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Automated Dam Crack Detection Using YOLOv10 and UAV Imagery for Structural Health Monitoring

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Abstract. Dams are critical components of national infrastructure, and the presence of undetected surface cracks can lead to severe safety hazards. Conventional inspection methods are often time-consuming, limited by human error, and difficult to implement on a large scale, making timely assessments a persistent challenge. To overcome these limitations, this study presents an automated crack detection framework that leverages YOLOv10 in conjunction with UAV-captured imagery. The speed and accuracy of YOLOv10, combined with the UAV's ability to access hard-to-reach areas, significantly enhance the efficiency and reliability of the inspection process. The proposed system achieved promising results, recording a precision of 0.93, a recall of 0.81, and an F1-score of 0.86—reflecting its capability to rapidly and accurately detect surface-level cracks. This approach represents a step forward in advancing intelligent infrastructure management by facilitating early maintenance and contributing to safer and more sustainable dam operations, particularly through its potential integration with digital twin technologies.

1. Introduction

Concrete infrastructures such as dams are fundamental to water resource management, hydroelectric power generation, and flood mitigation efforts [1]. Despite their robust construction, these structures are vulnerable to crack formation due to factors like environmental stressors, material fatigue, seismic events, and prolonged exposure to hydrostatic pressure [2]. If not identified and addressed in time, such cracks can threaten structural stability and lead to catastrophic failures, resulting in severe economic losses and environmental damage [1], [3]. To mitigate these risks, Structural Health Monitoring (SHM) has become a critical practice in maintaining the safety and longevity of civil infrastructure. Traditionally, SHM relies on manual inspections, which are not only labor-intensive and time-consuming but also pose safety challenges—especially in difficult-to-access areas like the vertical faces of dams [4], [3]. In recent years, automated approaches based on computer vision and deep learning have gained momentum as viable alternatives for improving inspection efficiency and consistency [5], [6].

The advent of Unmanned Aerial Vehicles (UAVs) has significantly transformed data acquisition in SHM. UAVs offer a flexible, cost-effective, and safe means of capturing high-resolution imagery from various angles and elevations [4], [7]. Their ability to access otherwise unreachable locations allows for comprehensive monitoring without disrupting operations or requiring intrusive setups like scaffolding.

Processing the imagery collected by UAVs requires robust analytical tools. In this context, deep learning—particularly convolutional neural networks (CNNs)—has shown impressive performance in tasks such as image classification and object detection [8], [9], [10]. CNNs excel at identifying complex visual features and have been successfully employed for detecting surface-level defects, including cracks in concrete structures [5], [11], [6].

Within the deep learning landscape, the YOLO (You Only Look Once) series has become a leading choice for real-time object detection due to its combination of speed and accuracy [12]. The most recent version, YOLOv10, introduces an architecture that eliminates non-maximum suppression (NMS), thereby enhancing detection performance by reducing redundancy in bounding boxes without compromising precision [13].

In this study, we propose a dam crack detection system that integrates UAV-collected imagery with the YOLOv10 model to automate and optimize the inspection workflow. By leveraging the strengths of UAV technology and advanced object detection, our framework aims to enhance the reliability, safety, and efficiency of crack monitoring in large concrete infrastructures. For model training and evaluation, we use the SDNet2018 dataset, which includes annotated images of cracks on concrete surfaces [14]. We assess the system's performance using standard metrics such as precision, recall, and F1-score.

The primary contributions of this research are summarized as follows:

- We introduce a UAV-based inspection system utilizing the YOLOv10 model for detecting surface cracks in dam structures.
- We train and evaluate the YOLOv10 architecture using the SDNet2018 dataset to measure its effectiveness in crack identification.
- We present a detailed analysis of the model's performance based on key evaluation metrics, demonstrating its applicability in real-world SHM scenarios.

2. Literature Review

Recent Recent advancements in deep learning—particularly the use of Convolutional Neural Networks (CNNs) and the YOLO (You Only Look Once) family of object detection models—have significantly contributed to automated crack detection in concrete structures. Earlier models such as YOLOv3, YOLOv5, and YOLOv7 demonstrated strong performance in identifying surface-level defects, particularly when trained on clean, well-labeled datasets. However, the introduction of YOLOv10 has marked a notable advancement in this domain. Compared to its predecessors, YOLOv10 incorporates several key improvements, including:

- **NMS-Free architecture** – which eliminates the need for non-maximum suppression during post-processing, thereby reducing latency and simplifying the detection pipeline [13].
- **Enhanced Feature Pyramid Networks (FPN-PAN)** – which support robust multi-scale feature extraction, a critical factor for accurately identifying cracks of varying dimensions.

- **Transformer-based self-attention modules** – enabling the model to better focus on subtle and fine-grained features such as micro-cracks and hairline fractures [13].

Compared to traditional CNN-based approaches—which often require extensive datasets and intricate post-processing—YOLOv10 streamlines the detection process while maintaining or even improving performance. This is particularly advantageous in real-world environments where noise, shadows, and texture inconsistencies often lead to false positives in older models and classic CNN techniques [12], [11].

Numerous studies have validated the effectiveness of YOLO-based architectures using benchmark datasets such as SDNet2018 and the Structural Defects Network (SDN). These datasets offer a broad spectrum of annotated concrete images, allowing for robust model training and evaluation in academic research. For instance, Cha et al. employed CNNs for crack detection in concrete bridge structures [5], while Zhang et al. applied deep CNNs to road surface crack detection [11]. More recently, Madaan et al. demonstrated the application of YOLOv4 on UAV-captured images, highlighting the model's suitability for aerial inspection and crack mapping tasks [10 -7].

Non-Deep Learning Techniques for Crack Detection

Before the rise of deep learning, several traditional image processing techniques were commonly employed for detecting cracks:

- **Edge Detection Algorithms:** Filters like Canny and Sobel were widely used to identify discontinuities in pixel intensity that might signify cracks [2]. While these methods are straightforward, they are highly sensitive to noise, lighting variations, and surface textures, often leading to unreliable results.
- **Thresholding and Morphological Operations:** These approaches use intensity-based segmentation and structuring elements to isolate crack-like patterns [2]. However, their performance degrades significantly under inconsistent lighting and irregular surfaces.
- **Wavelet Transforms:** Techniques like two-dimensional wavelet analysis were explored for defect detection in structures such as bridge decks and concrete slabs [15]. Though moderately successful, they required manual tuning and were computationally expensive, especially on large-scale image datasets.
- **Histogram of Oriented Gradients (HOG) with Support Vector Machines (SVM):** Prior to the emergence of CNNs, HOG features combined with SVM classifiers were used for recognizing crack patterns. These methods, however, struggled to adapt to high-variance, complex datasets and required substantial manual feature engineering [16].

While these earlier methods laid the groundwork for automated detection, they were often constrained by limited scalability and robustness. Most notably, their inability to generalize across varying environmental conditions posed significant challenges in practical dam inspection scenarios.

Challenges and Advancements

Despite the progress made through deep learning, several challenges remain:

- Environmental factors such as uneven lighting, textured surfaces, and shadow interference can still impact model accuracy.
- The limited availability of annotated datasets—especially those sourced from real-world dam environments—continues to hinder generalization and real-world deployment [14], [2].

To address these issues, this study integrates the high-resolution imaging capabilities of Unmanned Aerial Vehicles (UAVs) with the advanced detection capabilities of the YOLOv10 model.

UAVs enable comprehensive coverage of large and complex dam structures while capturing images under diverse environmental conditions, thereby enriching the training dataset with greater variability [4]. This integration supports the development of more resilient and adaptable models suited for field deployment.

In conclusion, while earlier methods—both traditional and deep learning-based—provided a foundation for automated crack detection, the proposed approach advances the field by combining UAV technology with YOLOv10 to deliver a scalable, efficient, and field-ready solution for structural health monitoring. This represents a shift from controlled, laboratory-based validation toward practical, real-world implementation for large-scale infrastructure inspection.

3. Model for Dam Crack Detection

The proposed system presents an automated, deep learning- based pipeline for detecting structural cracks in concrete dams, utilizing the latest advancements in object detection—specifically, YOLOv10. The model is designed for real- time, high-precision crack detection and classification using aerial images captured by Unmanned Aerial Vehicles (UAVs). The architecture of YOLOv10 has been selected for its exceptional balance of speed, accuracy, and computational efficiency, which makes it particularly well-suited for on-field infrastructure monitoring. The architecture of automated dam crack detection model is depicted in the fig.1.

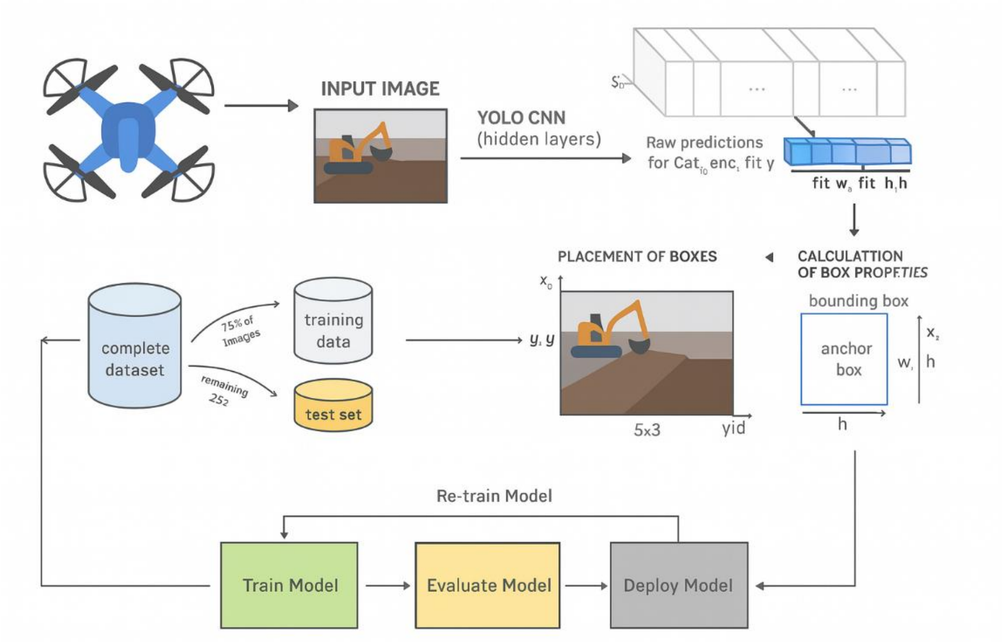

Figure 1. Architecture of automated dam crack detection model.

The system architecture is designed as an end-to-end detec- tion framework and consists of three main components:

- Backbone: The backbone of YOLOv10 is responsible for extracting robust hierarchical features from the input images. It includes advanced modules such as:

– CBS (Convolution + BatchNorm + SiLU): A funda- mental block for stable and efficient feature extraction.

– SCDown (Stride Conv Downsampling): Enhances downsampling efficiency while retaining feature integrity.

– PSA (Parallel Spatial Attention): Integrates multi- scale spatial features, allowing the model to better focus on fine crack patterns that may be spread across various regions of the image.

- Neck: The neck component of the network acts as a bridge between the backbone and the detection head. It employs the FPN-PAN (Feature Pyramid Network with Path Aggregation Network), enabling:

– Multi-level feature aggregation from different spatial resolutions.

– Enhanced feature fusion that captures both high-level semantic information and low-level details—critical for detecting thin, irregular cracks of varying sizes and orientations.

- Head: The detection head is lightweight and employs a decoupled design. Instead of relying on traditional Non-Maximum Suppression (NMS) for post-processing, YOLOv10 adopts a dual allocation strategy, which:

– Separates classification and localization tasks to avoid conflicts during learning.

– Improves inference speed and reduces false positives in closely located cracks.

To enhance the generalization capabilities of the model, data augmentation techniques are applied to the training dataset. These include geometric transformations such as rotation, flipping, scaling, brightness/contrast adjustments, and random cropping. These augmentations simulate real-world conditions like varying angles, lighting, and orientations, improving the model's ability to detect cracks under diverse circumstances. High-resolution images captured via UAVs (Unmanned Aerial Vehicles) serve as the input to the system. UAVs offer the flexibility to inspect large dam surfaces and reach areas that are otherwise dangerous or inaccessible for human inspectors.

Once cracks are detected, the model assesses their severity using two metrics:

- Crack Width (Estimated Pixel Width): Used to differentiate between minor and critical structural cracks.
- Confidence Score (From YOLOv10 Output): Provides the model's certainty regarding the crack detection, aiding in risk prioritization.

Cracks exceeding predefined severity thresholds automatically trigger alerts, making the system suitable for proactive maintenance and real-time structural health monitoring. The end goal is to reduce reliance on manual inspections, increase operational efficiency, and promote public safety through smarter, AI-driven dam infrastructure surveillance.

4. Proposed Algorithm

```
Input: High-resolution crack image dataset (e.g., SD- Net2018, SDN)
Output: Trained YOLOv10 model for crack detection
Step 1:
    Load and label the dataset: Load image dataset with cracked and non-cracked concrete surfaces
    Annotate crack regions using bounding boxes
Step 2: Preprocess images
    for each image in dataset do
```

```
        Resize to 256 × 256 pixels
        Normalize pixel values to [0,1]
    Apply data augmentation (rotation, flip, noise, brightness)
    end for
Step 3: Configure YOLOv10 model
    Define anchor boxes, classes, input size, detection layers Adjust hyperparameters (batch
    size, learning rate, stride, etc.)
Step 4: Split dataset
    Split dataset into 80% training and 20% validation sets
Step 5: Train the model
    Define loss functions:
        Binary Cross-Entropy for classification
        IoU Loss for bounding box accuracy Use Adam or SGD optimizer
    for each epoch do
        Perform forward pass and backpropagation Update weights and compute loss
    end for
Step 6: Evaluate model
    Compute metrics on validation set:
        Precision, Recall, F1-score
        mAP (mean Average Precision)
Step 7: Deploy model to UAV platform
    Integrate trained model into UAV inference pipeline
Step 8: Post-processing
    for each frame from UAV do
        Run YOLOv10 inference
        Apply confidence threshold (e.g., 0.5)
        Render bounding boxes with confidence scores
    end for
Step 9: Visualize and report
    Generate annotated output images and performance reports:
      Confusion matrix, Precision-Recall curve
Step 10: Onboard integration (Optional)
      Deploy model on Jetson Nano or similar edge device
      if critical crack detected then
          Trigger alert and log GPS coordinates Schedule maintenance inspection
```

```
        end if
    Return: Scalable, accurate, and field-ready crack detection model.
```

5. Implementation and Deployment

The proposed crack detection system is developed using the PyTorch deep learning framework, integrating the YOLOv10 architecture for robust real-time object detection. The implementation pipeline consists of several well-structured stages, from data preparation to deployment on UAV platforms for live infrastructure monitoring.

5.1 Data Acquisition and Labeling

High-resolution images are captured using Unmanned Aerial Vehicles (UAVs), which provide a comprehensive and flexible method for inspecting dam surfaces, especially in areas that are difficult or unsafe for manual inspection. The images are then annotated using labeling tools such as LabelImg or Roboflow, where cracks are bounded with boxes and categorized accordingly. Fig 2 shows the sample annotated images from the dataset used for crack detection,

Figure 2. Sample annotated images from the dataset used for crack detection.

5.2 Data Preprocessing

To ensure consistency and improve model generalization, the images are subjected to a sequence of preprocessing steps. These include:

- Resizing all images to match the model's input dimen- sions.
- Normalization to scale pixel values, which facilitates faster and more stable training.
- Data Augmentation techniques such as rotation, flipping, noise addition, and contrast adjustments, which simulate real-world variability and reduce overfitting.

5.3 Model Configuration and Training

The YOLOv10 model is configured with custom settings optimized for small object detection—essential for identifying narrow surface cracks. Configuration parameters include:

- Number of object classes (cracked / non-cracked)
- Anchor boxes optimized for crack geometries
- Input image size

- Training batch size, learning rate, and optimizer settings (Adam/SGD)

The model is trained on the SDNet2018 dataset, a bench- mark dataset consisting of real-world concrete crack images. During training, loss functions such as Binary Cross Entropy for classification and IoU-based loss for localization are used to optimize performance.

5.4 Model Saving and Exporting

Upon completion of the training process, the model's learned weights are saved in a .pt format for PyTorch. These weights are used during inference and can be transferred to edge devices or onboard UAV systems.

5.5 Real-time Inference and Deployment

The trained model is deployed on UAV systems equipped with edge computing modules such as NVIDIA Jetson Nano or Google Coral TPU. As the UAV captures images during a flight mission, the YOLOv10 model processes each frame in real time to detect cracks.

5.6 Alert Mechanism Based on Crack Severity

Each detected crack is evaluated not only for presence but also for severity. Severity assessment is based on:

- Crack width (in pixels or real-world units via UAV altitude calibration)
- Confidence score of the detection

If the crack exceeds a predefined severity threshold, the system triggers an alert, which may include logging the GPS coordinates, capturing additional high-resolution imagery, or notifying maintenance teams.

5.7 Post-processing and Confidence Filtering

To improve the quality of predictions, post-processing is applied. Detections with a confidence score below a set thresh- old (e.g., 0.5) are filtered out to reduce false positives. Non- Maximum Suppression (NMS) or the decoupled head strategy of YOLOv10 ensures overlapping boxes are consolidated.

5.8 Visualization and Reporting

The results are visualized by overlaying bounding boxes and class labels on the original UAV images. This visual feedback assists engineers in quickly identifying damage-prone regions. Fig 3 shows the detected cracks using YOLOv10 model during UAV- based inspection.

Figure 3. Detected cracks using YOLOv10 model during UAV- based inspection.

Performance metrics such as precision, recall, F1-score, and mAP are computed and visualized using confusion matrices, PR-curves, and detection heatmaps for analytical review and system validation.

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6. Performance Evaluation of the UAV-Based Crack Detection System

The UAV-based crack detection system we developed shows promising performance, demonstrating both reliability and precision in practical conditions. The evaluation of the system was carried out using standard performance metrics, defined as follows:

$$Precision = \frac{TP}{TP + FP} \dots\dots\dots\dots (1)$$

$$Recall = \frac{TP}{TP + FN} \dots\dots\dots\dots (2)$$

$$F1 - Score = \frac{TP2 \times \text{Precision} \times \text{Recall}}{Precision + Recall} \dots\dots\dots\dots (3)$$

Where:

TP : True Positives (correctly identified cracks)
FP : False Positives (incorrectly identified cracks)
FN : False Negatives (missed cracks)

Table I summarizes the system’s key performance metrics, derived using Equations 1–3.

Table 1. Performance Metrics of the Proposed Model.

Metric	Value

Precision	0.93
Recall	0.81
F1-Score	0.86

- [5] and [11] employed CNN- based approaches using ground-level images. While they achieved moderate precision and recall in the 0.80–0.85 range, their methods faced limitations in scalability and were not designed for real-time monitoring over large- scale infrastructure.
- [7] utilized traditional image processing on UAV-captured data. However, their system did not in- corporate real-time deep learning models, which reduced accuracy, particularly in visually complex scenarios.
- [10] provided a comprehensive survey of deep learning for structural damage detection but relied heavily on manual data labeling and lacked end-to-end solutions ready for on-site deployment.
- By comparison, our proposed system leverages the ca- pabilities of YOLOv10 and UAV-based data collection, achieving a precision of **0.93**, recall of **0.81**, and an F1-score of **0.86**. YOLOv10's NMS-free design and improved spatial attention mechanisms allow for accurate detection of even small cracks under challenging condi- tions.
- Moreover, our framework includes crack progression tracking via regression analysis over time, enabling pre- dictive maintenance planning. Such forecasting capabili- ties are not addressed in the referenced works.

A detailed confusion matrix further validates the system's balanced detection, showing low rates of both false positives and false negatives. The integration with IoT and UAV tech- nologies enhances real-time alerting and supports continuous, scalable monitoring of infrastructure health.

7. Conclusion

This work introduces a scalable and effective approach for detecting structural cracks using the latest YOLOv10 deep learning model, combined with high-resolution UAV imagery tailored for dam inspection. The system exhibits strong accuracy and real-time responsiveness, enabling reliable identification of surface cracks while keeping false positives and false negatives to a minimum. By automating the inspection workflow, this model reduces dependency on manual efforts, which are often labour-intensive, expensive, and potentially unsafe. The automated process also supports faster decision-making by quickly highlighting areas in need of repair, ultimately strengthening infrastructure safety. Due to its adaptability and scalability, the method is not limited to dams alone—it holds promise for a broader range of civil structures, including bridges and high-rise buildings.

To assess the performance of our model, we relied on three widely used evaluation metrics: *Precision*, *Recall*, and *F1- Score*, defined as follows:
In our experiments, the model achieved a **Precision of 0.93**, a **Recall of 0.81**, and an **F1-score of 0.86**, as calculated using Equations (1-3) These metrics reflect the model's strong capability to accurately detect cracks with a low rate of false alerts.

The priority between precision and recall depends on the specific goals of the application. In the case of dam inspections:

- **High Recall** (Equation 2) is essential to ensure that the majority of cracks are identified, reducing the risk of missing critical structural issues.
- **High Precision** (Equation 1) ensures that only true cracks are reported, which helps minimize unnecessary inspections and avoid false alarms.

Given the safety-critical nature of dams, recall typically takes precedence, as missing a defect could have serious consequences. Nonetheless, precision is also crucial to keep maintenance efforts focused and cost-effective. Our system strikes a meaningful balance between both, as evidenced by the robust F1-score (Equation 3)

Future Directions

Looking ahead, our research will focus on expanding the dataset to encompass a broader range of crack types and environmental conditions, improving the model's generalization capabilities. Further enhancements to the YOLOv10 architecture—such as the inclusion of attention modules and multi-scale feature processing—are planned to boost detection accuracy, particularly for fine or less-visible cracks. We also aim to optimize the system for onboard UAV processing by developing lightweight models suited for edge devices, enabling efficient and real-time field deployment. In addition, deeper integration with IoT ecosystems will support continuous monitoring and predictive maintenance through real-time analytics of crack progression and structural health.

Overall, this study lays the groundwork for intelligent, UAV- enabled inspection systems, offering a promising pathway toward safer, smarter, and more sustainable infrastructure management.

References

[1] Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2015). You Only Look Once: Unified, Real-Time Object Detection. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 779-788. https://doi.org/10.1109/CVPR.2016.91.

[2] Wang, A., Chen, H., Liu, L., Chen, K., Lin, Z., Han, J., & Ding, G. (2024). YOLOv10: Real-Time End-to-End Object Detection. ArXiv, abs/2405.14458. https://doi.org/10.48550/arXiv.2405.14458.

[3] Russel, N., & Selvaraj, A. (2024). MultiScaleCrackNet: A parallel multiscale deep CNN architecture for concrete crack classification. *Expert Syst. Appl.*, 249, 123658. https://doi.org/10.1016/j.eswa.2024.123658

[4] Zhou, S., & Gheisari, M. (2018). Unmanned aerial system applications in construction: a systematic review. Construction Innovation. https://doi.org/10.1108/CI-02-2018-0010.

[5] Fan, J., , C., & Zhong, Y. (2019). A Selective Overview of Deep Learning. Statistical science : a review journal of the Institute of Mathematical Statistics, 36 2, 264-290 . https://doi.org/10.1214/20-STS783.

[6] Farrar, C., & Worden, K. (2007). An introduction to structural health monitoring. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 365, 303 - 315. https://doi.org/10.1098/rsta.2006.1928.

[7] Cha, Y., Choi, W., & Büyüköztürk, O. (2017). Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks. Computer-Aided Civil and Infrastructure Engineering, 32. https://doi.org/10.1111/mice.12263.

[8] Zhang, L., Yang, F., Zhang, Y., & Zhu, Y. (2016). Road crack detection using deep convolutional neural network. 2016 IEEE International Conference on Image Processing (ICIP), 3708-3712. https://doi.org/10.1109/ICIP.2016.7533052.

[9] Yu, Y., Rashidi, M., Dorafshan, S., Samali, B., Farsangi, E., Yi, S., & Ding, Z. (2024). Ground penetrating radar-based automated defect identification of bridge decks: a hybrid approach. Journal of Civil Structural Health Monitoring. https://doi.org/10.1007/s13349-024-00895-6.

[10] Bhowmick, S., Nagarajaiah, S., & Veeraraghavan, A. (2020). Vision and Deep Learning-Based Algorithms to Detect and Quantify Cracks on Concrete Surfaces from UAV Videos. Sensors (Basel, Switzerland), 20. https://doi.org/10.3390/s20216299.

[11] He, P., Pan, J., & Li, Y. (2022). Long-term dam behavior prediction with deep learning on graphs. J. Comput. Des. Eng., 9, 1230-1245. https://doi.org/10.1093/jcde/qwac051.

[12] Dang, H., Raza, M., Nguyen, T., Bui-Tien, T., & Nguyen, H. (2020). Deep learning-based detection of structural damage using time-series data. Structure and Infrastructure Engineering, 17, 1474 - 1493. https://doi.org/10.1080/15732479.2020.1815225.

[13] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. ArXiv, abs/1505.04597. https://doi.org/10.1007/978-3-319-24574-4_28.

[14] Chen, F., & Jahanshahi, M. (2018). NB-CNN: Deep Learning-Based Crack Detection Using Convolutional Neural Network and Naïve Bayes Data Fusion. IEEE Transactions on Industrial Electronics, 65, 4392-4400. https://doi.org/10.1109/TIE.2017.2764844.

[15] Koch, C., Georgieva, K., Kasireddy, V., Akinci, B., & Fieguth, P. (2015). A review on computer vision based defect detection and condition assessment of concrete and asphalt civil infrastructure. Adv. Eng. Informatics, 29, 196-210. https://doi.org/10.1016/j.aei.2015.01.008.

[16] Mohan, A., & Poobal, S. (2017). Crack detection using image processing: A critical review and analysis. Alexandria Engineering Journal. https://doi.org/10.1016/J.AEJ.2017.01.020.