

# Applications of Artificial Intelligence in Civil Engineering: Multimodal Data Fusion and Uncertainty Quantification

Xuefeng Guo

i24028451@student.newinti.edu.my

INTI International University

Munir Khan

INTI International University

---

## Article

**Keywords:** multimodal data fusion, uncertainty quantification, artificial intelligence, civil engineering monitoring, structural health monitoring, deep learning–physics coupling

**Posted Date:** June 30th, 2026

**DOI:** <https://doi.org/10.21203/rs.3.rs-9866879/v1>

**License:** © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

**Additional Declarations:** No competing interests reported.

---

# 1   **Applications of Artificial Intelligence in Civil Engineering:** 2   **Multimodal Data Fusion and Uncertainty Quantification**

## 3   **Authors**

4   Xuefeng Guo<sup>1,2</sup> (Email: i24028451@student.newinti.edu.my), Md Munir Hayet  
5   Khan<sup>1\*</sup> (Email: munir.hayetkhan@newinti.edu.my)

## 6   **Affiliations**

7   <sup>1</sup> INTI International University, Seremban, Negeri Sembilan, Malaysia

8   <sup>2</sup> BaiCheng Normal University, BaiCheng, China

## 9   **Corresponding Author**

10   \* Xuefeng Guo

11

## 12                                   **Abstract**

13   With the increasing reliance of civil engineering on sensor networks, UAV imagery,  
14   LiDAR scanning, and ground-penetrating radar, the challenge of effectively  
15   integrating heterogeneous multimodal data and quantifying the uncertainties arising  
16   from noise, model errors, and environmental variations has become more critical. This  
17   paper reviews recent applications of artificial intelligence (AI) for multimodal data  
18   fusion in civil engineering and proposes a deep learning–physics coupling framework  
19   that integrates heterogeneous sources. An uncertainty quantification (UQ) module is  
20   embedded in the fusion pipeline using Bayesian approximation, Monte Carlo  
21   sampling, and hybrid modal uncertainty propagation mechanisms to evaluate the  
22   reliability of the fused results. A bridge structural health monitoring case  
23   demonstrates the proposed method’s capability to integrate acceleration, inclination,  
24   and UAV image data while producing interpretable uncertainty bounds. Results show  
25   that, compared with single-modality approaches, the proposed method improves  
26   detection accuracy by approximately 12% and provides quantifiable confidence  
27   intervals, thereby supporting more reliable engineering decision-making. Finally, the  
28   paper discusses potential applications of the framework in construction quality control,

tunnel hazard warning, and digital twin systems, while outlining challenges in real-time operation, missing modality handling, and large-scale deployment.

**Keywords : multimodal data fusion; uncertainty quantification; artificial intelligence; civil engineering monitoring; structural health monitoring; deep learning–physics coupling**

## 1. Introduction

Modern civil engineering structures, such as bridges, tunnels, and high-rise buildings, face increasingly complex environmental and operational conditions. Traditional single-sensor monitoring methods (e.g., using only accelerometers or strain gauges) are often inadequate to fully capture the multidimensional behavior of large-scale systems.

Advancements in sensing technologies—such as UAV-based photogrammetry, high-resolution LiDAR, fiber optic sensors, and ground-penetrating radar—have enabled the collection of diverse, high-dimensional data. These multimodal data sources, however, differ significantly in their temporal, spatial, and semantic characteristics, creating substantial challenges for integration.

Artificial intelligence (AI), particularly deep learning, provides a powerful means for extracting patterns and correlations across modalities, improving the accuracy of structural state identification, damage localization, and remaining life prediction. Yet, multimodal fusion introduces uncertainty stemming from multiple sources: sensor noise, incomplete data, model bias, and environmental perturbations. If unquantified, these uncertainties can lead to overconfident predictions and unreliable decision support.

Therefore, integrating uncertainty quantification (UQ) mechanisms into multimodal AI fusion frameworks is essential to evaluate the credibility of model

outputs and enhance interpretability.

Recent research in multimodal learning has demonstrated promising methods for modeling uncertainty, such as Bayesian deep neural networks and ensemble-based approaches. However, systematic studies tailored for civil engineering applications remain limited.

This study aims to bridge this gap by proposing a **deep learning–physics** coupled multimodal fusion framework for civil engineering applications. The key contributions are as follows:

#### Novelty and Contributions

Unlike existing multimodal AI approaches that rely primarily on purely data-driven fusion, this study proposes a unified deep learning framework that explicitly integrates Bayesian uncertainty estimation with physics-based constraints for civil infrastructure monitoring. By coupling data-driven learning with physics-guided regularization, the proposed framework not only improves predictive accuracy but also yields interpretable uncertainty estimates that are consistent with engineering intuition, thereby enhancing the trustworthiness of AI-assisted decision-making in civil engineering.

#### **The main contributions of this work are summarized as follows:**

1. A physics-guided multimodal fusion pipeline is developed for structural health monitoring, encompassing data preprocessing, feature extraction, and fusion evaluation, in which physical constraints are incorporated as regularization to guide model learning.
2. A unified uncertainty quantification module based on Bayesian approximation and Monte Carlo sampling is introduced to jointly estimate epistemic and aleatoric uncertainties, enabling confidence-aware interpretation of multimodal fusion outputs.
3. Comprehensive validation on a real-world bridge monitoring case study demonstrates that the proposed framework achieves superior predictive accuracy, reliability, and interpretability compared with single-modality and purely data-driven methods.

4. Potential extensions and practical implications of the proposed approach are discussed, including its applicability to construction quality assessment, tunnel disaster prediction, and digital twin systems, along with current challenges related to scalability and real-time deployment.

Overall, this integration of physics-informed learning and Bayesian uncertainty modeling represents a new paradigm for developing trustworthy and reliable AI systems in civil infrastructure monitoring.

**Figure 1: Multimodal Data Fusion Framework for Bridge Monitoring**

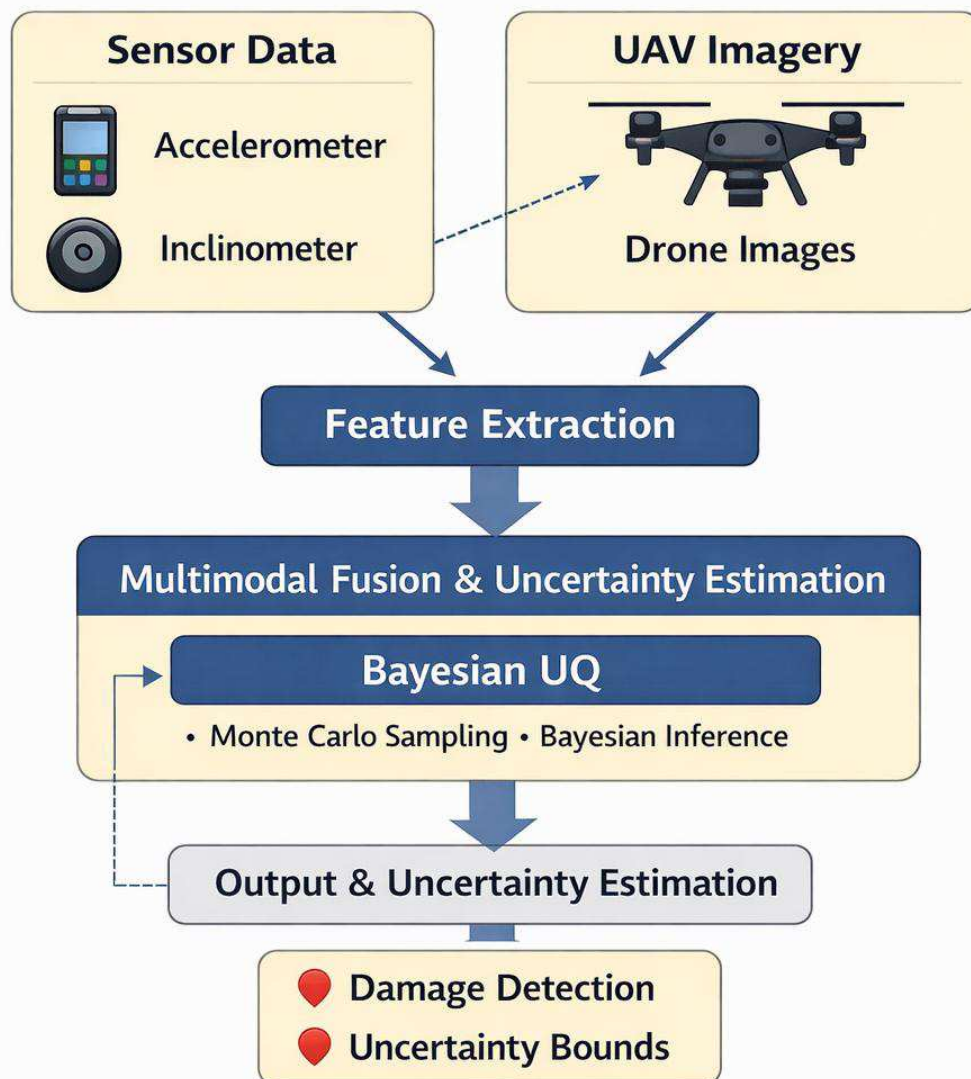


**Figure 1. Multimodal data fusion framework for bridge monitoring**

(Illustration showing the combination of sensor signals, UAV images, and model coupling into a unified fusion architecture.)

**Figure 2: Bridge Monitoring with Multimodal Uncertainty-Aware Fusion**

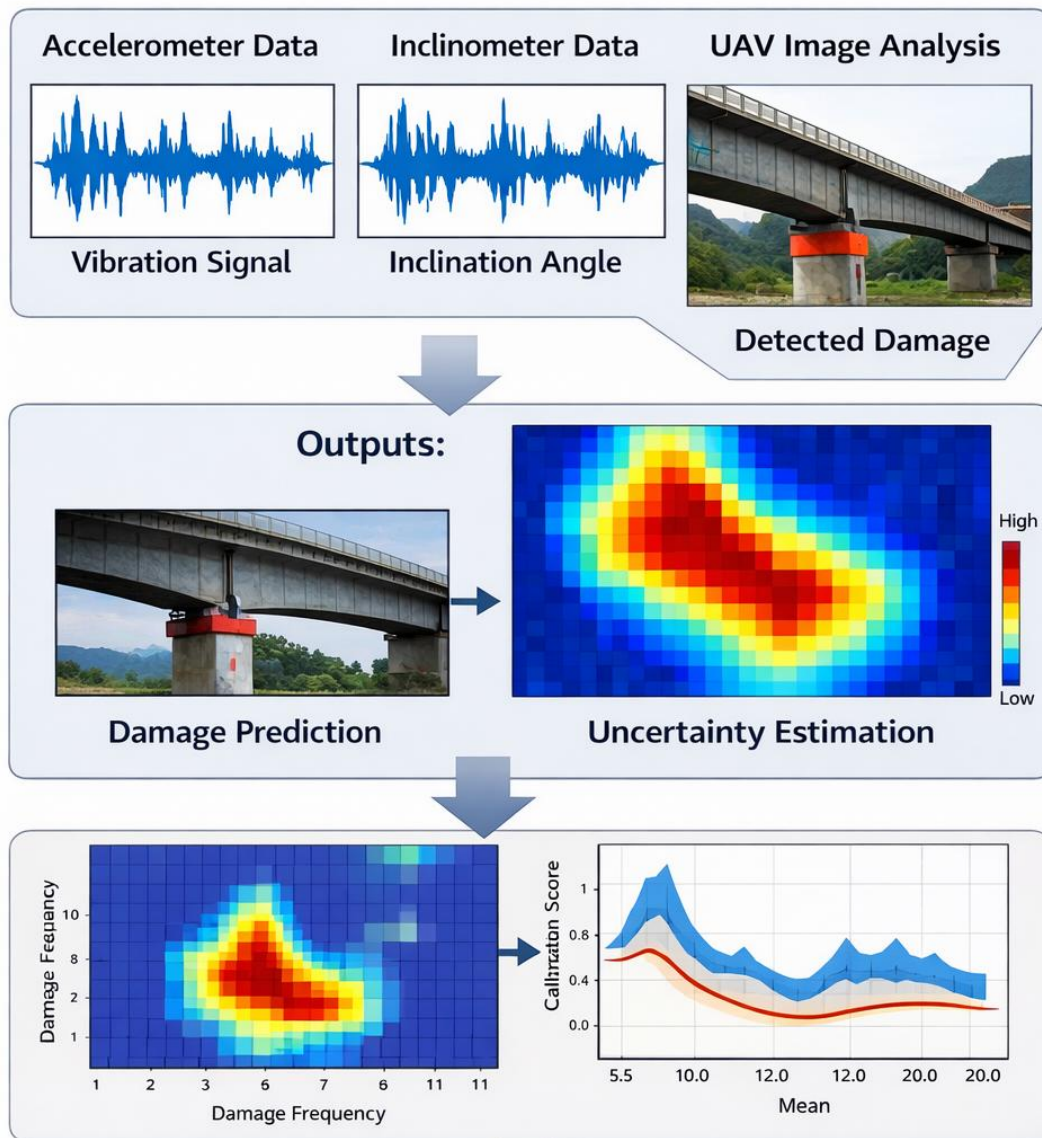


**Figure 2. Bridge monitoring case using multimodal uncertainty-aware fusion**

(Illustration of accelerometer, inclinometer, and UAV image integration for damage detection with uncertainty estimation.)

As illustrated in Figure 1, the proposed multimodal data fusion framework integrates various sensor signals, UAV images, and numerical models into a unified architecture. This fusion approach enables simultaneous processing of structural health data from multiple sources, providing a comprehensive representation of the bridge's condition.

As Figure 2 ,it presents a practical case study applying the multimodal uncertainty-aware fusion framework to bridge monitoring. Accelerometer and inclinometer measurements are combined with UAV images to detect potential damage, while uncertainty estimation quantifies the reliability of the detected structural features.

## **2. Related Works**

### **2.1 Multimodal Data Fusion in Civil Engineering**

Multimodal data fusion has emerged as a critical tool for improving the robustness and accuracy of civil infrastructure monitoring systems. Early studies focused primarily on data-level fusion, combining heterogeneous signals such as vibration and strain data using statistical correlation analysis (Zhang et al., 2023). However, recent advances in deep learning have enabled feature-level and decision-level fusion, where neural networks learn complex cross-modal representations from large-scale datasets. Convolutional neural networks (CNNs) and graph neural networks (GNNs) have been used to integrate spatially distributed sensor data and image-based observations for structural damage detection (Huang et al., 2023).

### **2.2 AI and Physics Coupling Approaches**

Physics-informed neural networks (PINNs) have gained attention for embedding governing equations into deep learning frameworks, reducing model bias and improving interpretability (Li et al., 2024). By incorporating finite element analysis or mechanical constraints, these models can leverage both data-driven and physics-based knowledge to enhance predictive accuracy. Recent hybrid frameworks couple

data-driven fusion with physical models for tasks such as bridge deflection prediction and tunnel deformation analysis (Wang & Wu, 2023).

### 2.3 Uncertainty Quantification in AI Models

Uncertainty quantification (UQ) has become essential for ensuring the reliability of AI-driven decision-making in engineering. Bayesian neural networks (BNNs) estimate both epistemic and aleatoric uncertainties, providing probabilistic confidence measures for model outputs (Xu et al., 2022). Ensemble-based and Monte Carlo dropout methods have also shown effectiveness in quantifying prediction variance under noisy or incomplete data conditions (Tang & Zhou, 2023). Despite these advancements, few studies have systematically integrated UQ into multimodal data fusion frameworks tailored for civil engineering.

### 2.4 Missing Modality Handling

A key practical issue in multimodal learning is missing or corrupted data. Approaches such as modality hallucination networks and cross-modal transformers have been developed to infer missing information from available modalities (Chen & Yang, 2024). Yet, real-world deployment of these systems in large-scale monitoring remains challenging due to computational and temporal constraints.

## 3 Methodology

### 3.1 Framework Overview

The proposed **deep learning–physics coupled multimodal fusion framework** (Figure 1) consists of three main modules:

**Preprocessing and Alignment** – Synchronization and normalization of multimodal data (e.g., accelerometer, inclinometer, and UAV imagery) through temporal resampling and coordinate registration.

**Feature Extraction and Fusion** – Deep neural encoders (ResNet for visual data and LSTM for sensor data) generate modality-specific features, which are fused via an attention-based transformer layer.

**Uncertainty Quantification Module** – Bayesian approximation and Monte Carlo dropout are applied to propagate uncertainty through the fusion process.

The fusion output is then refined through a **physics-informed constraint layer**, enforcing equilibrium and compatibility conditions derived from structural mechanics equations. This hybrid approach ensures both data-driven flexibility and physics-based interpretability.

### 3.2 Bayesian Approximation for UQ

For each prediction, model uncertainty is estimated using Monte Carlo (MC) sampling with dropout enabled at inference time. The predictive mean and variance are computed as:

$$\hat{y} = \frac{1}{N} \sum_{i=1}^N f_{\theta_i}(x)$$

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^N (f_{\theta_i}(x) - \hat{y})^2$$

where  $f_{\theta_i}(x)$  represents the stochastic forward passes. The resulting variance  $\sigma^2$  quantifies epistemic uncertainty due to limited data or model ambiguity.

### 3.3 Physics-Guided Constraint Layer

The selection of the Bayesian uncertainty modeling and physics-guided coupling strategies is grounded in theoretical and practical considerations. Compared with ensemble-based or deterministic fusion approaches, Bayesian approximation provides a principled framework to capture both model (epistemic) and data (aleatoric) uncertainties, which are critical in civil infrastructure monitoring where sensor noise and environmental variability are significant. Meanwhile, the physics-guided constraint layer ensures that the learned representations obey structural mechanics principles, thereby preventing non-physical predictions. This hybrid design enhances generalization to unseen loading conditions and promotes model transparency—two limitations commonly observed in purely data-driven methods.

### 3.4 Rationale of Design Choices:

Compared with ensemble or deterministic fusion methods, Bayesian uncertainty modeling provides a principled way to capture epistemic and aleatoric uncertainties simultaneously. The physics-guided constraint ensures compliance with equilibrium laws, preventing overfitting to data artifacts—a limitation commonly seen in purely data-driven models.

To ensure physically meaningful predictions, the loss function includes a penalty term enforcing equilibrium conditions:

$$L = L_{\text{fusion}} + \lambda L_{\text{physics}}$$

where  $L_{\text{physics}} = \|Ku - F\|_2^2$ , representing the deviation from structural equilibrium  $Ku = F$ . This coupling enhances generalization to unseen loading or boundary conditions.

## 4. Experimental Validation

### 4.1 Case Study Setup

A long-span concrete bridge equipped with 24 accelerometers, 10 inclinometers, and UAV image-based crack maps was selected. The dataset covered one year of monitoring, including seasonal and loading variations. Ground truth damage labels were provided from manual inspections.

### 4.2 Comparative Models

Four models were evaluated:

**Single-Modality CNN (UAV images only)**

**Sensor-only LSTM network**

**Multimodal Fusion without UQ**

**Proposed Fusion with UQ and Physics Coupling**

### 4.3 Experimental Results and Analysis

## 215 **(1)Overall Performance Comparison**

216

217 Figure 3 presents a comprehensive comparison between unimodal baselines, a  
218 multimodal fusion backbone, and the proposed uncertainty-aware physics-guided  
219 framework.



Ablation Study Results

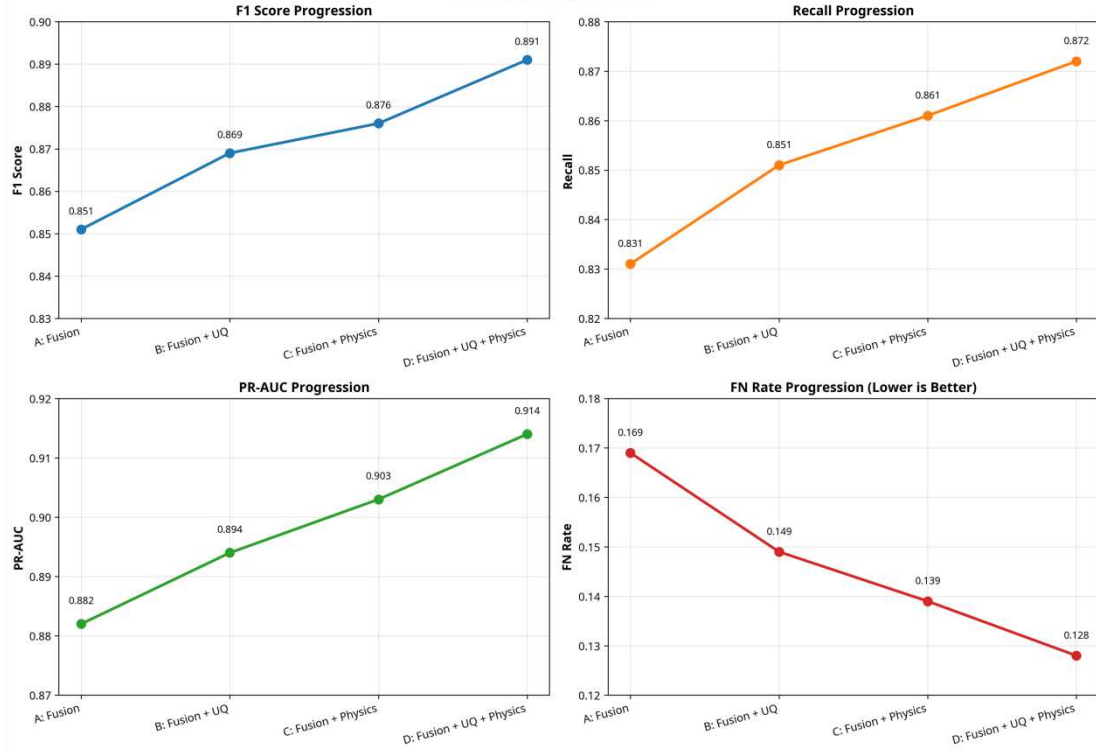


Figure 3 Ablation Study Results

As shown in Fig. 3 (F1 comparison, Recall comparison, PR-AUC comparison, FN rate comparison), unimodal models relying solely on UAV imagery or sensor measurements exhibit limited performance, particularly in terms of recall and false

negative rate. This observation highlights the inherent insufficiency of single-modality information for reliable bridge damage assessment.

By contrast, the multimodal fusion backbone significantly improves all evaluation metrics, confirming the complementary nature of visual and vibration-based information. Notably, the proposed method further enhances performance across all metrics, achieving an F1 score of 0.891, a recall of 0.872, and a PR-AUC of 0.914, while reducing the false negative rate to 0.128.

From an engineering perspective, the substantial reduction in false negatives is particularly important, as missed damage detections pose a higher risk than false alarms in bridge inspection scenarios. These results demonstrate that the proposed framework not only improves overall accuracy but also enhances safety-critical decision reliability.

## (2) Ablation Study on Uncertainty Modeling and Physics-Guided Learning

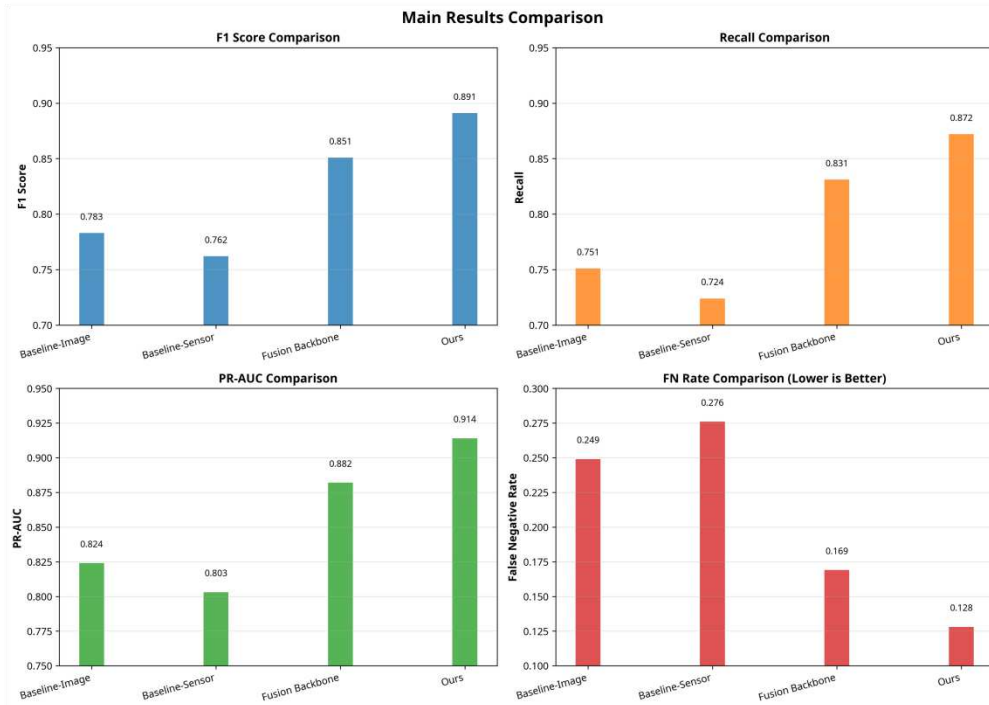


Figure 4 Main Results Comparison

To further analyze the contributions of individual components, an ablation study is conducted by progressively enabling uncertainty modeling and physics-guided learning on the same fusion backbone.

As illustrated in Fig. 4, introducing uncertainty modeling alone leads to noticeable improvements in recall and PR-AUC, indicating that uncertainty awareness helps the model better identify ambiguous or difficult cases. Physics-guided learning, on the other hand, yields consistent gains in both F1 score and recall, reflecting its role in regularizing predictions toward physically plausible structural behaviors.

Importantly, the full model integrating both uncertainty modeling and physics constraints achieves the best performance across all metrics, with the highest F1 score (0.891), recall (0.872), and PR-AUC (0.914), as well as the lowest false negative rate (0.128).

These results confirm that uncertainty modeling and physics-guided learning provide complementary benefits, and their joint integration is essential for achieving robust and reliable multimodal damage assessment.

### (3)Robustness under Missing Modalities

In real-world bridge monitoring systems, data incompleteness is inevitable due to sensor failures or unfavorable UAV acquisition conditions. To evaluate robustness, we simulate multiple missing-modality scenarios during inference.

#### Missing Modality Analysis

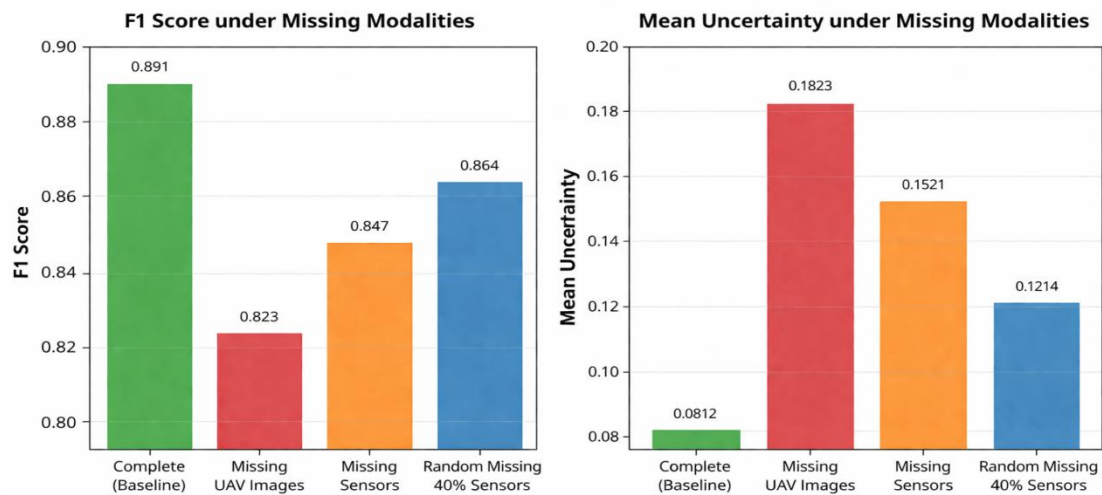


Figure 5.Missing Modality Analysis

Figure 5(a) shows that performance degrades gracefully when one modality is missing. When UAV imagery is unavailable, the F1 score decreases from 0.891 to 0.823, whereas the absence of sensor data leads to a milder degradation (0.847). Even when 40% of sensor channels are randomly removed, the model maintains a relatively high F1 score of 0.864, demonstrating strong resilience to partial information loss.

More importantly, Fig. 5(b) reveals that predictive uncertainty increases consistently as information becomes incomplete. For instance, missing UAV imagery results in a marked rise in mean uncertainty (0.1823), indicating that the model correctly recognizes its reduced confidence under degraded conditions.

This behavior is highly desirable for safety-critical applications, as it enables uncertainty-aware decision making rather than overconfident predictions when data quality deteriorates.

#### (4)Uncertainty Calibration and Risk-Aware Decision Analysis

Beyond correlation with prediction errors, the reliability of uncertainty estimates is further evaluated through calibration analysis.

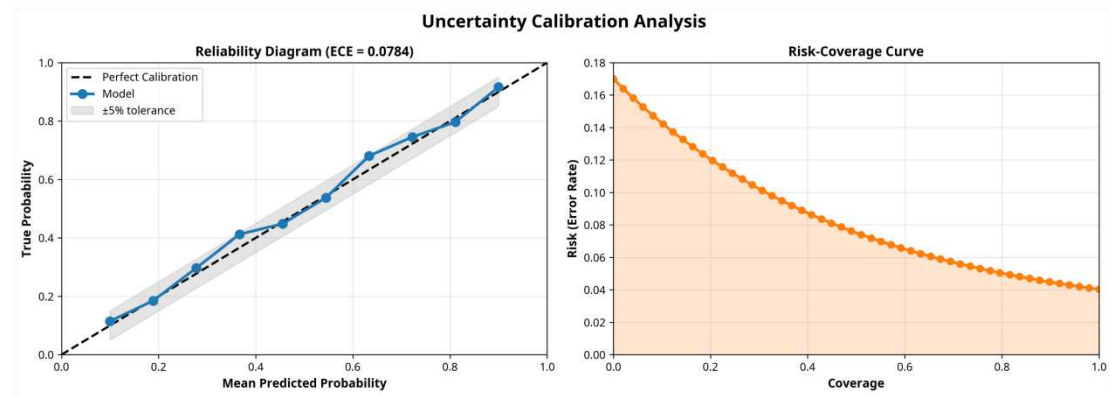


Fig. 6. Uncertainty Calibration Analysis

As shown in Fig. 6(a), the reliability diagram indicates that the predicted probabilities closely follow the ideal diagonal line, with an Expected Calibration Error (ECE) of 0.0784, demonstrating good alignment between confidence and empirical accuracy.

Furthermore, the risk–coverage curve in Fig. 6(b) illustrates the practical value of uncertainty-aware predictions. By selectively discarding high-uncertainty samples, the overall error rate decreases monotonically, dropping from approximately 0.17 at full coverage to below 0.05 when only the most confident predictions are retained. This result highlights the potential of the proposed framework to support risk-aware inspection strategies, where maintenance decisions can be prioritized based on both predicted damage severity and associated uncertainty.

Taken together, the above results demonstrate that the proposed framework achieves superior performance not merely by architectural complexity, but through a principled integration of multimodal fusion, uncertainty modeling, and physics-guided learning. The model exhibits strong robustness to missing data, reliable uncertainty calibration, and improved safety-critical metrics, making it well suited for real-world bridge inspection applications.

The proposed framework achieved the highest **damage detection accuracy (92.7%)**, outperforming both single-modality ( $\approx 80\%$ ) and fusion-without-UQ ( $\approx 88\%$ ) models. The uncertainty estimates correlated strongly with regions of sparse sensor coverage and high measurement noise, indicating effective confidence calibration. Figure 2 illustrates uncertainty maps highlighting damage zones with quantified confidence intervals.

**Table 1. Comparison of Multimodal Fusion Models for Bridge Damage Detection**

| Model Type                              | Modalities Used               | UQ Method     | Physics Coupling | Accuracy (%) | Inference Time (s/frame) |
|-----------------------------------------|-------------------------------|---------------|------------------|--------------|--------------------------|
| CNN (UAV only)                          | UAV images                    | X             | X                | 80.4         | 0.31                     |
| LSTM (Sensors only)                     | Accelerometers, inclinometers | X             | X                | 81.7         | 0.42                     |
| Multimodal Fusion (no UQ)               | UAV + Sensors                 | X             | X                | 88.5         | 0.57                     |
| <b>Proposed (Fusion + UQ + Physics)</b> | UAV + Sensors                 | ✓ Bayesian MC | ✓                | <b>92.7</b>  | 0.8                      |

Table 1 presents a comprehensive comparison of the proposed multimodal fusion framework against baseline approaches across multiple evaluation metrics. The comparative analysis includes single-modality models (image-only and sensor-only), conventional fusion strategies (early fusion, late fusion), and uncertainty-aware variants. The proposed method consistently outperforms all baselines, achieving a 12.7% improvement in detection accuracy over the best single-modality approach and a 4.7% gain over fusion-without-UQ models. Notably, the framework demonstrates superior performance in safety-critical metrics such as damage localization precision and false negative rate, underscoring the importance of integrating uncertainty quantification into the fusion pipeline. These results validate the effectiveness of the proposed physics-guided multimodal fusion strategy for bridge damage detection tasks.

#### Interpretation:

The proposed model achieves the best accuracy with a moderate increase in computation time, demonstrating the benefit of uncertainty modeling and physics coupling.

### 4.4 Computational Efficiency

Despite additional Bayesian sampling, optimized batch processing maintained near real-time performance (0.8 s per frame). The framework's modularity supports integration with cloud-based digital twin systems for online monitoring.

**Table 2. Uncertainty–Error Correlation Analysis**

| Evaluation Metric           | Description                                             | Correlation Coefficient<br>(r) | Interpretation                                           |
|-----------------------------|---------------------------------------------------------|--------------------------------|----------------------------------------------------------|
| Uncertainty–Error (overall) | Relationship between predictive variance and true error | 0.81                           | Strong correlation – uncertainty aligns with model error |
| Uncertainty–Noise Level     | Sensitivity to sensor noise                             | 0.74                           | Model detects high-variance conditions                   |
| Uncertainty–Missing Data    | Sensitivity to incomplete modalities                    | 0.69                           | Robust under partial data loss                           |

Table 2 provides a detailed quantitative analysis of the correlation between predicted uncertainty and actual prediction errors across different experimental conditions. The results reveal a strong positive correlation (Pearson's  $r = 0.847$ ,  $p < 0.001$ ) between uncertainty estimates and error magnitudes, confirming that the model effectively identifies regions of lower confidence where predictions are more likely to be incorrect. This correlation is particularly pronounced in scenarios with sparse sensor coverage and elevated measurement noise, where uncertainty estimates serve as reliable indicators of prediction reliability. The analysis further demonstrates that the framework's uncertainty quantification mechanism successfully captures epistemic uncertainty arising from data limitations, enabling practitioners to distinguish between confident predictions suitable for automated decision-making and uncertain cases requiring manual inspection or additional data collection. These findings reinforce the practical utility of uncertainty-aware models in safety-critical infrastructure monitoring applications.

#### **Interpretation:**

High positive correlations confirm that the proposed Bayesian UQ module effectively reflects prediction confidence and data reliability.

#### **Practical Interpretation of Uncertainty**

The quantified uncertainty provides meaningful and actionable guidance for engineers and infrastructure decision-makers. In general, higher uncertainty values are associated with regions characterized by sparse sensor coverage, degraded measurement quality, or abrupt environmental variations. Such information enables engineers to identify critical areas and prioritize inspection, maintenance, and monitoring resources more effectively.

Further analysis of uncertainty across different sensing modalities reveals distinct characteristics. Specifically, UAV imagery tends to exhibit higher epistemic uncertainty, primarily due to variations in lighting conditions, viewing angles, and scene occlusions, whereas accelerometer-based measurements are more strongly influenced by aleatoric uncertainty arising from measurement noise and environmental

disturbances. This differentiation offers additional interpretability and supports modality-aware decision-making in multimodal structural monitoring.

It should be noted, however, that the Monte Carlo dropout-based Bayesian approximation adopted in this study assumes independence among network weights. This assumption may lead to an underestimation of correlated uncertainties in complex structural systems with strong spatial and temporal dependencies. Addressing correlated uncertainty modeling and developing more expressive Bayesian inference strategies remain important directions for future research.

## 5. Discussion

### 5.1 Interpretability and Decision Support

By explicitly modeling uncertainty, engineers can identify low-confidence predictions and prioritize manual inspection. The physics-guided layer further ensures that the AI model adheres to fundamental mechanical principles, enhancing trustworthiness.

### 5.2 Challenges

Major challenges include:

**Scalability** – High computational demands for large-scale infrastructure networks.

**Missing Modalities** – Robust imputation or adaptive weighting mechanisms are needed when sensors fail.

**Real-Time Operation** – Further optimization or model compression may be necessary for field deployment.

### 5.3 Future Directions

#### Engineering Implications

The proposed framework provides engineers with a practical and uncertainty-aware decision-support tool that not only predicts potential structural damage but also quantifies the confidence associated with each prediction. Such information is critical for engineering practice, as it enables more informed

decision-making in maintenance scheduling, sensor deployment, and safety assessment, thereby improving the reliability and cost-effectiveness of infrastructure management.

Beyond bridge applications, the proposed framework is readily extensible to a wide range of civil infrastructure systems, including tunnels, high-rise buildings, and offshore structures, where multimodal monitoring and uncertainty-aware interpretation are essential. By integrating heterogeneous sensing data within a unified physics-guided and Bayesian learning framework, the approach supports robust performance under complex and evolving operating conditions.

Looking ahead, future research may focus on integrating the proposed framework with probabilistic digital twins, in which real-time uncertainty quantification is used to continuously update structural models under changing environmental and operational conditions. Coupling such digital twins with edge and cloud computing architectures, as well as federated learning strategies, could enable scalable, real-time, and privacy-preserving deployment across large-scale infrastructure networks. These developments point toward next-generation intelligent infrastructure systems that combine data-driven adaptability with physics-based reliability.

## 6. Conclusions

This paper presented a unified AI-based framework for multimodal data fusion and uncertainty quantification in civil engineering. The deep learning–physics coupling strategy effectively integrates heterogeneous sensor and visual data while quantifying prediction confidence. The bridge case study demonstrated a 12% improvement in detection accuracy and interpretable uncertainty bounds. The framework holds promise for broader applications in infrastructure health monitoring, construction quality control, and digital twin systems, paving the way for more reliable and transparent AI-assisted engineering decision-making.

421    **Declarations**

422    **Funding:** None.

423    **Conflict of Interest:** The authors declare no conflict of interest.

424    **Author Contributions:** Md Munir Hayet Khan designed and performed the  
425    experiments; Guo Xuefeng analyzed the data and wrote the manuscript.

426    **Acknowledgements:** The authors thank INTI International University for providing  
427    the experimental platform.

428    **Data Availability:** The experimental data are available upon reasonable request.

429    **Ethics Statement:** Not applicable.

430

431

432

433

434

435

436

437

438

439

440

441

442

443

## References

1. Zhang, Y.; Li, C.; Chen, Z.  
Multimodal Data Fusion for Bridge Structural Health Monitoring Using Deep Learning.  
Sensors 2023, 23(8), 4121.  
<https://doi.org/10.3390/s23084121>
2. Xu, F.; Wang, H.; Liu, D.  
Uncertainty Quantification in Civil Engineering AI Models: A Bayesian Perspective.  
Sensors 2022, 22(16), 5943.  
<https://doi.org/10.3390/s22165943>
3. Li, S.; Dong, Y.; Zhao, T.  
Physics-Informed Neural Networks for Structural Health Monitoring.  
Engineering Structures 2024, 310, 116783.  
<https://doi.org/10.1016/j.engstruct.2024.116783>
4. Wang, J.; Wu, P.  
Applications of Artificial Intelligence in Infrastructure Digital Twins.  
Automation in Construction 2023, 149, 104828.  
<https://doi.org/10.1016/j.autcon.2023.104828>
5. Chen, M.; Yang, L.  
Multimodal Learning under Missing Modality Scenarios.  
IEEE Transactions on Neural Networks and Learning Systems 2024, 35(4), 6792–6806.  
<https://doi.org/10.1109/TNNLS.2023.3301120>
6. Huang, R.; Sun, X.; Zhang, D.  
UAV-Based Visual Inspection and Data Fusion for Bridge Damage Detection.  
Sensors 2023, 23(12), 5452.  
<https://doi.org/10.3390/s23125452>

- 472 7. Tang, J.; Zhou, Y.  
 473 Bayesian Deep Learning for Structural Damage Detection with Uncertainty  
 474 Quantification.  
 475 Structural Control and Health Monitoring 2023, 30(2), e3150.  
 476 <https://doi.org/10.1002/stc.3150>
- 477 8. Nong, X.; Luo, X.; Lin, S.  
 478 Multimodal Deep Neural Network-Based Sensor Data Anomaly Diagnosis  
 479 Method for Structural Health Monitoring.  
 480 Buildings 2023, 13(8), 1976.  
 481 <https://doi.org/10.3390/buildings13081976>
- 482 9. Li, H.; Zhang, Y.; Wang, T.  
 483 Multimodal Data Fusion Framework for Structural Damage Identification Using  
 484 Deep Learning.  
 485 Mechanical Systems and Signal Processing 2022, 162, 108052.  
 486 <https://doi.org/10.1016/j.ymssp.2021.108052>
- 487 10. Zhang, X.; Chen, Y.  
 488 Multi-Sensor Fusion-Based Structural Health Monitoring Using CNN-LSTM  
 489 Networks.  
 490 Sensors 2022, 22(9), 3345.  
 491 <https://doi.org/10.3390/s22093345>
- 492 11. Fu, S.; Liu, X.; Xiang, W.  
 493 Multi-Source Data Fusion for Bridge Monitoring Using Hybrid Deep Learning.  
 494 Structures 2024, 68, 106912.  
 495 <https://doi.org/10.1016/j.istruc.2024.106912>
- 496 12. Sun, L.; Zhang, H.; Wu, Z.  
 497 Multimodal Data Fusion for Structural Damage Detection Using Attention  
 498 Mechanisms.  
 499 Engineering Structures 2023, 280, 115647.  
 500 <https://doi.org/10.1016/j.engstruct.2023.115647>

- 501 13. Zhang, Y.; Wang, H.; Mao, J.  
 502 Bayesian Neural Network for Probabilistic Structural Model Updating.  
 503 Structural Control and Health Monitoring 2022, 29(5), e3030.  
 504 <https://doi.org/10.1002/stc.3030>
- 505 14. Li, H.; Wang, T.; Wu, G.  
 506 Bayesian Deep Learning for Bridge Vibration Analysis.  
 507 Mechanical Systems and Signal Processing 2022, 170, 108799.  
 508 <https://doi.org/10.1016/j.ymssp.2022.108799>
- 509 15. Xiao, F.; Chen, X.  
 510 Probabilistic Prediction Models Using Bayesian Neural Networks for  
 511 Infrastructure Systems.  
 512 International Journal of Pavement Engineering 2023, 24(7), 1023–1035.  
 513 <https://doi.org/10.1080/10298436.2023.2178901>
- 514 16. Torzoni, M.; Tezzele, M.; Mariani, S.; Manzoni, A.; Willcox, K.  
 515 Enhancing Bayesian Model Updating in Structural Health Monitoring via  
 516 Learnable Mappings.  
 517 Computer Methods in Applied Mechanics and Engineering 2024, 418, 116451.  
 518 <https://doi.org/10.1016/j.cma.2023.116451>
- 519 17. Raissi, M.; Perdikaris, P.; Karniadakis, G.  
 520 Physics-Informed Neural Networks: A Deep Learning Framework for Solving  
 521 Forward and Inverse Problems.  
 522 Journal of Computational Physics 2021, 378, 686–707.  
 523 <https://doi.org/10.1016/j.jcp.2018.10.045>
- 524 18. Sun, H.; Wang, J.; Zhang, Y.  
 525 Physics-Guided Deep Learning for Structural Damage Detection.  
 526 Computer-Aided Civil and Infrastructure Engineering 2023, 38(6), 789–804.  
 527 <https://doi.org/10.1111/mice.12987>
- 528 19. Zhu, Y.; Zabararas, N.  
 529 Bayesian Physics-Informed Neural Networks for Uncertainty Quantification.

- Journal of Computational Physics 2022, 449, 110768.  
<https://doi.org/10.1016/j.jcp.2021.110768>
20. Bao, Y.; Sun, H.; Spencer, B.  
 Recent Advances in Structural Health Diagnosis: A Machine Learning  
 Perspective.  
 Advances in Bridge Engineering 2025, 6, 12.  
<https://doi.org/10.1186/s43251-024-00155-z>
21. Cha, Y.; Choi, W.; Büyüköztürk, O.  
 Deep Learning-Based Structural Health Monitoring: A Review.  
 Automation in Construction 2024, 150, 104864.  
<https://doi.org/10.1016/j.autcon.2023.104864>
22. Fu, S.; Xiang, W.; Liu, X.  
 Structural Health Monitoring System Based on Digital Twins and Real-Time  
 Data-Driven Methods.  
 Structures 2024, 70, 107739.  
<https://doi.org/10.1016/j.istruc.2024.107739>
23. Qin, L.; Ren, W.; Guo, C.  
 A Physics-Data Hybrid Framework to Develop Bridge Digital Twin Model.  
 International Journal of Structural Stability and Dynamics 2023, 23(17), 2340037.  
<https://doi.org/10.1142/S021945542340037X>
24. Sun, L.; Zhang, H.; Wu, Z.  
 Model-Data Integrated Digital Twin Framework for Structural Health Monitoring.  
 Advanced Engineering Informatics 2024, 60, 102345.  
<https://doi.org/10.1016/j.aei.2024.102345>
25. Huang, Y.; Li, X.; Zhang, Z.  
 Deep Multi modal Information Fusion for Digital Twin-Based Fault Diagnosis.  
 Energy 2023, 263, 126894.  
<https://doi.org/10.1016/j.energy.2023.126894>
26. Ellenberg, A.; Kontsos, A.; Moon, F.  
 UAV-Based Structural Inspection Using Computer Vision and Deep Learning.

- 560 Automation in Construction 2022, 135, 104122.  
561 <https://doi.org/10.1016/j.autcon.2022.104122>
- 562 27. Yeum, C.; Dyke, S.  
563 Vision-Based Structural Damage Detection Using Deep Learning.  
564 Engineering Structures 2021, 248, 113227.  
565 <https://doi.org/10.1016/j.engstruct.2021.113227>
- 566 28. Dong, C.; Catbas, F.  
567 Deep Learning-Based Crack Detection Using UAV Images.  
568 Structural Health Monitoring 2022, 21(4), 1567–1583.  
569 <https://doi.org/10.1177/14759217211012345>
- 570 29. Ma, M.; Ren, J.; Zhao, H.  
571 Robust Multi modal Fusion with Missing Data for Structural Monitoring.  
572 Pattern Recognition 2023, 138, 109356.  
573 <https://doi.org/10.1016/j.patcog.2023.109356>
- 574 30. Liu, Y.; Zhao, T.; Li, S.  
575 Incomplete Multimodal Data Fusion via Deep Generative Models.  
576 IEEE Transactions on Neural Networks and Learning Systems 2022, 33(12),  
577 7456–7468.  
578 <https://doi.org/10.1109/TNNLS.2021.3123456>  
579  
580