Висновки

У ході дослідження було розроблено та проєктно обґрунтовано базу даних для інформаційної системи студмістечка, що дозволяє ефективно управляти ключовими об'єктами системи — студентами, працівниками, гуртожитками, кімнатами, інвентарем та фінансовими операціями. У процесі проєктування застосовано сучасні методи аналізу предметної області, побудови ER-діаграм, нормалізації до третьої нормальної форми та створення реляційної моделі. Результатом є логічно структурована база даних, що забезпечує цілісність, несуперечність і зручність доступу до інформації. Запропоноване рішення сприяє підвищенню ефективності управління студмістечком, автоматизації рутинних процесів та покращенню якості обслуговування студентів у закладах вищої освіти.

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ANALYSIS OF PRECISION OF FINDING THE DESTROYED REMAINS BUILDINGS ON PHOTOS USING MOBILENETV3 AND VIT NEURAL NETWORKS

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In recent years, the frequency and severity of both natural and man-made disasters – ranging from earthquakes and hurricanes to armed conflicts and industrial accidents – have placed unprecedented strain on emergency response teams and urban planners worldwide. Rapid and reliable identification of structural damage is paramount not only for directing search-and-rescue efforts but also for assessing longer-term recovery needs [1]. Traditional visual inspections, conducted by human experts in the field, are often hampered by safety hazards, limited accessibility and subjective variability. Consequently, the development of automated, image-based techniques has emerged as a critical research frontier, promising to deliver faster, more consistent damage assessments directly from photographic data captured in disaster zones [2, 3].

Within this landscape, deep learning approaches have demonstrated remarkable success in a variety of computer vision tasks [4, 5]. Convolutional neural networks (CNNs) have long been celebrated for their ability to extract hierarchical features from images, while Transformer-based architectures have more recently shown that self-attention mechanisms can capture complex spatial relationships and contextual dependencies with exceptional precision [6]. The MobileNetV3 architecture, optimized for computational efficiency on edge devices, offers an attractive solution for rapid on-site inference when deployed on drones or ground robots. In parallel, Vision Transformer (ViT) models have elevated the state of the art in scene understanding and object detection tasks, albeit at a typically higher computational cost. Despite these individual strengths, a rigorous side-by-side evaluation of both paradigms – particularly in the specific context of detecting and localizing the fragmented remains of collapsed buildings – remains underexplored.

Precision and recall are two fundamental metrics that underpin the reliability of any detection system [7, 8]. Precision measures the proportion of correctly identified damage instances among all detections made by the model, while recall reflects the model's ability to find all true damage instances in an image [9]. In disaster scenarios, a high precision prevents wasted effort on false alarms, whereas a high recall ensures that no genuine structural hazards are overlooked. Balancing these metrics is especially challenging when the dataset includes both conspicuous damage (e.g., large debris fields and collapsed walls) and subtle indicators of compromise (e.g., fine cracks or partial displacements) [10]. Evaluating how MobileNetV3 and ViT architectures perform in terms of precision and recall across this spectrum of damage types is essential for guiding the selection and deployment of robust, field-ready vision systems.

This study aims to fill a critical gap by conducting a comprehensive comparative analysis of the precision and recall outcomes yielded by MobileNetV3 and Vision Transformer networks when tasked with identifying destroyed building remains in real-world photographic datasets. We assemble a diverse collection of aerial and ground-level images drawn from multiple disaster incidents and subject them to uniform preprocessing and annotation pipelines. Each network's outputs are then evaluated against expert-verified ground truth masks to quantify detection accuracy and completeness. By elucidating the trade-offs between model size, inference speed, and detection quality, our work seeks to provide actionable insights for practitioners who must choose between lightweight, on-device inference models and transformer-based solutions with superior contextual reasoning capabilities. Ultimately, the findings of this research are intended to inform the design of next-generation disaster-response tools, ensuring that critical decisions – from dispatching rescue teams to prioritizing structural repairs – are underpinned by reliable and timely visual intelligence.

The purpose of the work is analysis of precision and recall of finding the destroyed remains buildings on photos using MobileNetV3 and ViT neural networks.

The input data comprise two neural network architectures – ViT and MobileNetV3 – and a curated dataset of images depicting the remnants of destroyed buildings. During the training phase, this image set is used to train both models. In the first stage, all input images are preprocessed to satisfy the requirements of each architecture [11]. For MobileNetV3, this involves resizing images to 224 × 224 pixels, converting them to tensors, and normalizing pixel values to the [0, 1] range. For ViT, the same resizing and tensor conversion take place, but normalization is applied over the [–1, 1] interval. In the second stage, both networks are further fine-tuned [12], their performance is assessed using key accuracy metrics [13], and the optimal model variants are stored for later integration [14].

The training results (Table 1) of the MobileNetV3 and ViT neural network models demonstrate high efficiency in classifying images of the remains of destroyed buildings.

Table 1. Training results of the MobileNetV3 and ViT neural network models

	MobileNetV3		ViT	
Remains category	Precision	Recall	Precision	Recall
Brick	0.97	0.97	0.98	0.98
Concrete	0.98	0.97	0.99	0.99
Foam	0.91	0.95	0.98	0.99
General_w	0.91	0.92	0.91	0.92
Gypsum_board	0.97	0.96	0.99	0.98
Pipes	0.81	0.90	0.88	0.92
Plastic	0.83	0.76	0.90	0.83
Stone	0.99	0.98	1.00	0.99
Tile	0.96	0.95	0.98	0.97
Wood	0.98	0.97	0.98	1.00

Both models showed high values of precision, recall and f1-score in most classes. In particular, the ViT model achieved an accuracy of 0.97, which is higher than the similar MobileNetV3 indicator (0.95). The average macrometrics also indicate the superiority of ViT with an indicator of 0.96 against 0.93 for MobileNetV3. The highest results for ViT were recorded in the classes "Stone", "Concrete", "Wood" and also in the class "Foam". The MobileNetV3 model is slightly inferior in accuracy values in categories with more visually complex textures such as "Pipes" and "Plastic". Overall, both models demonstrated suitability for the multiclass classification task, but the ViT model showed better generalization ability.

The graph (Fig. 1) shows the Precision-Recall (PR) curves for the ViT multi-class classification model of building materials.

The graph contains PR curves for each class: brick, concrete, foam, general_w, gypsum_board, pipes, plastic, stone, tile, wood. Most of the curves are close to the upper right corner of the coordinate plane, which indicates high accuracy and completeness of the model for the corresponding classes. However, for some classes, in particular, pipes, plastic and gypsum_board, a decrease in accuracy is observed at high values of completeness. This indicates that the model for these classes incorrectly classifies some of the negative examples as positive, which reduces the overall accuracy.

Such results may indicate the difficulty of distinguishing some classes. For a complete analysis of the effectiveness of the model, it is necessary to calculate the integral metric – the average value of the area under the PR curve (average precision) for each class, as well as the weighted average for all classes.

The graph (Fig. 2) shows the Precision-Recall curves for the MobileNetV3 model trained on the construction waste classification problem. PR curves are constructed for each of the material classes included in the set of target labels. The distribution of curves at the top of the graph demonstrates the model's ability to provide both high accuracy and completeness in most cases. At the same time, classes such as plastic, pipes, and partly gypsum_board show a decrease in accuracy at high completeness values, which indicates the presence of false positive predictions in these categories.

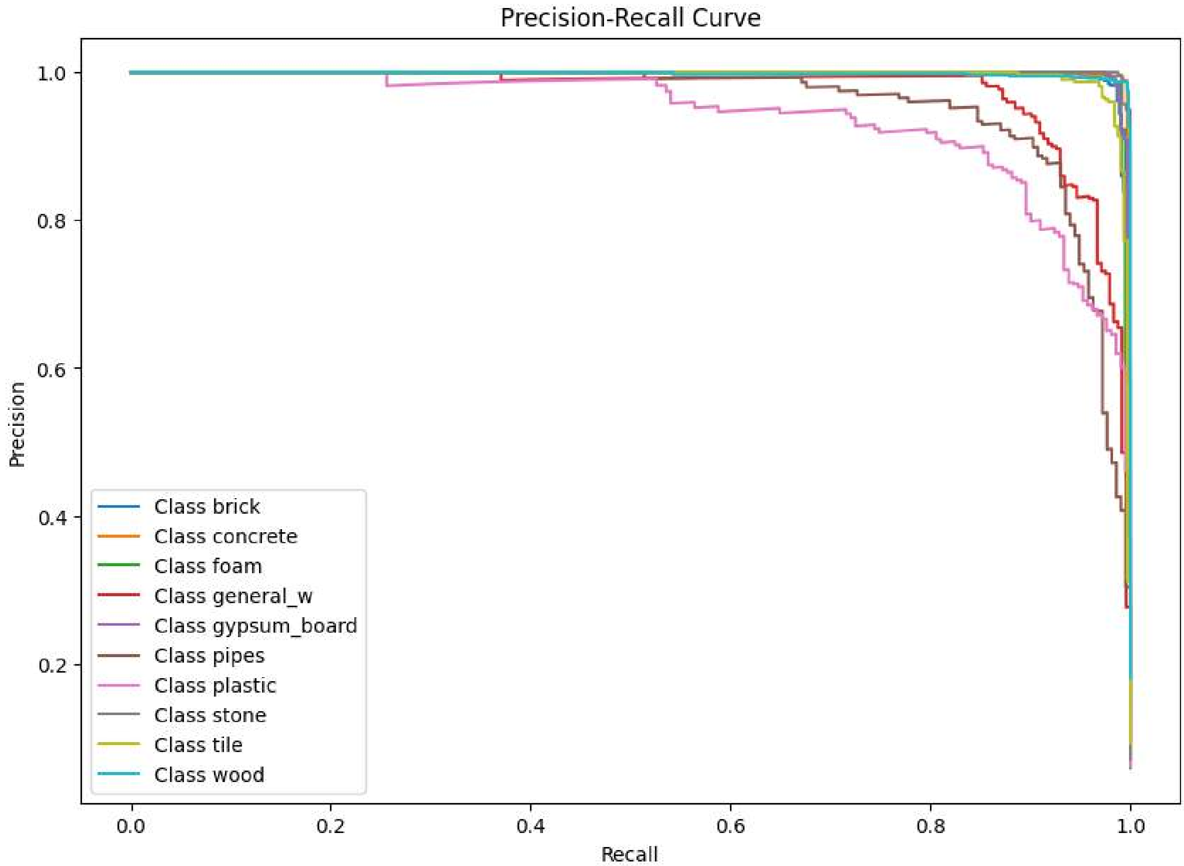

Figure 1. Precision-Recall curves for the ViT model.

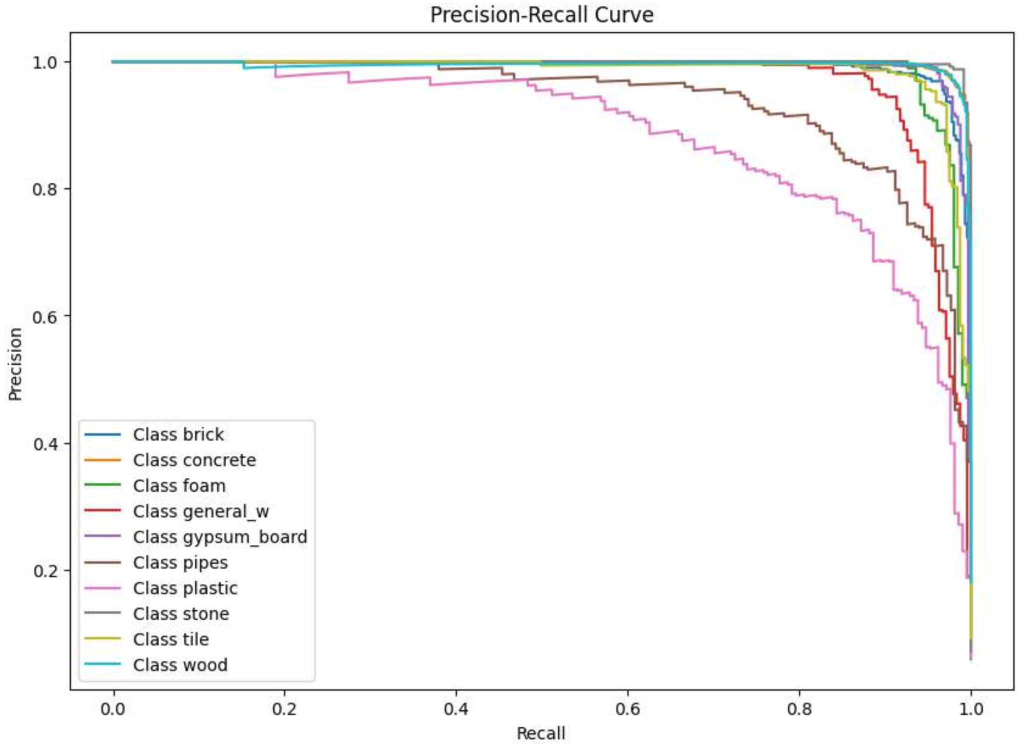

Figure 2. Precision-Recall curves for the MobileNetV3 model.

A similar behavior of the curves can be due to either the intersection of characteristic spaces between certain classes, or the presence of an uneven distribution of examples in the training sample. For a formalized evaluation of the model's effectiveness, it is advisable to calculate the average area under the PR curve (Average Precision) for each class, as well as an integral metric (for example, macro- or weighted-average) for the entire model.

The study examined the capabilities of neural-network–based analysis for photographic data of building debris captured by robotic platforms. Through a controlled experiment, we compared the performance of two deep learning architectures – MobileNetV3 and Vision Transformer (ViT) – on the task of classifying remnants of collapsed structures. While both networks proved capable, the ViT model consistently outperformed MobileNetV3 in terms of accuracy and generalizability.

Building on these findings, we developed an end-to-end workflow encompassing data preprocessing, model design, user interface construction, and test module integration. Each architecture was trained and evaluated using standard classification metrics. The ViT implementation achieved a peak accuracy of 97%, surpassing the results obtained with MobileNetV3.

These outcomes underscore the practical value of integrating advanced neural networks into robotic inspection systems for post-disaster environments. By automating the detection and processing of structural debris, our approach can dramatically accelerate situational awareness and decision-making during recovery operations. Consequently, this work offers both theoretical insights and a foundation for real-world applications in automated disaster assessment and management, paving the way for further innovation in critical infrastructure monitoring.

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СТВОРЕННЯ 3D PRODUCT ANIMATION ДЛЯ ПРОМОЦІЇ ПРОДУКТУ

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Сучасні маркетингові стратегії активно використовують мультимедійні рішення для презентації продуктів, що дозволяє брендам ефективніше комунікувати зі своєю аудиторією. Візуально привабливий контент, зокрема 3D-анімація, здатний не лише демонструвати товар, але й створювати емоційний зв'язок із потенційними покупцями. Завдяки швидкому розвитку цифрових технологій та зміні поведінки споживачів, 3D-анімація стала ключовим елементом сучасних рекламних кампаній, що дозволяє продуктам виділятися серед конкурентів.

Одним із ключових інструментів таких стратегій є 3D-анімація, яка дозволяє наочно показати унікальні особливості продукту та забезпечити інтерактивний досвід для користувача. Це не лише підвищує візуальну привабливість реклами, але й створює додаткову цінність для бренду. 3D-анімація відкриває можливості для творчого підходу до демонстрації товару, що підсилює вплив на аудиторію та покращує сприйняття рекламного повідомлення. Такий підхід дозволяє брендам виходити за межі традиційної реклами, надаючи їй відчуття інноваційності та технологічного підходу, що особливо важливо у цифрову епоху.

Створення якісної 3D-анімації має значний вплив на результати маркетингових кампаній. Вона не лише сприяє збільшенню продажів, але й