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A Comprehensive Review of Machine Learning Algorithms for Predictive Maintenance in U.S. Bridge and Highway Infrastructure to Minimize Economic Disruptions

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Abstract: The aging condition of U.S. bridge and highway infrastructure, combined with rising maintenance backlogs and the economic consequences of unplanned failures, has intensified the need for proactive, data-driven maintenance strategies. The objective of this paper is to address the existing gap by delivering an extensive analysis of machine learning algorithms for predictive maintenance within U.S. bridge and highway infrastructure in recent years, emphasizing their capacity to mitigate economic disruptions. This review synthesizes peer-reviewed studies and agency reports from 2020–2026 to evaluate the application of machine learning for predictive maintenance aimed at minimizing economic disruptions. Using a qualitative review methodology, the study examines machine-learning models used for condition prediction, deterioration modeling, anomaly detection, and maintenance optimization across bridges, pavements, and highway networks. Findings show that tree-based ensemble models, particularly random forests and gradient boosting, consistently deliver the strongest predictive performance for bridge and pavement condition ratings, while deep learning and multimodal vision models excel in automated distress detection from imagery. Emerging research integrates these predictions with optimization routines to support budget-constrained maintenance planning, though most studies remain asset-specific and rarely quantify avoided user delay costs or broader economic impacts. Key challenges include data quality limitations, lack of standardized benchmarks, limited uncertainty quantification, and slow institutional adoption. The review highlights the need for integrated, network-level frameworks that couple machine-learning predictions with traffic assignment, user-cost modeling, and multi-objective optimization to better align predictive maintenance with economic resilience goals. These insights underscore the potential of machine learning to enhance early-stage decision-making, extend asset life, and reduce economic losses associated with infrastructure failures.

Keywords: predictive maintenance; machine learning; bridge and highway infrastructure; economic disruption.

INTRODUCTION

United States (U.S.) bridge and highway infrastructure remains a critical backbone of national mobility and economic productivity, yet a substantial share of assets is aging and under mounting maintenance pressure. Recent National Bridge Inventory (NBI) numbers show roughly 35 percent of bridges need major work or full replacement. Almost half sit in “fair” condition and about 6.8 percent are already poor, even after small gains in the last five years (American Road and Transportation Builders Association [ARTBA], 2024; American Society of Civil Engineers [ASCE], 2025). Placed end-to-end, these structurally deficient and fair-condition bridges extend for thousands of miles, and current estimates suggest that more than 400 billion dollars would be required to address the accumulated repair backlog (ARTBA, 2024). This persistent infrastructure deficit persists even as states draw on new federal resources such as the Infrastructure Investment and Jobs Act bridge formula program, where only about half of the currently released funds have been committed to projects, signaling both opportunity and implementation challenges (ARTBA, 2024).

The real damage from poor maintenance goes way beyond cracked concrete and safety risks to having effect on the Economy. When a major bridge fails or stays closed for months, the fallout spreads fast: jobs disappear, regional Gross Domestic Product (GDP) takes a beating, and supply chains get knocked sideways. Scenario analyses of big bridge-and-port shutdowns put the potential GDP losses in the billions, with clear drops in employment and real disposable income across affected areas (Kane *et al.*, 2024). The deteriorating condition of U.S. bridges poses significant safety and economic risks, with recent reports highlighting widespread structural concerns and their potential impact on national logistics and public safety (Kelly, 2024). On a bigger scale, policy reports warn that ignoring these infrastructure shortfalls could strip trillions from U.S. GDP by 2039 (ASCE, 2021). Showing how reliable bridges and infrastructure tend to influence long-term economic strength.

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This pressure is forcing transportation agencies and owners to ditch purely reactive or schedule-driven maintenance towards proactive, data-driven systems that can spot trouble coming and fix it before it becomes a crisis. In the last five to seven years, cheaper sensors, better data handling, and more computing power have sparked a fresh wave of machine-learning research on bridges and pavements. However, most existing approaches remain dependent on periodic inspections and retrospective analysis, limiting their ability to support real time, early stage decision making during infrastructure development.

Studies using NBI and National Bridge Elements (NBE) data, as well as state-level inspections and traffic or climate information, have employed algorithms such as decision trees, random forests, gradient boosting, support vector machines, artificial neural networks, and deep learning architectures to predict element conditions and overall ratings far more accurately than before (Banaei-Kashani & Arens, 2022; Mia & Kameshwar, 2023; Fard & Sadeghi Naeini, 2024; Abu Dabous *et al*., 2025). One standout example pairs random-forest deterioration forecasts with linear programming to plan maintenance over fifty-year horizons while staying inside real budget limits (Ghafoori *et al*., 2024). At the same time, pavement engineers have used spatial AI, ensemble methods, and deep neural networks to track condition indices and distress growth across entire networks, making resurfacing and rehabilitation decisions sharper and more targeted (Majidifard *et al*., 2020; Afridi *et al*., 2025; Milad *et al*., 2025).

Even though some research has been on this topic, the literature is still inconsistent to inform nationally important decisions. First, most studies look at either bridges or pavements on their own, and not enough at how predictive maintenance strategies should be coordinated across whole bridge-highway networks. This is important because failures on one asset can change traffic patterns, put too much strain on other links, and increase economic losses (Han & Frangopol, 2022). Second, machine learning papers often talk about performance metrics like accuracy, F1-scores, or root mean squared error, but they do not usually turn model performance into clear estimates of avoided disruption costs, user delay savings, or macroeconomic benefits. This leaves a gap between technical capability and economic policy relevance (Ghafoori *et al*., 2024; Abu Dabous *et al*., 2025). On the other hand, studies of the economic effects of bridge failures and closures often do not take into account the specific predictive maintenance technologies that could reduce these risks. This makes them less useful for helping people decide how to invest in data-driven monitoring (Alliance for Innovation and Infrastructure, 2024). Third, relatively few reviews synthesize machine learning applications for U.S. bridges and highways under the current regulatory, funding, and data-governance environment, even though national initiatives and state-level digital-twin pilots are rapidly evolving (Shahrivar *et al*., 2025).

These gaps are particularly salient for the emerging vision of smart, data-driven infrastructure monitoring systems designed to reduce premature failures and cost overruns in U.S. transportation projects. Machine learning-based predictive maintenance has the potential to serve as a core component of such systems by transforming heterogeneous data streams into actionable forecasts that inform inspection prioritization, intervention timing, and budg*et al*location. However, to fully realize this potential, we need to have a comprehensive understanding of the algorithms that have been used for predictive maintenance on bridges and highways in the last few years, how they work on real U.S. datasets, what data and institutional barriers they face, and how their outputs can be integrated into decision-making frameworks that aim to reduce economic disruptions instead of just engineering performance metrics (Banaei-Kashani & Arens, 2022; Ghafoori *et al*., 2024; Abu Dabous *et al*., 2025).

The objective of this paper is to address the existing gap by delivering an extensive analysis of machine learning algorithms for predictive maintenance within U.S. bridge and highway infrastructure in recent years, emphasizing their capacity to mitigate economic disruptions. The review combines recent peer-reviewed studies and high-quality agency reports on using machine learning to predict bridge conditions, model the deterioration of highways and pavements, and optimize maintenance. In addition, the paper highlights the need for continuous, data driven technologies in enhancing early stage infrastructure assessment and decision making, which are critical for emerging approaches in construction phase monitoring. It also puts these technical advances in the larger context of the need for infrastructure investment and economic risk.

METHODS

This paper is a review of recent studies on machine learning for predictive maintenance in U.S. bridge and highway infrastructure. It focuses on peer-reviewed articles, conference papers, and agency reports published between 2020 and 2026. The literature was gathered from sources such as Google Scholar, Scopus, Web of Science, and reports from transportation agencies.

Studies were included if they discussed bridges, highways, or pavements, used machine learning for condition prediction or maintenance planning, and were relevant to the U.S. context. The selected studies were reviewed and grouped by topic, including bridge applications, highway and pavement applications, and links to economic disruption. Because the studies used different data, models, and evaluation methods, the findings were summarized qualitatively rather than combined statistically.

FINDINGS FROM LITERATURE

Predictive Maintenance, U.S. Networks and Economic Disruptions

The U.S. has a network of bridges and highways that supports national mobility, freight movement, and regional competitiveness. Recent evaluations of the condition and performance of roads and bridges show that a large number of them are still in bad or mediocre shape and that tens of thousands of bridges need major repairs. This is despite some progress since the early 2020s and new federal funding streams (American Society of Civil Engineers [ASCE], 2025; Federal Highway Administration [FHWA], 2024). These condition shortfalls lead to higher vehicle operating costs, congestion, and reliability losses for users. This is in line with other evidence that investments in transportation and utilities have a big impact on regional economic growth (Hope *et al*., 2025). National estimates say that U.S. drivers spend hundreds of dollars a year on repairs and delays because of bad roads. The backlog of repairs needed for both highways and bridges is still in the hundreds of billions of dollars (ASCE, 2025). In this setting, small changes in how maintenance is planned, prioritized, and scheduled can have big effects on both the economy and the performance of the infrastructure.

The economic effects of unplanned failures or long-term closures on important links show how important it is to stop these kinds of outages from happening in the first place. Studies of major bridge disruption scenarios show that closures that last for months or years can cost the region hundreds of millions to billions of dollars in lost GDP, lower employment and real disposable income, and cause long-term changes in the supply chain (Kane *et al.*, 2024). The Francis Scott Key Bridge in Baltimore fell in 2024, cutting off access to a port that handles tens of millions of tons of cargo every year. This has caused daily economic losses in the tens of millions of dollars when you factor in the cost of port operations, trucking detours, and other logistical issues (U.S. Chamber of Commerce, 2024).

Infrastructure investment studies further show that proactive upgrades in transportation networks yield substantial economic returns, especially when targeted toward high-impact regions (Oduro & Laryea, 2025). Similar assessments of past bridge failures and extended closures emphasize that even when detours are available, increased travel time, higher operating costs and reliability losses impose sizable burdens on households and firms, reinforcing that bridge and highway reliability is inseparable from regional and national economic resilience (Kane *et al*., 2024).

Predictive maintenance provides a means to reduce these risks by shifting from reactive or purely time-based strategies to data-driven regimes that anticipate deterioration and intervene before capacity-reducing failures occur. Sensor-driven structural health monitoring combined with machine learning enables continuous tracking of structural response and exposure, anomaly detection and forecasting of remaining life, offering earlier and more targeted intervention opportunities than periodic visual inspections can typically provide (Sensor Networks Research Group, 2024). Industry and practice-oriented analyses of critical infrastructure suggest that comprehensive predictive maintenance programs can substantially reduce unplanned outages and lower lifecycle maintenance expenditures by emphasizing condition-based actions triggered by data-informed thresholds rather than fixed inspection cycles (Banaei-Kashani & Arens, 2022). At network scale, these capabilities can be aligned with economic objectives by explicitly prioritizing interventions on assets whose failure would impose the largest user delay costs and freight disruptions, effectively treating predictive maintenance as an economic-risk management and resilience tool in addition to a technical optimization instrument (Han & Frangopol, 2022). In the United States, where highways and bridges carry the bulk of domestic freight and remain subject to persistent funding gaps, embedding machine learning-based predictive maintenance into asset-management practice thus has the potential to play a central role in minimizing economic disruptions, extending asset life and improving network-level reliability.

Machine Learning for Bridge Predictive Maintenance

Recent work on machine learning for bridge predictive maintenance has been driven largely by the increasing availability of historical inspection data from the National Bridge Inventory (NBI), National Bridge Elements (NBE) and state-level databases. These datasets provide time-stamped ratings for deck, superstructure and substructure components, along with traffic, geometric and environmental attributes, enabling the development of data-driven models for condition prediction and deterioration forecasting across large bridge portfolios (Banaei-Kashani & Arens, 2022; Mia & Kameshwar, 2023). Numerous studies have utilized multi-decade NBI/NBE records to develop health indices for concrete bridge components and to assess the relative impact of variables such as age, average daily traffic, structural type, and location on deterioration, frequently concluding that traffic loading and age prevail in feature importance rankings, consistent with engineering anticipations (Abu Dabous *et al*., 2025). More recent state- or city-scale analyses using NBI data for Washington, D.C. and state inventories such as MassDOT's have confirmed that compact feature sets drawn from standard inspection fields can support accurate condition-rating models at network scale (FHWA, 2024; Hua, 2025).

A variety of machine learning algorithms have been evaluated for forecasting present or forthcoming bridge conditions within this data framework. Tree-based ensemble methods, especially random forests and gradient boosting implementations, have become very popular because they can find nonlinear relationships, work with different types of data, and give clear measures of feature importance (Ghafoori *et al*., 2024; Abu Dabous *et al*., 2025). Research forecasting bridge health indices or component-level ratings from NBI/NBE data indicates that random forest models frequently exhibit the lowest mean absolute error and root mean square error across various elements, surpassing traditional regression and single-tree models (Ghafoori *et al*., 2024). Simultaneously, NBI-based regional network gradient boosting and XGBoost classifier trained on NBI-based datasets have provided high F1-scores and ROC-AUC scores, with misclassifications concentrated more in adjacent rating classes, which suggest they are effective at ranking structures around critical thresholds (Hua, 2025). Complementary literature has developed feature-selection and deep learning models to predict deterioration, such as feed-forward neural networks and long short-term memory (LSTM) models which use time-varying sequences of inspections to learn time-varying deterioration patterns (Zhu & Wang, 2021). These studies generally find that while deep learning can provide marginal performance gains when sufficient temporal data are available, ensemble tree models remain competitive and often easier to interpret for practitioners.

A key development in the last few years has been the integration of predictive models with maintenance optimization and decision-support frameworks. Ghafoori *et al*. (2024) propose a system that combines machine learning-based predictions of the conditions of concrete bridge elements, which are made using decision trees, random forests, gradient boosting, and support vector machines, with a binary linear programming model that plans maintenance work over a 50-year period to get the best performance from the bridge while staying within the annual budget. In their case study, random forest models yield the most precise condition forecasts, which the optimization module subsequently employs to determine cost-effective maintenance strategies across various budget scenarios, demonstrating how predictive accuracy can enhance long-term performance and facilitate more efficient allocation of constrained resources (Ghafoori *et al*., 2024). Related federal research has expanded this idea by creating machine learning models to predict conditions and costs as part of a larger maintenance optimization system. This system is meant to help highway agencies get the most out of their budgets each year (FHWA, 2024). These contributions collectively illustrate a transition from isolated predictive models to cohesive decision-support tools that more directly incorporate machine learning into bridge management processes.

Recent studies have looked into problems with data quality and modeling that are important for strong deployment, in addition to advances in prediction and optimization. Research on "upstream" data workflows has looked at how missing values, inconsistent coding, and time gaps in NBI data can hurt predictive performance. It has also suggested preprocessing pipelines and feature-engineering strategies to make machine learning pipelines for bridge asset management more reliable (Banaei-Kashani & Arens, 2022).

The application of machine learning to improve the quality of bridge inspection data alone has been studied by other researchers, e.g. by alerting about potential inconsistencies or outliers in inspection data before they are incorporated in deterioration models (Zhang *et al*., 2025). The need to optimize hyperparameters and model calibration has also been pointed out as a crucial aspect of research on concrete bridge deck deterioration, demonstrating that, with careful tuning of ensemble and deep learning models, classification of deck condition states on multi-decade time scales can be significantly enhanced (Zhu & Wang, 2021; Almarahlleh *et al*., 2024). These results indicate that to make predictive maintenance applications work in safety-critical fields, model selection should be accompanied by stringent data preparation, validation and interpretability deliberation to allow agencies to trust and act upon model results. Other safety-critical domains, like next-generation nuclear energy systems, report similar concerns as AI-based predictive maintenance necessitating high-reliability automation, sensor fusion, and diagnostics (Opoku & Adeoye, 2025).

Regarding the aspect of economic disruption, the existing literature on machine learning centered around bridges offers the predictive building blocks but often stops short of quantifiable economic results. Most studies stop at reporting prediction metrics and, in some cases, demonstrating improved maintenance scheduling or budg*et al*location at the bridge or project level (FHWA, 2024; Ghafoori *et al*., 2024). Few explicitly estimate how improved prediction reduces expected user delay costs, freight disruptions or regional GDP losses that would arise from unexpected closures on high-criticality bridges. This gap suggests a clear opportunity for future work, including your own, to couple these emerging predictive and optimization frameworks with economic impact models and network-level criticality assessments so that machine learning-based predictive maintenance can be evaluated and designed directly in terms of minimized economic disruptions rather than only engineering performance metrics.

Machine Learning for Highway and Pavement Predictive Maintenance

Machine learning for highway and pavement predictive maintenance has advanced rapidly in the last five–seven years, driven by the need to move from labor-intensive visual surveys toward scalable, data-driven condition assessment. A significant part of this work is dedicated to predicting the Pavement Condition Index (PCI) and other performance indicators based on traffic, climatic and structural data or image-based distress data, with the purpose of making more timely and cost-effective decisions on maintenance (Majidifard *et al*., 2020; Ashqar *et al*., 2025). Initial analyses with Long-term pavement performance (LTPP) and other data sets in the US revealed that ensemble machine learning models like random forests and support vector machines can predict PCI using standard measures of roughness and surface condition with large coefficients of determination and small error values, compared to traditional regression models and exhibit strong potential to manage pavements at a network scale (Majidifard *et al*., 2020; Afridi, 2021).

This foundation has since been extended to recent municipal and state-level projects which have created practical tools incorporating machine learning into the process of managing pavement. As an example, Afridi (2025) examined machine learning models to forecast street-level PCI over a multi-year horizon of a municipal road network and discovered that ensemble schemes offer strong performance despite unbalanced condition data and suggests a small set of PCI classes to enhance prediction accuracy and practicality in local agencies. Ashqar *et al*. (2025) introduce an open-source software, which categorizes PCI into discrete categories through a set of machine learning algorithms and provides a replicable, inexpensive option to agencies with no proprietary pavement management systems (Ashqar *et al*., 2025). In related work, spatial artificial intelligence methods that combine geographic information systems (GIS) with Bayesian-optimal machine learning models to forecast PCI and detect spatial clusters of bad pavements have been discussed as complementary work to connect predictive analytics with spatially constrained maintenance planning (Milad *et al*., 2025).

A similar body of work uses computer vision and deep learning to automate distress detection, and map image-based results to condition indices. Majidifard *et al*. (2020) created a deep learning model that takes the result of a YOLO-based distresses classifier and a U-Net-based segmentation model to identify and measure various types of asphalt pavement distresses in a Google Street View image, and uses the results to construct a new pavement condition index that is highly correlated with existing rating systems but much less dependent on manual analysis. Later designs have shown that deep convolutional networks and similar designs can obtain PCI-comparable measures in just a few percent of the time and at considerably lower marginal cost, essentially making real-time screening of any network possible (Milad *et al*., 2025). More recently, multimodal and generative AI models have been tested for road surface condition assessment, indicating that modern vision-language models can identify surface distresses, assess severity and even estimate maintenance intervals from street-level imagery, suggesting a future in which high-level predictive maintenance assessments can be obtained using commodity image data and advanced AI pipelines (Xu *et al*., 2026).

From a predictive maintenance perspective, these developments collectively point toward a toolkit in which ensemble machine learning models support numerical PCI and performance forecasting, while deep learning and multimodal models automate distress detection and condition estimation from imagery and sensor data. Nevertheless, like the bridge literature, the majority of pavement-specific research continues to assess models based on statistical accuracy instead of their role in helping to mitigate user delay costs, vehicle operating cost or overall economic effects. A small fraction of recent literature directly addresses the implementation of improved PCI predictors and automated evaluations into optimization-based maintenance planning or as a tool to prioritize segments that would cause disproportionate economic damage in case of failure (Ashqar *et al*., 2025; Milad *et al*., 2025). This suggests a clear opportunity for future research to couple pavement prediction models with network-level criticality and cost models so that highway and pavement predictive maintenance can be evaluated directly in terms of minimized economic disruption, complementing the bridge-oriented frameworks discussed in the previous section.

Cross-cutting Themes: Algorithms, Data and Deployment

In both bridge and pavement, a comparatively steady array of machine learning families have taken their place as the workhorses of predictive maintenance. Recent studies on bridge condition and deterioration using NBI/NBE data and state inventories are dominated by the use of tree-based ensemble models, especially random forests and gradient boosters, which have strong predictive capabilities, ability to handle mixed data types, and handy feature importance diagnostics, all of which can be intuitively explained by engineering insights (Abu Dabous *et al*., 2025; Ghafoori *et al*., 2024). Other applications of similar ensembles and support vector machines are common in PCI prediction and pavement performance models, where they are superior to conventional regression models and are also stable to noisy or imbalanced condition datasets (Majidifard *et al*., 2020; Afridi *et al*., 2025; Ashqar *et al*., 2025). Feed-forward networks and other convolutional network and LSTM variants are also gaining popularity in applications where rich temporal or image data are accessible, especially bridge deck deterioration and automated pavement distress detection, though their complexity and data requirements are higher than the simpler architecture such as feed-forward networks, so they are not the default option in all agencies yet (Majidifard *et al*., 2020; Zhu & Wang, 2021).

The main limitation found in the literature reviewed is the quality and availability of data. Some of these studies indicate that missing values, inconsistent coding and limited temporal depth in NBI and state inspection records can substantially reduce model performance, leading to the creation of so-called upstream data workflows to clean, impute, and engineer features and then train models (Banaei-Kashani & Arens, 2022; FHWA, 2024). In the case of pavements, the quality and the geographic coverage of PCI surveys, the resolution and calibration of imaging systems and the combination of traffic and climate covariates have a significant impact on model reliability and transferability (Majidifard *et al*., 2020; Milad *et al*., 2025). Recent studies also point to the fact that models that have been trained on a specific state or region do not tend to generalise, and that to compare and use predictive maintenance tools, standard benchmark datasets and evaluation procedures are necessary (Mia & Kameshwar, 2023; Ashqar *et al*., 2025).

There is disparity in deployment maturity. Some more successful attempts today combine predictive models with optimization modules to assist budget-constrained maintenance planning as seen in bridge maintenance optimization systems that take machine learning predictions as inputs to linear programming or other decision models (Ghafoori *et al.*, 2024). Open-source PCI prediction tools and AI-based image-processing pipelines are starting to leave research prototypes and transition into agency pilots, such as federal efforts to characterize pavements and safety with artificial intelligence (Ashqar *et al.*, 2025).

Yet most applications remain at the proof-of-concept or limited case-study stage, and relatively few have been fully embedded into state DOT workflows with clear governance, validation and update procedures **(Antwi & Nnaji, 2026)**. Interpretability, uncertainty quantification and institutional capacity for managing data pipelines and model life cycles are recurring concerns that must be addressed if machine learning-based predictive maintenance is to support high-stakes decisions about U.S. bridges and highways at scale.

Table 1: Representative Machine-Learning (ML) Studies for Predictive Maintenance of U.S. Bridges and Pavements (2020–2026).

Literature	Asset Type	Primary ML approach	Main data Source	Key contribution	Economic disruption link
Abu Dabous *et al.* (2025)	Bridge	Random forest (RF), Deep Learning (DL)	NBI/NBE	High accuracy in condition rating prediction	No
Ghafoori *et al.* (2024)	Bridge	RF + Linear Programming	NBI/NBE	ML-driven deterioration forecasting integrated with long-term budget optimisation	Budget impact only
Zhu & Wang (2021)	Bridge	LSTM, feed-forward networks	NBI temporal	Marginal gains over ensembles	No
Banaei-kashani & Arens (2022)	Bridge	Ensemble Learning	NBI + state data	Improved preprocessing and network-level prediction workflows	No
Majidifard *et al.* (2020)	Pavement	YOLO + U-Net (DL)	Google Street View	PCI equivalent within few % points	No
Afridi *et al.* (2025)	Pavement	Ensemble models	Municipal network	Robust with imbalanced data	No
Asquar *et al.* (2025)	Pavement	Multiple ensemble models	PCI survey data	Practical open-source decision-support tool	Qualitative
Milad *et al.* (2025)	Pavement	Spatial AI + Bayesian ML	GIS + PCI	Spatial clustering for targeted maintenance	Partial
Xu *et al.* (2026)	Pavement	Multimodal generative AI	Street-level imagery	Automated distress identification + maintenance interval estimation.	No

Note: *NBI = National Bridge Inventory; NBE = National Bridge Elements; LSTM = Long Short-Term Memory; YOLO = You Only Look Once; GIS = Geographic Information System; PCI = Pavement Condition Index*

Table 1 summarizes representative machine-learning studies published between 2020 and 2026 that address predictive maintenance for U.S. bridge and pavement infrastructure. The table contrasts asset types, dominant algorithm families, primary data sources, and the extent to which each study explicitly accounts for economic disruption. Across both bridge- and pavement-focused literature, tree-based ensembles and deep learning models dominate predictive performance, particularly when trained on national inventories or large-scale imagery. However, while several studies integrate predictions into budget-constrained optimization or agency decision tools, explicit modeling of user delay costs, freight impacts, or macroeconomic losses remains rare, highlighting a persistent gap between predictive accuracy and economic outcome assessment.

TOWARD ECONOMIC-IMPACT-AWARE PREDICTIVE MAINTENANCE FRAMEWORKS

The current body of work demonstrates that machine learning can substantially improve forecasts of bridge and pavement conditions, yet most studies still evaluate success primarily through statistical metrics or localized maintenance performance rather than explicit economic outcomes. Bridge maintenance optimization research that integrates machine learning forecasts with linear programming or similar decision models typically aims to maximize structural performance under annual budget constraints but does not quantify user delay costs or broader economic losses avoided by preventing unplanned closures on high-criticality links (Banaei-Kashani & Arens, 2022; Ghafoori *et al*., 2024). Network-level maintenance and life-cycle optimization models developed prior to the recent wave of machine learning applications show that user costs, failure costs and agency costs can be combined in multi-objective formulations, indicating that established economic and reliability modeling tools could be coupled with modern predictive models to create more economically meaningful decision-support systems (Han & Frangopol, 2022). In the pavement domain, road user cost models and life-cycle planning tools have long been used to quantify delay, operating and safety costs associated with maintenance and rehabilitation, but they are rarely linked directly to machine learning-based PCI forecasts or distress predictions (Kedarisetty *et al*., 2022).

A logical next step is to develop integrated frameworks that treat machine learning predictions as inputs to explicit economic-risk and resilience models. Conceptually, this involves mapping predicted deterioration trajectories and failure probabilities for bridges and pavements to capacity reductions and closure probabilities on a transportation network, then using traffic assignment and user-cost models to estimate the economic consequences of alternative maintenance and failure scenarios (Han & Frangopol, 2022; Kedarisetty *et al*., 2022). These economic impact estimates, including user delay costs, freight time-value losses, crash risks and, where possible, regional GDP or employment effects, can then be embedded into multi-objective optimization formulations that balance agency costs, reliability and economic disruption, extending existing cost-reliability optimization approaches to explicitly include disruption metrics (Liu & Frangopol, 2006; Han & Frangopol, 2022).

At the operational level, such frameworks would enable agencies to prioritize predictive maintenance on assets whose projected deterioration, if unaddressed, would yield the largest marginal reductions in expected economic losses per dollar invested, thereby aligning machine learning-based monitoring and maintenance planning more directly with economic resilience objectives. As agencies integrate machine learning predictions with traffic assignment and user-cost models, persistent challenges in data governance, interoperability, and digital readiness must also be addressed (Antwi & Nnaji, 2026).

RESEARCH GAPS AND FUTURE DIRECTIONS

The review of the recent literature on machine learning applied to predictive maintenance of bridges and highways in the U.S. indicates that the current research has a number of persistent gaps that constrain the contribution of the current methods to the economic resilience and network-level decision making. First, the majority of studies are still asset specific and fail to model bridges and pavements as part of an interdependent network where failures in one facility redirect traffic, change loading patterns, and could hasten deterioration in other facilities (Banaei-Kashani & Arens, 2022). Very few studies attempt to include bridge and pavement predictive models as part of cohesive network models that express such feedback, although economic effects of closures and disruptions manifest at exactly such network interactions (Kane *et al*., 2024). Second, whereas ensemble and deep learning models frequently can be used to obtain high predictive accuracy, comparatively little focus is placed on uncertainty estimation, explainability and resilience to data changes, all of which are essential to safety-critical maintenance decision-making (Zhu & Wang, 2021). Third, as noted earlier, existing literature does not often bridge the gap between better prediction and explicit estimates of the averted user costs or more general economic losses, limiting the capacity of agencies to justify predictive maintenance investments in well-defined economic terms (Kedarisetty *et al*., 2022; Ghafoori *et al*., 2024).

These gaps can hint at different ways to develop future research that can improve methodological rigor and practical significance. A development of integrated and network-level predictive maintenance systems, which integrate machine learning-based deterioration and condition models with traffic assignment and user-cost modeling, are among the priorities so that agencies could assess the impacts of alternative maintenance strategies on asset condition and economic disruption across bridge-highway systems (Han & Frangopol, 2022; Kane *et al*., 2024). In these schemes, agency costs can be allocated based on agency cost optimization, reliability, user costs and environmental impacts, and, where feasible, regional economic indicators, through multi-objective optimization schemes that extend the existing cost-reliability formulae (Liu & Frangopol, 2006; Han & Frangopol, 2022). The second direction is the development of standardized, publicly available benchmark datasets and evaluation protocols of U.S. bridge and pavement predictive maintenance, based on NBI/NBE, state inventories and federal AI efforts on the condition of pavements, to enhance reproducibility and interchangeability across studies (Banaei-Kashani & Arens, 2022; FHWA, 2024). These benchmarks would also be used to conduct systematic studies of transfer learning and domain adaptation strategies to allow models trained in one state or region to be generalized to other regions with different climates, traffic patterns and data practices (Mia & Kameshwar, 2023; Ashqar *et al*., 2025).

A third critical direction is to enhance the management of data governance, uncertainty and interpretability of predictive maintenance applications. Future research might directly measure predictive uncertainty and propagate it with optimization and economic models and thus risk-sensitive maintenance policies that capture confidence in condition forecasts and economic results. Simultaneously, interpretable machine learning methods, including transparent tree ensembles, post hoc explanation tools and causal models, which aid practitioners in understanding why a model suggests certain interventions and how significant variables contribute to predicted deterioration, are needed, especially when recommendations are made on high-criticality assets (Banaei-Kashani & Arens, 2022). Lastly, empirical research that reports pilot deployments of machine learning-based predictive maintenance tools in cooperation with U.S. state departments of transportation or metropolitan agencies, including institutional arrangements, model validation, stakeholder acceptance and observed implications on maintenance timing and user costs, would be a welcome addition to evidence on the feasibility of implementing machine learning-based predictive maintenance tools (FHWA, 2024; U.S. Department of Transportation, 2025). Placed between these gaps, the current review makes clear the areas of the current predictive maintenance research that are most developed, where the research has failed in the face of economic disruptions and network-level resilience, and where the specific methodological and applied efforts would provide the most beneficial impact to U.S. bridge and highway infrastructure. Future research should further explore advanced monitoring approaches that enable continuous monitoring and support early-stage decision making during infrastructure development.

CONCLUSIONS

This review has integrated recent developments in machine learning to predictive maintenance of U.S. bridge and highway infrastructure with special consideration given to how it could minimize economic disruptions.

Across the reviewed literature, tree-based ensemble models, especially Random Forests and Gradient Boosting Machines (GBMs), emerge as the most consistently effective machine-learning approaches for predictive maintenance of U.S. bridges and pavements. Their strength lies in their ability to model non-linear deterioration patterns, handle heterogeneous inspection and environmental data, and provide interpretable feature-importance rankings that align with engineering intuition. Deep learning architectures, including convolutional neural networks (CNNs), U-Net segmentation models, and multi-modal generative AI, demonstrate superior performance for automated distress detection and image-based condition assessment, enabling rapid, scalable evaluations of large networks. Overall, the most effective approaches combine ensemble predictive accuracy with deep-learning-based visual assessment, forming a complementary toolkit that supports both numerical forecasting and automated condition identification. These methods represent the current state of the art and form the foundation for next-generation predictive maintenance systems.

It is demonstrated that tree-based ensemble models, deep learning structures and new spatial and multimodal models have greatly enhanced the accuracy and scalability of predicting damage conditions in bridges and pavements. These technical advances along with early adoption of optimization modules and open-source software suggest that machine learning-based predictive maintenance is no longer in the exploratory research phase but is used in operational decision support in at least some agencies, although implementation remains patchy.

Meanwhile, the review highlights significant shortcomings that need to be overcome to make machine learning a fully contributing factor to national economic resilience objectives. Current literature is mostly asset-oriented and seldom incorporate predictive outputs in network-scale economic models and pay little attention to uncertainty, interpretability and data governance, which limits their applicability to high-stakes investment and maintenance decisions. An undoubted chance exists to build combined models that pair predictive models with traffic allocation, user-cost and multi-objective optimization applications that enable agencies to assess maintenance choices based on anticipated improvements in user delay, freight disruption and overall economic losses, and not just engineering performance metrics. Placing machine learning-based predictive maintenance in a context that includes such economically informed, network-conscious structures, future studies can assist in closing the gap between sophisticated analytics and policy requirements in order to support the overall shift towards data-driven smart infrastructure monitoring systems that minimize premature failures, limit cost overruns and increase the resilience of the U.S. transportation systems. These findings also highlight the growing importance of continuous, data driven monitoring approaches that extend beyond traditional predictive maintenance and support early stage infrastructure decision making.

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