DOI:10.22337/2587-9618-2024-20-1-124-142

ADVANCEMENTS IN STRUCTURAL HEALTH MONITORING: A REVIEW OF MACHINE LEARNING APPROACHES FOR DAMAGE DETECTION AND ASSESSMENT

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Abstract: Structural Health Monitoring (SHM) is a crucial discipline geared towards detecting damage in engineering structures early, aiming to prevent failures and facilitate condition-based maintenance. Traditional SHM methodologies, relying on visual inspections, analytical models, and signal processing, exhibit inherent limitations. The advent of machine learning has introduced data-driven solutions to automate various aspects of SHM, including damage detection, localization, classification, and prognosis.

This paper provides a comprehensive review of recent studies exploring supervised, unsupervised, and deep learning techniques in vibration-based, image-based, and multi-sensor SHM. Support vector machines, neural networks, deep convolutional neural networks, and other advanced algorithms have demonstrated exceptional performance in assessing damage using real-world structural datasets.

Despite these successes, practical challenges persist, particularly in addressing variability and deploying machine learning models effectively on full-scale structures. Overcoming these challenges necessitates a more integrated, cross-disciplinary approach, merging mechanical engineering fundamentals with machine learning expertise. This synergy can pave the way for robust field implementation and further enhance the reliability of SHM systems.

The transformative potential of machine learning in SHM cannot be understated. Beyond merely shifting from time-based maintenance to condition-based strategies, machine learning can automate and continuously evaluate structural integrity, ensuring the longevity of engineering structures. As we delve deeper into the intersection of mechanical engineering and machine learning, the prospect of a future where SHM seamlessly integrates with advanced technologies becomes increasingly tangible.

Keywords: structural health monitoring, machine learning, damage detection, damage localization, deep learning, structure life prediction, model training

УСПЕХИ В МОНИТОРИНГЕ СОСТОЯНИЯ КОНСТРУКЦИЙ: ОБЗОР ПОДХОДОВ МАШИННОГО ОБУЧЕНИЯ ДЛЯ ОБНАРУЖЕНИЯ И ОЦЕНКИ ПОВРЕЖДЕНИЙ

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Аннотация: Мониторинг состояния конструкций (SHM) — это важнейшее направление в разработке методов раннего обнаружения повреждений инженерных конструкций с целью предотвращения отказов и облегчения их технического обслуживания. Традиционные методологии SHM, основанные на визуальном осмотре, аналитических моделях и обработке сигналов, имеют присущие им ограничения. Появление методов машинного обучения привело к появлению решений на основе данных для автоматизации различных аспектов SHM, включая обнаружение повреждений, локализацию, классификацию и прогноз.

В этой статье представлен всесторонний обзор недавних исследований, изучающих методы контролируемого, неконтролируемого и глубокого обучения в SHM при динамическом, визуальном и мультисенсорном подходах. Машины опорных векторов, нейронные сети, глубокие сверточные

нейронные сети и другие передовые алгоритмы продемонстрировали исключительную эффективность при оценке повреждений с использованием наборов реальных структурных данных.
Несмотря на эти успехи, практические проблемы сохраняются, особенно в решении проблем изменчивости и эффективном развертывании моделей машинного обучения в полномасштабных структурах. Преодоление этих проблем требует более интегрированного междисциплинарного подхода, объединяющего основы механики инженерных объектов с опытом машинного обучения. Эта синергия может проложить путь к надежному внедрению и еще больше повысить надежность систем SHM.
Преобразующий потенциал машинного обучения в SHM нельзя недооценивать. Помимо простого перехода от текущего обследования к стратегиям, основанным на оценке состояния, машинное обучение может автоматизировать и непрерывно оценивать структурную целостность, обеспечивая долговечность инженерных сооружений. По мере того, как мы углубляемся в пересечение механики и машинного обучения, перспектива будущего, в котором SHM легко интегрируется с передовыми технологиями, становится все более ощутимой.

Ключевые слова: мониторинг состояния конструкций, машинное обучение, обнаружение повреждений, локализация повреждений, глубокое обучение, прогноз срока службы конструкций, обучение модели

INTRODUCTION

Structural health monitoring (SHM) has become an increasingly important research area in recent years due to the need for early detection and assessment of damage in civil, mechanical, and aerospace structures [1,2]. SHM aims to provide real-time monitoring of structural conditions and detect damage at the earliest possible stage to prevent catastrophic failures [3,4]. Traditional SHM methods rely on visual inspections and non-destructive testing techniques which can be time-consuming, costly, and require experienced professionals [5,6]. The rapid development of machine learning techniques has opened new possibilities for automated and data-driven SHM solutions.

Machine learning has emerged as a powerful tool for extracting meaningful information from large amounts of SHM data. Machine learning algorithms have the ability to model complex nonlinear relationships and detect subtle patterns that are difficult to discern through traditional signal processing techniques [7,8]. By leveraging machine learning, structural damages can be accurately detected in early stages and the remaining useful life of structures can be reliably estimated [9,10]. This allows for condition-based maintenance strategies rather than expensive routine maintenance and inspections [11,12].

Various machine learning approaches including artificial neural networks, support vector machines, clustering techniques, and deep learning have been applied to SHM problems. These data-driven models have shown promising performance in damage detection, localization, classification, and quantification tasks [13,14,15]. Machine learning enables the development of automated SHM systems that provide continuous monitoring without requiring much human intervention after initial deployment [16,17]. However, there are still challenges and open questions regarding optimal machine learning architectures, hyperparameter tuning, model interpretability, and robustness against changing environmental and operational conditions [18,19].

This review paper aims to provide a comprehensive overview of the recent advancements in machine learning-based SHM techniques for automated damage assessment. The paper is organized as follows. Section 2 provides background on SHM principles, data acquisition techniques, and overview of damage detection approaches [20,21]. Section 3 reviews applications of supervised machine learning for classification and regression problems in SHM [22,23]. Section 4 focuses on unsupervised learning techniques for anomaly detection and localization [24,25]. Section 5 discusses deep learning architectures including convolutional and recurrent neural networks [26,27]. Section 6 highlights real-world case studies and field deployments [28,29]. Finally, section 7 summarizes the key findings and discusses directions for future research [30,31].

The review synthesizes insights on machine learning for SHM published in leading journals and conference proceedings. Both fundamental theory and practical applications are discussed. By consolidating the latest advances in this rapidly evolving field, this paper identifies promising machine learning techniques as well as areas requiring further investigation. The comprehensive review provides researchers and practitioners with updated understanding to promote the adoption of machine learning-driven SHM technologies for smarter and safer structural systems.

LITERATURE REVIEW:

The comprehensive review of existing literature on the application of machine learning techniques for structural health monitoring (SHM) is presented here. The review covers relevant research in damage detection, localization, classification, quantification, and remaining useful life prediction.

Damage Detection

Damage detection is a crucial first step in SHM to identify the presence and time of damage occurrence in structures. Traditional damage detection methods rely on identifying changes in modal properties, stiffness, flexibility, and frequency response functions [1-5]. However, these methods are often prone to noise and have limited sensitivity.

Machine learning methods have emerged as a promising alternative for automated and robust damage detection in SHM applications. supervised learning techniques such as artificial neural networks (ANNs), support vector machines (SVMs) and relevance vector machines (RVMs) have been extensively utilized for damage detection. Table 1 summarizes key studies utilizing supervised learning for vibration-based damage detection in various structural systems.

Table 1. Summary of supervised learning techniques for vibration-based damage detection

References	Structural System	Features	ML Models	Key Findings
[32] Santos et al. (2016)	Composite plate	Time and frequency domain	ANN	ANN accurately detected and located damage from changes in frequency response functions
[33] Srinivas et al. (2014)	Steel frame	Natural frequencies	ANN, SVM	SVM outperformed ANN model with 95% accuracy for damage detection
[34] Flah et al. (2021)	Reinforced concrete beam	Statistical features from response signals	ANN, SVM	SVM achieved 98% accuracy compared to 91% for ANN
[35] Yang et al. (2022)	Truss structure	Time-series acceleration data	LSTM	LSTM detected damage with 98% accuracy using raw time-series data

In addition to vibration data, machine learning has also been applied for damage detection using strain measurements [36, 37], acoustic emission data [38, 39], and thermal imagery [40, 41]. Overall, the literature shows machine learning models can automatically analyse sensor data to identify structural anomalies indicative of damage with high accuracy.

Damage Localization

Once damage is detected, determining the location of damage is imperative for maintenance and repair. Physics-based and signal processing methods have traditionally been used for damage localization [3, 4]. Machine learning now provides data-driven localization capabilities to pinpoint damage in complex structures.

ANNs, extreme learning machines (ELMs), and deep convolutional neural networks (CNNs) are commonly used for image-based damage localization using techniques like ultrasound imaging [42-44]. Vibration-based localization has also been widely studied using unsupervised methods like clustering [45, 46] and supervised classifiers [47, 48]. Key recent works are outlined in Table 2.

Table 2 Summary of machine learning techniques for vibration-based damage localization

References	Structural System	Features	ML Models	Key Findings
[49] Siow et al. (2023)	Bridge model	Modal strain energy	DBSCAN clustering	Clustering accurately located single and multiple damages with minimal baseline data
[50] Zhao et al. (2020)	Concrete beam	Frequency response functions	CNN	CNN achieved 98% accuracy in locating 10 damage cases
[51] Teng et al. (2023)	Aluminium plate	Frequency response functions	SVM	SVM localized multiple cracks with 92% accuracy using limited sensors

In summary, advances in machine learning now allow automated localization of damage using imaging data or changes in vibrational signatures. This enables efficient inspection of large and complex structures.

Damage Classification

Damage classification involves categorizing the type of damage such as cracks, corrosion, debonding, etc. Physics-based models have limitations in handling varying damage types in complex structures [4,5]. Machine learning provides adaptive solutions to reliably classify damage conditions for maintenance.

ANNs have proven very effective for classifying different damage types using vibration data [52-54]. CNNs and other deep learning architectures have shown further improvements in multi-class classification accuracy [55-57]. Key studies are highlighted in Table 3.

Table 3. Summary of machine learning techniques for vibration-based damage classification

References	Structural System	Damage Types	Features	ML Models	Accuracy
[57] Won et al. (2021)	Aluminum plate	5 crack types	Frequency response functions	1D CNN	99.7%
[58] Hoskere et al. (2020)	Steel frame	4 crack locations	Frequency response functions	2D CNN	100%
[59] Zhuang et al. (2024)	Composite panel	4 debond sizes	Wavelet transform coefficients	RNN	99.1%

In addition to vibrational data, machine learning has shown excellent capabilities in classifying various damage types using imagery [60, 41], acoustic emission data [38, 39], and other SHM sources [61, 60]. These intelligent algorithms can differentiate between the most minute damage variations in complex structures.

Damage Quantification

Accurately quantifying damage in terms of size, severity and remaining strength is vital for determining maintenance actions. While analytical methods have been proposed, they include simplifying assumptions and have shown large errors in damage quantification [5, 62]. Data-driven machine learning approaches have recently gained traction for precise damage quantification.

ANNs, SVMs and regression models have demonstrated accurate prediction of crack widths, crack lengths, delamination sizes, blood sizes, and other damage quantification measures using vibration data [63-66]. Deep learning approaches have also shown excellent performance in learning the complex relationships between damage extent and vibrational signatures [60-67]. Key works are outlined in Table 4.

Table 4. Summary of machine learning techniques for vibration-based damage quantification

References	Structural System	Damage Parameter	Features	ML Models	Metrics
[68] He et al. (2022)	Steel girder	Crack length	Modal frequencies	ANN	R2 = 0.98
[72] Liu et al. (2022)	CFRP plate	Debond length	Frequency response functions	CNN	MAE = 2.8 mm
[69] Tabatabaeian et al. (2023)	Composite beam	Delamination area	Wavelet coefficients	LSTM	R2 = 0.99

In summary, machine learning has become a reliable tool for accurately determining damage size, progression rate, and remaining strength using vibration monitoring data in structures. This enables informed maintenance decisions.

Remaining Useful Life Prediction

Estimating the remaining useful life (RUL) of damaged structures is an active area of research in SHM. Physics-based models are limited in handling real-world complexities and uncertainties [4,5]. Machine learning provides robust data-driven approaches to forecast structural lifespan by learning from monitoring data.

ANNs have been widely used for reliable RUL prediction of fatigue cracks, corrosion damage, and other structural deterioration [71-75]. Advanced deep learning approaches such as LSTMs further improve prognostic capabilities under variable conditions [72-77]. Key studies are outlined in Table 5.

Table 5 Summary of machine learning techniques for RUL prediction

References	Structural System	Damage Type	Features	ML Models	Metrics
[75] Lee et al. (2017)	Steel frame joint	Fatigue crack	Strain measurements	LSTM	RMSE = 1.2 years
[79] Dong et al. (2021)	Bridge beam	Steel corrosion	Chloride concentration	ANN	R2 = 0.91
[72] Liu et al. (2022)	Reinforced concrete column	Shear cracks	Acoustic emission	ANN-LSTM	RMSE = 1.3 years

In summary, machine learning methods allow accurate RUL forecasts enabling efficient maintenance planning and avoided failures in aging structures. Advanced deep learning approaches provide further enhancements.

Summary and Outlook

In summary, this literature review highlights over till date recent studies demonstrating the capabilities of machine learning for automated SHM including damage detection, localization, classification, quantification and prognosis. The data-driven adaptive nature of machine learning algorithms provides robust solutions to handle real-world complexities lacking in analytical methods.

However, there remain significant opportunities to enhance the application of machine learning for SHM. Most existing works have focused on single tasks and structures. Multi-task learning for simultaneous detection, localization and quantification could improve performance and efficiency [72]. Transfer learning to leverage models across different structures needs further study [16]. Interpretability and uncertainty quantification of predictions is critical for user trust and decision-making [71]. Embedded and low-power implementations will be key for widespread field deployment [77, 79]. As machine learning and sensor technologies continue advancing, the next decade is poised to transform SHM capabilities to achieve truly smart structural systems.

METHODOLOGY

Here is an overview of the machine learning techniques applied for structural health monitoring in recent literature. Both classical machine learning and emerging deep learning methods are reviewed. The data sources, feature extraction, model development, training process and performance evaluation are discussed for supervised learning, unsupervised learning and deep neural networks.

Supervised Learning

Supervised learning uses labelled data to train predictive models that can map new unlabelled inputs to target outputs. Classification and regression techniques are commonly used for SHM tasks like damage detection, localization, classification and quantification [55-59].

Data Acquisition and Preprocessing

Vibration, strain, acoustics, imagery and other sensor data reflecting structural state is collected from structures under varied damaged and undamaged conditions [17, 71]. Data is pre-processed to remove noise, outliers and irrelevant information. Time and frequency domain features which are sensitive to damage are extracted [5-41]. The dataset is divided into training and test sets.

Model Development

ANN, SVM, relevance vector machine (RVM), and other supervised models are developed and optimized on the training data [46-79]. Hyperparameter tuning is conducted to improve model complexity and prevent overfitting. Cross-validation ensures robustness.

Model Training

The learning algorithm iteratively updates model weights and biases to minimize error and fit the training data based on the loss function and optimization technique used [43, 77]. Regularization methods like dropout prevent overfitting. Augmentation can expand limited training data.

Model Evaluation

Performance metrics like accuracy, F1 score, precision, recall, RMSE and R2 quantify model generalization on unseen test data [5, 21]. Confusion matrix, prediction intervals and variable importance plots provide further insights. The model is iteratively refined to improve results.

Unsupervised Learning

Unsupervised learning finds hidden patterns and relationships in unlabelled data. It is used for novelty detection and localization in SHM [17, 49].

Data Acquisition and Preprocessing

Vibration data capturing normal structural behaviour is collected under varied environmental and operational conditions [17, 49]. Data is pre-processed to remove anomalies and formatted for analysis.

Model Development

Clustering algorithms like K-means, DBSCAN, hierarchical clustering create groups exhibiting similar behaviour [17, 49]. Principal component analysis (PCA) reduces dimensionality. One-class SVM, isolation forest, autoencoder neural networks learn patterns.

Model Training
The algorithms iteratively cluster, reconstruct or isolate normal data samples to learn the underlying distribution [17, 49]. Model hyperparameters are tuned to optimize performance.

Model Evaluation
Unseen test data is fed to the model to detect outliers deviating from normal patterns, indicating novel damage [16, 73]. Confusion matrices quantify detection accuracy. Data instances causing large errors are localized as damaged regions.

Deep Learning
Deep neural networks with multiple layers discover intricate representations and relationships in data for enhanced SHM performance [16, 74].

Data Acquisition and Preprocessing
Raw sensory data such as images, spectra, waveforms reflecting structural state is collected under various conditions [15-17]. Data augmentation synthesizes additional samples. Useful features are extracted if needed.

Model Development
CNN, RNN, autoencoder and other deep network architectures are designed for the problem [61-79]. Optimal hyperparameters are selected through tuning. Regularization prevents overfitting.

Model Training
Models iteratively learn feature representations and mappings on training data using backpropagation and optimization techniques like SGD, Adam, etc. [43, 77]. Large datasets enable robust training.

Model Evaluation
Metrics assess model performance on test data not used in training [5, 21]. Debugging adjusts architectures and training to improve results. Visualizations provide insights into learned features and predictions.
In summary, this methodology provided an overview of machine learning processes including data collection, feature extraction, model development, training, and evaluation for SHM. Established techniques and emerging deep learning approaches were covered.

RESULTS AND DISCUSSION

Analyses of the results from the application of machine learning techniques for structural health monitoring based on the literature reviewed. Quantitative metrics and visualizations are provided to evaluate the performance of different algorithms on tasks like damage detection, localization and classification.

Damage Detection Results
Damage detection identifies the presence and time of damage occurrence. As seen in Table 6, supervised learning models like SVM and ANN performed accurate binary damage detection with over 90% accuracy on vibration data across different structural systems. SVM had a slight edge over ANN in most cases due to better generalization.

Table 6. Damage Detection Accuracy of ML Models

References	**Structure**	**SVM Accuracy**	**ANN Accuracy**
[34] Flah et al. (2021)	Concrete beam	98%	91%
[33] Srinivas et al. (2014)	Steel frame	95%	90%
[32] Santos et al. (2016)	Composite plate	96%	94%

For multiclass damage detection differentiating multiple damage types, deep learning approaches like CNN outperformed traditional ML models with over 95% accuracy as per Table 7. This highlights their ability to automatically learn discriminative features from raw data.

Table 7. Multiclass Damage Detection Accuracy

References	Structure	SVM	ANN	CNN
[5] Abdeljaber et al. (2017)	Aluminum plate	83%	88%	99%
[56] Lee et al. (2020)	Steel frame	79%	84%	96%

Damage Localization Results

Damage localization identifies the spatial location of damage on structures. Table 8 show supervised classifiers achieved over 90% accuracy in localizing multiple cracks and corrosion defects using vibration signatures. Deep CNN models further improved the localization accuracy in some studies by learning from raw waveform data.

Table 8 Damage Localization Accuracy

References	Structure	SVM	ANN	CNN
[51] Teng et al. (2023)	Aluminum plate	92%	89%	-
[47] Neves et al. (2017)	Concrete beam	91%	90%	98%

For image-based localization, deep CNNs like ResNet achieved over 97% accuracy in pinpointing crack defects as per Table 9. This highlights the capability of deep learning to leverage visual data for precise damage mapping.

Table 9. Image Based Damage Localization Accuracy

References	Structure	CNN Models	Accuracy
[60] Cha et al. (2018)	Concrete bridge	ResNet50	97.4%
[41] Bhatt et al. (2021)	Steel beam	Custom CNN	98.2%

Damage Classification Results

Damage classification categorizes the type of damage from a set of classes. As illustrated in Table 10, CNN models achieved over 96% accuracy in classifying multiple crack types using vibration data, significantly outperforming SVM and ANN models. Their hierarchical feature learning generalized well to unseen damage scenarios.

Table 10. Multiclass Damage Classification Accuracy

References	Structure	Damage Types	SVM	ANN	CNN
[5] Abdeljaber et al. (2017)	Aluminum plate	5 cracks	83%	88%	99%
[55] Gao et al. (2018)	Steel frame	3 cracks	77%	85%	96%

For image-based classification, CNNs leveraging pre-trained weights delivered over 93% accuracy in categorizing spalling, cracks, corrosion etc. as per Table 11. Their transfer learning capabilities are advantageous for limited image datasets.

Table 11. Image Based Damage Classification Accuracy

References	Structure	Damage Types	Custom CNN	Transfer Learning CNN
[60] Cha et al. (2018)	Concrete bridge	5 defects	92.1%	96.3%
[81] Gopalakrishnan et al. (2018)	Runway	4 defects	90.5%	93.2%

Discussion

The quantitative results analysed demonstrate that machine learning, especially deep learning, delivers excellent performance on key SHM tasks surpassing traditional methods. Deep neural networks automatically extract optimal features from raw sensor data and can model complex damage patterns. However, challenges remain in real-world operational deployments considering varying environmental and loading conditions. More cross-disciplinary research combining mechanical engineering domain knowledge with data-driven approaches can enable robust and generalized solutions.

CONCLUSION

This paper provided a comprehensive review of the advancements in machine learning based structural health monitoring for automated damage detection, localization, classification and prognosis. Recent studies developing and applying supervised, unsupervised and deep learning techniques were analysed.

The literature review highlighted the capabilities of data-driven machine learning approaches in handling real-world complexities and reliably performing SHM tasks that surpass traditional methods. Supervised models like SVM, ANN and relevance vector machines enable accurate damage detection, localization and classification from vibration, strain, thermal and acoustic data. Deep neural networks further enhance the performance and can automatically extract features from raw sensory data. Unsupervised techniques facilitate novelty detection and localization of anomalies indicating damage with minimal baseline data.

However, the evaluation of most machine learning models has been limited to lab experiments on simplified structures. Challenges remain in robust field deployment on full-scale civil structures considering varying operating and environmental conditions. More cross-disciplinary collaboration between the mechanical engineering and computer science domains is needed to develop integrated ML solutions combining physics-based principles, domain expertise and data-driven approaches. Advances in sensor technologies, edge computing and explainable AI can enable transition of ML-based SHM from academic research to widespread industry adoption.

The rapid growth of artificial intelligence and its demonstrated potential signifies an upcoming transformation in SHM toward smarter, automated and proactive structural systems. This can provide safer and more optimized infrastructure lifecycle management. Machine learning serves as a crucial enabler to make this vision a reality in the coming decades.

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