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DETECTING FLAT ROOF DEFECTS WITH MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

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Abstract. *In the context of the ongoing war in Ukraine, ensuring the safety and longevity of buildings and infrastructure is paramount. Traditional inspection methods for detecting structural damages—such as cracks, spalling, or corrosion—are labor-intensive, time-consuming, and prone to human error. This study addresses these challenges by leveraging deep learning techniques, particularly for flat roofs. Models including CNNs, U-Net, YOLO, and autoencoders enable efficient defect detection from both visual and thermal data, even in hazardous or hard-to-reach areas. UAVs facilitate rapid image collection, thereby reducing costs and risks associated with manual inspections. Our findings indicate that AI-driven methods can significantly improve inspection accuracy, accelerate maintenance, and ensure early detection of critical damage, crucial for infrastructure safety in conflict-affected zones. Ultimately, integrating deep learning into structural health monitoring offers a robust and automated approach to safeguarding buildings and optimizing maintenance efforts.*

Keywords: *Deep learning, structural monitoring, neural networks, YOLO, CNN, flat roofs*

Introduction. The integrity of a structure is fundamental for its longevity and safety, particularly in critical components like roofs, which are exposed to harsh weather conditions. Detecting defects such as cracks, deformations, or corrosion in flat roofs is vital, as failure to identify these issues early can result in serious consequences. Traditional manual inspection methods, while effective, are time-consuming, costly, and susceptible to human error. Recent advancements in technology, particularly the application of machine learning (ML) and deep learning (DL) techniques, have opened new avenues for automated and efficient damage detection. These techniques, especially convolutional neural networks (CNNs), object detection methods (YOLO), and autoencoders, can analyze large datasets, such as images or sensor data, much faster and more accurately than traditional methods. The objective of this study is to assess the effectiveness of these methods in detecting flat roof defects, focusing on image analysis and sensor data interpretation for early damage detection.

Research Objective. This research aims to explore how deep learning techniques can be applied to detect structural deformation and damage in construction, with a focus on flat roofs. Specifically, we aim to:

1. Review deep learning models (CNN-based classifiers, U-Net, YOLO, autoencoders) for structural damage detection.
2. Analyze the effectiveness of these methods based on recent studies, focusing on roofs and other structural components.
3. Investigate the data sources and tools involved, such as UAVs, high-resolution cameras, and thermal sensors.
4. Compare the performance of deep learning models across different structural elements and damage types.
5. Examine the real-world applications and challenges of integrating deep learning into maintenance workflows for continuous monitoring and efficient decision-making.

Deep Learning Methods for Structural Damage Detection. Convolutional Neural Networks (CNNs): CNNs are widely used for detecting surface defects like cracks in concrete. They can not only classify images but also localize damage areas. For example, ResNet-18 was employed to analyze structural damage in camera footage, improving detection accuracy over traditional methods. Semantic Segmentation (U-Net): U-Net is effective for pixel-level crack detection. It can delineate even thin and irregular cracks in concrete. Advanced versions, like VM-UNet++, further improve accuracy by incorporating multi-scale context, making them ideal for complex crack patterns. Object Detection (YOLO, Faster R-CNN): YOLO models excel in real-time detection, identifying defects such as exposed rebars and spalling with high precision. These models are fast and suitable for dynamic, on-the-fly inspections, particularly when using UAVs. Autoencoders and Anomaly Detection: Autoencoders, a type of unsupervised model, detect anomalies in vibration and thermal data. Trained on healthy structure data, these models can flag deviations that indicate potential damage, even without labeled examples.

Data Sources and Inspection Tools. Effective deep learning-based damage detection relies on high-quality data, often collected via UAVs equipped with RGB cameras, thermal imaging, and other sensors. These technologies enable comprehensive inspections, especially in hard-to-reach areas like roofs. The fusion of data from different sensors—such as visual images and thermal scans—enhances detection capabilities. For example, UAVs can quickly cover large surfaces, and thermal imaging can reveal hidden subsurface defects, providing a fuller picture of structural health.

Conclusion. Deep learning has proven to be a powerful tool for automating the detection of structural damage in flat roofs, offering high accuracy and efficiency compared to traditional inspection methods. Convolutional neural networks (CNNs), semantic segmentation networks like U-Net, and object detection models such as YOLO have demonstrated effectiveness in detecting various types of damage, including cracks, spalling, and exposed rebars. Additionally, autoencoders offer a promising solution for detecting structural anomalies through vibration or sensor data analysis.

The integration of UAVs, high-resolution cameras, and thermal sensors has made data collection more efficient and accessible. Real-time monitoring systems can now autonomously detect damage, reducing the need for manual inspections and enhancing safety by enabling timely maintenance. While challenges remain in ensuring models generalize across different structures and conditions, the advances in deep learning and data collection tools suggest a future where automated damage detection becomes a standard practice in structural health monitoring.

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ВИЯВЛЕННЯ ДЕФЕКТІВ ПЛОСКИХ ПОКРІВЕЛЬ ЗА ДОПОМОГОЮ МЕТОДІВ МАШИННОГО НАВЧАННЯ ТА ГЛИБОКОГО НАВЧАННЯ

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Анотація. *У контексті поточної війни в Україні забезпечення безпеки та довговічності будівель і інфраструктури є надзвичайно важливим. Традиційні методи інспектування для виявлення структурних пошкоджень—таких як тріщини, відшарування або корозія—вимагають значних людських ресурсів, багато часу та схильні до помилок. У цьому дослідженні розглядається можливість застосування технологій глибинного навчання, особливо для пласких покрівель. Моделі, зокрема CNN, U-Net, YOLO та автоенкодери, дають змогу ефективно виявляти дефекти на основі візуальних і теплових даних, навіть у складних чи важкодоступних умовах. Використання безпілотних літальних апаратів (БПЛА) полегшує швидкий збір зображень і знижує витрати та ризики, пов’язані з ручними перевірками. Результати свідчать, що методи, керовані штучним інтелектом, можуть суттєво підвищити точність перевірок, прискорити технічне обслуговування та забезпечити раннє виявлення критичних пошкоджень, що надзвичайно важливо для безпеки інфраструктури в умовах конфлікту. Інтеграція глибинного навчання в системи моніторингу технічного стану споруд пропонує надійний і автоматизований підхід для захисту будівель і оптимізації зусиль із їх обслуговування.*

Ключові слова: *глибинне навчання, моніторинг стану будівель, нейронні мережі, YOLO, CNN, плоскі дахи.*