in seismic loading using a large-scale FEA simulation in ANSYS Workbench, including fluid-structure dynamics. They showed that the FSI approach is more successful at modeling the dynamic behavior of the bridge [73].

6.3. Enhancing Bridge Safety: The Role of Robotics in Inspection Engineering

Table 3 presents the number of articles reviewed for robotics' advancements in bridge engineering, by different publishers.

Table 3
Number of articles from different publishers reviewed for advancements of robotics in bridge engineering

Publisher	Number of Articles Reviewed
IEEE	9
ASCE	2
Emerald	2
MDPI	2
arXiv (Cornell University)	1
ASNT	1
Intelligence Science and Technology Press Inc.	1
SPIE	1
Springer	1
Wiley	1
Total	21

Charron et al. (2019) addressed accessibility and data collection by using mobile ground and air robots. These results showed more direct access to difficult-to-access locations and more consistent data, and consequently, bridge inspections became more efficient than before. Potenza et al. (2020) developed a novel technique using unmanned aerial vehicles (UAVs) with new image processing methods. This method was able to quantify defects and shows that automated inspection and defect classification are much improved. The results showed the method was robust, in particular when it came to finding repeatable flaws in the infrastructure of the Italian railway network [74]. Wang et al. (2020) scanned steel box girders using a deep learning computer vision tool. It had a predictive accuracy rate of more than 90% in detecting structural decay, which indicates the potential of deep learning in bridge inspections [75].

Yan et al. (2021) talked about UAV automated bridge detection, a new path planning algorithm for UAV flight paths optimized to move through more challenging environments, such as pier jams. Their simulations showed successful full-coverage detection of bridges, proving the UAVs performance in infrastructure monitoring [76]. Gallegos Garrido and Sattar (2021), on the other hand, built SIRCAUR, a self-assisted wall-climbing robot that inspects RC buildings. They focused on improving adhesion forces through simulation and experimental testing so that the robot carried ground-penetrating radar (GPR) for corrosion and concrete degradation detection. These tests proved that the robot was capable of performing accurate and safe inspections, and therefore SHM became better [77]. Meanwhile, Lin et al. (2021) studied using flying robots to do full bridge inspections, automating the entire process of visual information capture, 3D mapping, destructibility detection, analysis, and reporting. They discovered that drones have dramatically increased the inspection speed and quality of data by picking up defects with high sensitivity and avoiding human error [78].

Ahmed et al. (2022) presented a bicycling robot designed for maintenance on steel-reinforced bridges. The sophisticated steel defect detection system was built using deep learning techniques such as LinkNet and UNet. Their study primarily focused on the robot's strength in operating through high-pressure steel buildings and showed promising results in defect detection by fully testing its visual sensor system [79]. In contrast, Zheng et al. (2022) launched the CCRobot-IV, a climbing robot that climbs over obstructions during cable inspections, which improved operational safety substantially. It was built with a quad-ducted propeller system so that the robot didn't need friction to run, carrying heavier loads while traversing rough terrain. It passed its navigation and inspection tests with success through experimental and field tests, which also prove to be useful [80]. Similarly, Motley et al. (2022) worked on a high-powered multi-steering climbing robot with a novel adhesion mechanism and different steering modes for greater control and stability while inspecting steel bridges. The design of the robot was subsequently proven, and they further showed how they could make substantial improvements in inspection methods in the industry [81].

Li et al. (2022) built a circularly rotating cable inspection robot with elastic suspension that was able to scale taller obstacles and ascend stable on vertical cables. They showed their experiments were able to carry a 12.4 kg payload and maneuver through obstacles without any harm to the robot, demonstrating its practical usage for real-world inspection [82]. In contrast, Gong et al. (2023) explored Building Information Modeling (BIM) and robotic mapping to reduce risk in bridge construction. Their study pointed out how critical it was to keep the industry safe and even used AI-powered nanobots to improve detection of hazards. Results suggested that the integrated model resulted in stricter on-site safety management solutions [83]. Meanwhile, Hoxha et al. (2023) were focused on a robotic system for mapping subsurface defects using impact-echo and GPR. They were impressed by the speed of the dual-sensor method, which collected data faster than expected and offered complete evaluations of concrete buildings [84].

Gucunski et al. (2023) focused on condition evaluation of RC bridges through nondestructive evaluation (NDE). They found that robots can speed data collection and safety for inspection employees, providing better measurements of bridge status and less costly traffic delays during inspections [85]. Alamdari and Ebrahimkhanlou (2023), on the other hand, combined cameras and LiDAR cameras to develop a novel method of crack detection that combined high-resolution photographs and 3D point clouds. Their results showed a better detection rate and faster data acquisition, and in the end, a more detailed picture of structural integrity than other approaches [86]. Popli et al. (2023) created Robotics-Assisted Onsite Data Collection (ROAD), a system that used deep learning to detect real-time cracks. In their research, they demonstrated that Xception was a better algorithm than others, with more than 90% accuracy and validation of the system in a variety of field conditions [87].

In the paper of Ade-Omowaye et al. (2024), they explored the impact of robotics and automation on engineering and made a literature review on the economic, social, and ethical implications of these technologies for the digital economy. Their results revealed the possibilities of robotics to enhance the efficiency and safety of engineering based on classic inspection issues [88]. In contrast, Lyu et al. (2024) built a wall-climbing, heavy-duty robot to inspect the concrete masonry of huge bridges. They figured out a way to get a similar adsorption force equation to maximize the capacity to carry load and then ran some tests to confirm that the robot was working as it should. The findings showed that this new design made inspection much safer because it accesses hard-to-reach areas without introducing the risks associated with manual inspection [89]. Pham et al. (2024) designed a compact analog magnetic sensing system for structural inspection of steel bridges. Their test was to engineer synthetic cracks in a steel test plate and then find that, coupled to robotic platforms, the sensor system allowed for the real-time detection of multiple kinds of cracks. This progress further improved the safety and maintenance of steel buildings [90].

Choi et al. (2024) tried to optimize visual inspection with a mixed reality system that used gaze tracking. It was shown that inspectors could directly view holographic data in real time, which improved the decision-making on complex inspections with higher quality outcomes than traditional techniques [91]. Pokhrel et al. (2024) sought to automate concrete bridge deck inspections with UAS and machine learning. This paper demonstrated CNNs and Vision Transformers (ViTs) successfully to find damage with 97% accuracy of the ViT model as compared to CNN. This development made it clear that the combination of UAS and machine learning could yield more accurate and efficient inspections [92]. Finally, Bian et al. (2024) analyzed all the robots currently used for cable inspections and suggested a new non-destructive sensor. This inspection machine that measured cable corrosion efficiently used two data input modules to provide better inspection precision and speed. The study showed that the proposed device exceeded the limitations of the existing techniques and provided a quicker and more accurate measurement of the bridge cable state [93].

7. Challenges and Future Scope in Bridge Engineering

In this article, some problems and opportunities related to applying machine learning, computing, and robotics in bridge engineering are discussed. Here are the main ones:

7.1. Challenges

- Data Availability: One of the biggest bottlenecks is that there is not enough labeled data to train machine learning models on. This dearth can interfere with the detection of damage and maintenance predictive approaches, as in the application of domain adaptation to counteract this.
- Explicitness of Implementation: Integrating new technology like robotics and machine learning in the existing engineering process is tricky. Engineers may struggle to translate old methodologies to implement these new tools, and the adoption rate might be slower.
- Cost and Ethical Issues: When it comes to economic issues associated with the use of robotics and automation in bridge inspection, questions surrounding the cost, and the elimination of human jobs arise. Questions about ethics in the deployment of autonomous systems in critical infrastructure also have to be settled.
- Environmental Issues: Dynamic environment variables influence bridge dynamics and are an obstacle to predictive maintenance models. Weather conditions and other natural disasters make it hard to calculate bridge status and how efficiently repairs were done.

7.2. Future Scope

- More Effective Machine Learning Models: We can next look for stronger machine learning models that can generalize to various bridge types and conditions. That may involve optimizing transfer learning to apply observations of well-observed bridges to assessments of under-observed buildings.
- Embedding of IoT and Real-Time Monitoring: Bridge engineering in the near future may more often include IoT technologies for real-time monitoring. It would provide the data collection and analysis continuously, more early maintenance plans, and better safety precautions.
- Robotics Development: As robotics develops further, we can expect to see even more advanced inspection systems that can do difficult tasks autonomously. That might mean creating drones and ground robots that can work in harsh conditions and make accurate diagnoses of bridge conditions.
- Environmental Concerns: The green credentials are being paid more attention to in bridge design. It can also be investigated in future research to apply machine learning and computations to the optimal maintenance regimes that extend the life of bridges and are sustainable

8. Conclusion

The review paper titled Machine learning, computation, and robotics for bridge engineering provides a detailed description of how these technologies can significantly advance the discipline. The use of machine learning and computational tools, such as FEA and CFD, has been vital to determining the structural behavior and modes of failure of bridges. These techniques allow for more accurate assessments of structural integrity and resilience in diverse environments. This is highlighted as an industry-leading innovation that increases safety and effectiveness when performing bridge inspections by robots. Robots will get into difficult places, eliminating the risks associated with manual inspections and facilitating accurate assessments of bridge conditions. These results point to the necessity of constructing bridge structures with greater durability in dynamic conditions such as earthquakes and flooding. With the use of advanced modeling, engineers can visualize bridge vulnerabilities and develop effective reinforcements. This paper emphasizes the need to continue exploring and developing them to adapt to changing engineering issues. Together, the use of these technologies enhances current practices and also prepares the ground for future innovations in bridge design. Finally, the review recommends a multidisciplinary approach that leverages machine learning, computation, and robotics to design safer, more efficient, and more durable bridges. This bundled approach is vital for resolving the nuances of the needs of contemporary infrastructure in the long term. Overall, the paper clearly demonstrates how these novel technologies can transform bridge engineering and deliver safer and more resilient infrastructure.

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