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Mykyta Hryhorovych

DETECTING FLAT ROOF DEFECTS WITH MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

Anotation. Deep learning has emerged as a transformative approach for detecting structural damage and deformations, particularly for flat roofs and large-scale infrastructure. This article synthesizes recent progress in applying convolutional neural networks (CNNs), segmentation models, object detectors (YOLO, Faster R-CNN), and autoencoders for unsupervised anomaly detection. Drones (UAVs), thermal imaging, and vibration sensing all contribute critical data. By training on images or signals indicative of healthy vs. damaged conditions, deep models can locate cracks, spalling, missing fasteners, or stiffness loss at high speed and with impressive accuracy - often above 85%. A review of more than 300 publications indicates that remote inspection with AI can drastically reduce manual labor and improve the consistency of damage identification, even in hazardous or inaccessible areas. A summary table compares deep learning effectiveness across beams, walls, decks, roofs, and other structural components. Real-world deployments on bridges, high-rise facades, and post-disaster zones confirm that deep learning, coupled with UAV-based inspections, can accelerate maintenance workflows, detect subtle defects, and reduce safety risks. Ongoing challenges include data scarcity for rare failure modes, generalizing models to new environments, and the integration of physics-based reasoning. Recommendations for future research involve fusing multispectral data, automating calibration of deep models, and embedding AI in digital twins for continuous structural health monitoring.
Key words: deep learning, machine learning, flat roof defects, structural damage, UAV, computer vision, CNN, semantic segmentation, object detection, autoencoders

Statement of the problem. Structural integrity is vital for safety and longevity. Flat roofs, in particular, are vulnerable to cracks, water infiltration, and other failures that may remain unnoticed in manual inspections. Conventional inspection methods can be cumbersome, time-consuming, and risky for inspectors. This creates a pressing need for automated, intelligent damage detection solutions. Recent technological progress especially in UAVs, camera hardware, and AI - has enabled large volumes of image or sensor data to be gathered rapidly. Yet this deluge of data poses its own challenge: manual review is impractical. Deep learning provides a way to handle these large datasets by learning patterns of healthy vs. damaged states, thus flagging potential defects with high accuracy.

Analysis of the latest research and publications. *Deep Learning Domination.* An extensive body of work shows that **CNNs** are the most widely adopted approach for structural defect detection [1]–[3]. They excel at identifying cracks, surface spalling, and other damage forms from images. Researchers worldwide including teams in the USA, Europe, Ukraine, and China have refined CNN-based models (e.g., ResNet, VGG) or segmentation architectures (U-Net, Mask R-CNN, YOLO) to accurately pinpoint cracks in concrete, masonry, or asphalt [4], [5]. A 2023 review [1] covering 337 papers found that 60% rely on CNN-based image analysis, with *crack detection* the most common application (30% of studies).

Extended Architectures and Unsupervised Methods. To capture more complex phenomena, newer models integrate transformers into U-Net, achieving 4–6% gains in segmentation metrics [6]. Some authors employ unsupervised autoencoders that learn a “healthy” baseline of vibrations or thermal images, then flag anomalies if reconstruction error spikes [7]. These methods reduce dependency on labeled damage data and can detect unseen defect types.

Role of Multimodal Sensing. Studies increasingly incorporate thermal infrared *(IR)* imaging to uncover hidden defects such as water intrusion or subsurface delamination in flat roofs. UAV-based IR surveys can detect temperature irregularities that correspond to moisture pockets [8]. Laser scanning or 3D LiDAR further aids in capturing geometric deformations. Multimodal fusion-combining RGB, IR, vibration data improves detection accuracy and can differentiate superficial discoloration from genuine cracks or moisture infiltration [9].

Real-World Applications. Pilot projects confirm that deep learning can reduce labor and cost. Case studies from the USA indicate an AI-assisted inspection can be 50–70% cheaper than rope-access methods for tall facades or rooftops [10]. Europe and East Asia have also tested UAV-based deep learning to identify post-disaster building damage, which is critical for emergency response [3]. In Ukraine, deep models trained on pre- vs. post-conflict imagery facilitate rapid mapping of war damage [11]. These validations highlight the global acceptance of AI-driven inspection, excluding few regions that lack open publication or data-sharing.

Research Objective. This article aims to *systematically review* how deep learning can detect flat roof defects alongside general structural damage using modern sensing platforms. We target five goals:

– Survey CNN-based classification, segmentation networks (U-Net, Mask R-CNN), object detectors (YOLO, Faster R-CNN), and autoencoders.

– Highlight data sources (drone imagery, IR, vibration) and preprocessing steps to prepare them for deep learning.

– Present a comparison table that synthesizes detection accuracy across structural elements, including flat roofs.

– Describe practical case studies showing how UAV-based AI solutions drastically shorten inspection times and reduce costs.

– Discuss future trends: physics-based digital twins, hybrid AI, and regulatory frameworks to ensure reliability.

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Presentation of the Main Research Material. ***Deep Learning Methods for Damage Detection.*** *Convolutional Neural Networks (CNNs).* CNNs have proven extremely effective at discerning cracks or corrosion directly from raw images. Classic approaches use patch-level classification (crack vs. no crack), while modern methods provide heatmaps or bounding boxes around damage. A ResNet-18 architecture, for example, might scan overhead photos of a roof, highlighting areas with potential membrane perforation. CNN performance depends heavily on image resolution and training data quality; small cracks (<0.3 mm) may go undetected if the camera or vantage point is insufficient.

Semantic Segmentation: U-Net Variants. Pixel-level damage identification is especially relevant for roofing systems, where water intrusion often occurs at small cracks or seam failures. Segmentation networks like U-Net and DeepLab can outline precise crack boundaries. Researchers incorporate improved skip connections or multi-scale context (e.g., U-Net++ or TransUNet) [6] Figure 1.

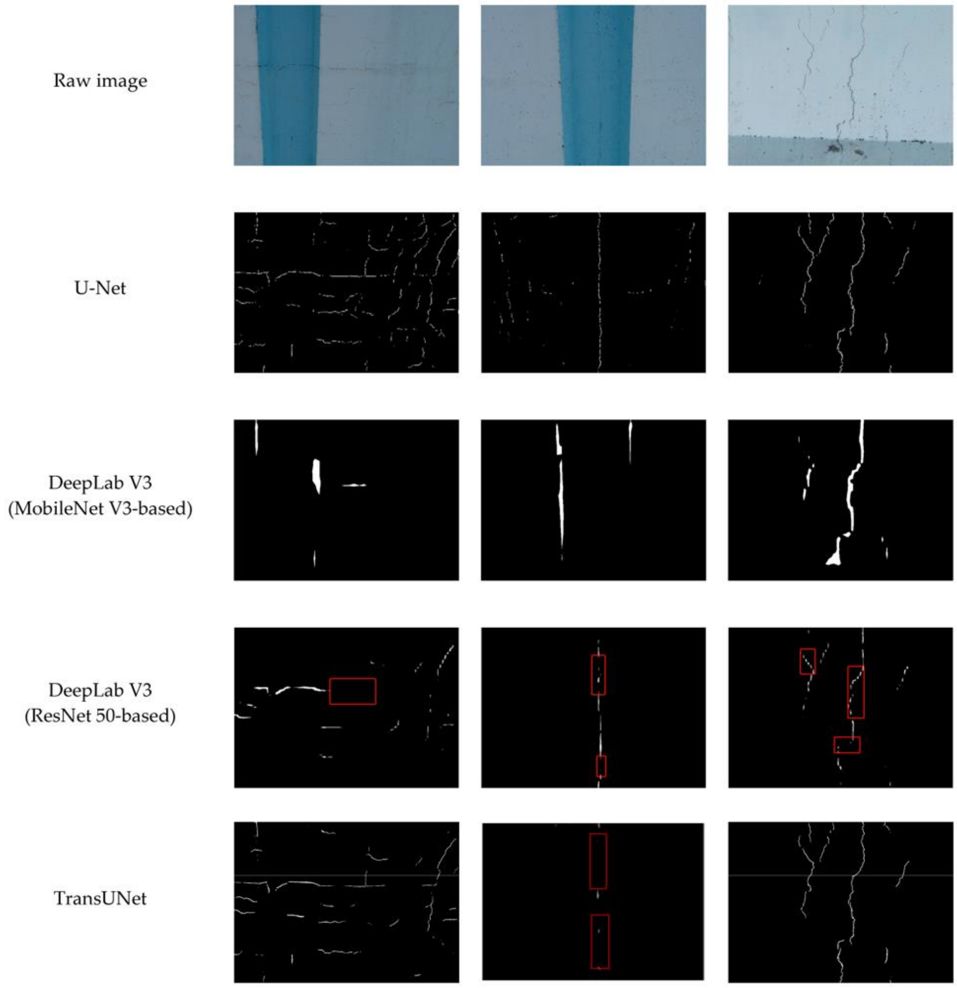

Figure 1 – Example comparison of crack segmentation outputs from different deep learning models on a concrete surface: a – raw UAV images of a bridge column with cracks; b – predicted crack masks using the U-Net model; c – predicted crack masks using the DeepLab V3 (MobileNet V3) model; d – predicted crack masks using the DeepLab V3 (ResNet 50) model; e – predicted crack masks using the TransUNet model. Red boxes indicate areas where some models missed or erroneously detected cracks

Object Detection: YOLO and Faster R-CNN. Large-scale defects such as spalled areas or missing roof shingles can be detected as “objects.” YOLO excels in real-time performance, allowing drones to stream video that is analyzed on-the-fly [4]. Two-stage detectors (Faster R-CNN) often yield slightly higher accuracy but are slower. For high-stakes tasks—e.g., final verification of severe roof damage—engineers might accept the computational cost for an extra margin of accuracy.

Autoencoders for Anomaly Detection. Autoencoders learn normal patterns from unlabeled data; deviations in reconstruction error can signal hidden damage, e.g., moisture infiltration beneath membranes or rebar corrosion in the roof slab. This approach helps when labeled “defect” data is scarce [7]. For instance, if a structural deck’s vibration signature shifts due to partial delamination, the autoencoder flags a higher anomaly score—even if the surface looks intact.

Data Sources and Inspection Tools. Drones (UAVs) are pivotal for surveying large flat roofs without requiring scaffolding or harnesses. Equipping drones with RGB and IR cameras enables the capture of complementary data: visible cracks vs. hidden moisture indicated by temperature variance [8]. Meanwhile, vibration sensors placed at roof supports or beams can detect changes in stiffness if a support girder is compromised. Preprocessing steps (stitching overlapping UAV photos into an orthomosaic) are crucial for large roofs. IR images must be calibrated to account for emissivity differences. Tools such as semi-automatic annotation can speed up dataset creation by suggesting crack outlines, which inspectors confirm.

Real-World Applications and Case Studies. *Roof Inspections.* Frequent roof inspections catch issues like ponding water, membrane punctures, or seam failures early. A UAV-based system in California used a YOLOv5 model on both visual and thermal images, achieving ~90% accuracy in identifying heat anomalies correlating with water infiltration [8]. Another pilot in Denmark used a tethered drone to scan entire industrial rooftops, detecting cracks and energy losses in near real-time. *Bridges, Facades, and Post-Disaster Surveys.* Although the focus is flat roofs, similar techniques apply to other structures. Bridges incorporate IR and optical cameras to find deck delamination or rebar exposure. Facade inspections in dense urban areas rely on UAVs or robotic systems to detect cracks in vertical surfaces. Post-disaster efforts (earthquakes, conflicts) use satellite or aerial images with deep learning to classify building damage severity across entire city blocks [3], [11].

Summary Table of Model Performance. Below is a condensed table highlighting results from various studies on different structural components, including roofs table 1. Accuracy ranges typically span 80–95%, with the highest results in well-controlled conditions. In practice, performance depends on lighting, image resolution, and training dataset diversity. Specialized tasks (cracks on rooftop membranes) may see slightly lower recall, demanding more advanced or higher-resolution imaging solutions.

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Table 1

Deep Learning Effectiveness Across Structural Components

Structural Component	Common Damage	Example DL Approach	Reported Performance
Roofs (flat or pitched)	Leaks, missing shingles, or cracks	YOLO for missing shingles, IR-based crack detection	~85–90% accuracy in real UAV tests [8]
Beams & Girders	Cracks, deflection	U-Net for cracks, autoencoder for anomaly detection	~95% precision on visible cracks [1]
Walls/Facades	Cracks, spalling	Mask R-CNN, YOLO, TransUNet for segmentation	90–96% accuracy in multiple studies [6]
Foundations	Settlement, moisture	Thermal imaging, GPR, LSTM on tilt sensors	80% detection of subsurface voids
Bridge Decks	Delamination, potholes	IR-based CNN, YOLO for real-time detection	~90–95% for cracks or delams [2], [4]

Workflow Integration. Workflow involves:

1. Data Collection: UAV captures overhead shots of the roof, possibly with IR.
2. Preprocessing: Stitch images into an orthomosaic, correct lens distortions, label any known defects.
3. Deep Learning Inference: Run object detectors or segmentation to highlight possible damage.
4. Post-Processing: Merge overlapping detections, measure crack length or area, and create a user-friendly map.
5. Verification: Inspectors confirm or dismiss AI findings, refining future model performance.

Challenges and Future Directions. *Data Scarcity:* Some critical roof failure modes (e.g., severe structural collapse) are thankfully rare, meaning few labeled examples. Generative Adversarial Networks (GANs) or synthetic data can help. *Generalization:* A model trained on typical commercial roofs might fail on older, historically significant structures with different materials. Transfer learning and domain adaptation remain vital. *Integration with Physics:* Combining AI with structural models (digital twins) can differentiate real damage from benign anomalies caused by thermal expansion or occupant load changes. *Regulatory Acceptance:* Standards for AI-based inspection remain in flux. Liability issues and guidelines for verifying algorithmic results need further clarification.

Conclusions. Deep learning is revolutionizing the detection of flat roof defects and broader structural damage, enabling cost-effective, frequent, and safer inspections. Across the literature, CNNs dominate for image-based analysis, while segmentation networks excel at mapping cracks or spalls. Object detectors (YOLO) provide fast bounding-box detection of missing shingles or open seams, and autoencoders enable anomaly detection without large-labeled datasets. Real-world pilots consistently show 80–95% detection accuracy, with some controlled-lab experiments exceeding 95%. The rise of drones and multimodal sensing has amplified AI’s impact. Thermal imaging reveals hidden moisture infiltration, vibration sensors detect stiffness changes, and LiDAR captures geometric deformation. Fusing these data streams can mitigate false positives. Meanwhile, the cost benefits—reducing manual labor-drive commercial adoption, from rooftop insurance surveys to post-disaster damage mapping. Challenges persist around model generalization, limited training data for rare failures, and robust interpretability to ensure safety-critical decisions. Nonetheless, the overarching trend is clear: advanced AI frameworks will continue to integrate into structural health monitoring, bridging data collection and engineering analysis to keep buildings, bridges, and roofs safer, longer. Future progress will likely focus on digital twin integration, improved domain adaptation techniques, and standardized guidelines for AI-based inspections.

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Виявлення дефектів плоских покрівель за допомогою методів машинного навчання та глибокого навчання

Глибоке навчання стало проривним підходом до виявлення конструктивних пошкоджень і деформацій, зокрема для плоских покрівель та великомасштабної інфраструктури. У цій статті узагальнено останні досягнення в застосуванні згорткових нейронних мереж (CNN), моделей сегментації, детекторів об'єктів (YOLO, Faster R-CNN) та автокодерів для безнаглядного виявлення аномалій. Дрони (БПЛА), тепловізійна зйомка та вібраційне зондування забезпечують критично важливі дані. Завдяки навчанню на зображеннях або сигналах, які відображають нормальний або пошкоджений стан, моделі глибокого навчання можуть швидко й точно виявляти тріщини, відшарування бетону, відсутні кріплення або втрату жорсткості — часто з точністю понад 85 %. Огляд понад 300 наукових публікацій свідчить, що дистанційна інспекція за допомогою ШІ може суттєво зменшити обсяг ручної праці та покращити стабільність ідентифікації ушкоджень навіть у небезпечних або важкодоступних зонах. Підсумкова таблиця порівнює ефективність глибокого навчання для балок, стін, перекриттів, покрівель та інших конструктивних елементів. Реальні приклади впровадження на мостах, фасадах висотних будівель і у зонах після стихійних лих підтверджують, що глибоке навчання у поєднанні з інспекцією БПЛА здатне прискорити обслуговування, виявити приховані дефекти та зменшити ризики для безпеки. Серед актуальних викликів — нестача даних для рідкісних типів пошкоджень, складність узагальнення моделей на нові умови та потреба у поєднанні з фізичними моделями. Серед рекомендацій для подальших досліджень — об'єднання мультиспектральних даних, автоматизація калібрування моделей та інтеграція ШІ в цифрові двійники для постійного моніторингу стану конструкцій.

Ключові слова: глибоке навчання, машинне навчання, дефекти плоских покрівель, пошкодження конструкцій, БПЛА, комп'ютерний зір, CNN, семантична сегментація, виявлення об'єктів, автокодери.

Григорович Микита Сергійович – здобувач Українського Державного Університету Науки і Технологій, ННІ «Придніпровська Державна Академія Будівництва та Архітектури», кафедра Технології Будівельного виробництва.

Hryhorovych Mykyta – applicant of Ukrainian State University of Technologies and Science, ESI "Prydniprovska State Academy of Civil Engineering and Architecture", ORCID ID: 0000-0002-5539-7493.