2. CodeSandbox. CodeSandbox Documentation. – 2024. – https://codesandbox.io/docs
3. GitHub. GitHub Codespaces Documentation. – 2024. – https://docs.github.com/en/codespaces
4. CodePen. CodePen Documentation. – 2024. – https://blog.codepen.io/documentation/
5. StackBlitz. StackBlitz Documentation. – 2024. – https://developer.stackblitz.com

NEURAL NETWORK CLASSIFICATION OF BUILDING DAMAGE LEVELS FROM EARTH REMOTE SENSING DATA

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This work addresses the problem of classifying building damage levels from Earth remote sensing imagery under heterogeneous acquisition conditions. The practical objective is to obtain building level damage labels that are reproducible, scalable, and suitable for integration into geospatial monitoring and decision support workflows [1]. The methodological premise is that robust damage classification is difficult to achieve directly at the full scene level due to clutter, occlusions, and strong appearance variability in urban environments. Therefore, the study relies on an object centered pipeline in which buildings are first localized or segmented and then classified into ordinal damage levels [2]. Experimental evaluation is conducted on a benchmark scale dataset with polygon footprints and a four level damage taxonomy, enabling quantitative verification with macro averaged classification metrics and supporting analysis of generalization under domain shift [3].

Introduction and motivation. The relevance of automated classification of building damage levels from Earth remote sensing data has increased significantly in the context of natural disasters, military conflicts, and large-scale technological accidents, where rapid and objective assessment of the built environment is critical for emergency response, recovery planning, and risk analysis. Traditional field-based inspections and manual interpretation of satellite imagery are time-consuming, costly, and often infeasible in hazardous or inaccessible areas. In this regard, computer vision methods based on convolutional neural networks provide an effective means for scalable [4], repeatable [5], and near–real-time [6] analysis of high-resolution remote sensing imagery. CNN are particularly well suited to this task due to their ability to automatically learn hierarchical spatial features [7], capturing both low-level visual cues such as edges, textures, and roof patterns, and high-level structural characteristics related to deformation, collapse, and contextual damage patterns [8].

Recent advances in deep learning for remote sensing have demonstrated that CNN-based architectures can robustly model complex visual variability caused by differences in sensor types [9], viewing angles [10], illumination conditions [11], and urban morphology [12]. For building damage assessment, CNNs enable the joint exploitation of spectral, spatial, and contextual information, allowing the model to distinguish subtle transitions between damage categories such as intact, partially damaged, and destroyed structures [13]. This capability is particularly important in post-event scenarios, where damage manifestations may be heterogeneous and visually ambiguous. By leveraging multi-scale receptive fields and deep feature representations, CNNs can capture both localized destruction cues and broader neighborhood-level patterns that are indicative of structural failure [14].

The application of CNNs to Earth observation data also supports the development of end-to-end automated pipelines, from raw satellite imagery to actionable damage maps, significantly reducing the latency between data acquisition and decision-making. When integrated with semantic segmentation or patch-based classification strategies, CNN-based systems can provide fine-grained spatial localization of damage while maintaining high classification accuracy [15]. Moreover, transfer learning from large-scale vision datasets and domain-specific pretraining on remote sensing corpora enhance model generalization, especially in scenarios with limited labeled damage data. This is particularly relevant for rapid deployment in newly affected regions, where annotated samples are scarce.

Overall, the use of convolutional neural networks and computer vision techniques for building damage level classification represents a critical step toward intelligent disaster monitoring systems. Such approaches not only improve the objectivity and consistency of damage assessments but also create a foundation for integrating remote sensing analytics into geographic information systems, early warning platforms, and decision-support tools. As satellite imagery becomes increasingly available with higher spatial and temporal resolution, CNN-based methods are expected to play a central role in scalable, data-driven assessment of the built environment under extreme events [16].

Damage assessment of buildings is a central component of post event response, recovery planning, and long term reconstruction management. In real deployments, stakeholders require not only point estimates but also consistency across large territories, the ability to update assessments as new imagery arrives, and a traceable methodological basis that supports audit and error analysis. Remote sensing offers the necessary coverage and revisit capability, yet it introduces its own complexity. Images acquired from different sensors, at different times, and under different illumination conditions can change appearance substantially even when the underlying physical state remains constant. When the physical state changes due to damage, the visual evidence can be subtle or ambiguous, especially for intermediate damage levels where roof structures may remain partially intact and the dominant cues are localized texture distortions, shadow anomalies, or peripheral debris [17].

A critical issue is that the damage label space is ordinal and visually overlapping. The four level taxonomy that is common in benchmark datasets includes no damage, minor damage, major damage, and destroyed.

Adjacent levels often share many visual patterns, and the boundary between minor and major damage can be particularly uncertain in overhead imagery. This motivates a framing where the objective is not to chase perfect class separation in all cases, but to achieve a stable, calibrated classifier that performs strongly on extreme categories and provides useful discrimination among intermediate categories while exposing uncertainty for human review when evidence is ambiguous.

Data foundation and label semantics. Supervised damage classification requires a dataset that couples imagery with building geometries and damage annotations. The benchmark foundation used here provides paired image chips and polygon footprints that define building instances, along with damage labels aligned to those instances. The dataset scale is large enough to support rigorous training and validation under event level and region level variability. It includes 22,068 image chips of 1024 by 1024 pixels collected across 19 events, spanning over 45,000 square kilometers, and containing 850,736 building polygons.

The availability of polygon footprints is essential because it enables object centered modeling and reduces dependence on weak proxies such as grid level labels that do not respect building boundaries. The benchmark also provides both vector geometries and raster representations derived from them, which supports consistent preprocessing for segmentation and crop generation.

The damage annotation scheme is ordinal and is typically defined with four discrete levels.

This structure must be considered throughout the methodology because the cost of errors is not symmetric. Confusing minor damage with major damage is frequently less consequential than confusing no damage with destroyed, particularly in triage scenarios. At the same time, remote sensing labels are based on visible cues rather than structural integrity measured in situ, which means that some apparent label noise is unavoidable, especially for intermediate categories. A scientifically credible evaluation must therefore report not only global metrics but also the pattern of confusions across neighboring categories, since that pattern reveals whether the classifier is learning a plausible progression of damage rather than exploiting spurious correlations.

Methodological approach: object centered damage classification. A key methodological decision in the study is to perform damage classification at the level of individual building instances, rather than at the level of the scene as a whole. This choice is due to the specifics of urban visual data, which are characterized by a high density of objects and the presence of numerous obstacles. A typical aerial or satellite image contains not only buildings, but also roads, sidewalks, vehicles, greenery, shadows from neighboring buildings, construction debris, temporary structures and other elements of the urban environment. In the case of a scene approach, the model is forced to form a conclusion about the level of damage, relying on a mixture of signals, a significant part of which is not directly related to the technical condition of a particular building.

In addition, classification at the scene level increases the risk of learning from indirect or contextual features related to geography, type of development or environmental features. For example, a model may associate certain road surfaces, vegetation density, or building density with specific damage classes, which leads to hidden domain shifts and reduced generalizability. As a result, there is an increased reliance on dataset specificity rather than on real visual markers of structural failure.

In contrast, building instance-level modeling limits the evidence domain to a localized image fragment that directly corresponds to the target object. This approach makes the definition of labels more operationally consistent, since each damage assessment refers to a specific building rather than an arbitrary scene. This is especially important in an applied context, where the results are used to form priority lists, plan engineering surveys, or assess the extent of damage within neighborhoods and cities.

The practical implementation of the instance-based approach is implemented as a two-stage neural network pipeline. In the first stage, a localization or segmentation model is applied, which automatically detects areas corresponding to buildings and forms masks or bounding boxes for them. This stage is responsible for spatially isolating the target objects from the background and creates a basis for further analysis. In the second stage, a separate classification model predicts the level of damage for each detected building based on the image cropped according to its spatial boundaries.

Such a decomposition of the problem is well consistent with the structure of the datasets used, which usually contain polygonal markings of buildings and allow for full supervised learning for segmentation. In addition, it ensures the modularity of the system and simplifies error analysis. Localization errors (e.g., missing buildings or inaccurate contours) can be separated from state classification errors, which allows for more precise identification of sources of quality degradation and targeted improvement of individual components of the pipeline.

The proposed approach is consistent with the use of segmentation models of the YOLO family for building segmentation and transformer architectures for damage classification, in particular, models of the Vision Transformer class. YOLO-like models provide efficient and fast detection of objects and their contours, which is critical for processing large arrays of aerial data. Transformer models, in turn, demonstrate a high ability to model complex spatial dependencies and global context, which is important for correctly distinguishing the degrees of damage.

At the output, the segmentation stage forms masks or bounding boxes that define areas for further analysis. The classification stage works with normalized images centered on the building, which reduces the variability of the scales and positions of objects. If necessary, a small contextual indentation is added to the cut fragment, which preserves the immediate surroundings of the building, in particular debris, traces of collapses or characteristic shadows. Such information is often useful for distinguishing intermediate levels of damage, where local facade defects are combined with signs of environmental impact.

In conclusion, the instance-oriented two-stage approach provides a more robust, interpretable, and operationally applicable solution to the problem of automated building condition assessment than direct scene classification, and creates a solid basis for practical use of the results in monitoring systems and planning of restoration works.

Preprocessing and dataset construction principles. The success of damage classification depends heavily on how building crops are constructed and how data splits are defined. The dataset contains paired imagery and repeated geographic content across temporal states.

If pre event and post event chips from the same region are not carefully separated, the evaluation can become overly optimistic because the model can exploit location specific textures and building styles rather than damage evidence. Therefore, a credible protocol must enforce geographic and event separation between training and validation where possible, ensuring that validation measures generalization rather than memorization.

Crop generation should preserve the spatial evidence of damage while normalizing irrelevant variability. Resizing is necessary to fit network input constraints, but it must not erase fine cues such as roof texture fragmentation or small debris patterns. A moderate context window around the building footprint is often beneficial because damage is not always confined strictly within the roof boundary. Collapsed elements, shadows, and local debris fields can appear adjacent to the building and contribute discriminative evidence. The context window must be controlled so that it does not unintentionally introduce label leakage from neighboring buildings whose damage levels differ.

Radiometric normalization and augmentation are also critical. Satellite and UAV imagery can differ substantially in color statistics, contrast, and sharpness. When UAV imagery is present, additional variation arises from oblique viewpoints, altitude changes, and local artifacts such as dust or smoke.

Augmentations should emulate these variations in a way that improves robustness without destroying the signal that defines damage categories. The guiding principle is that augmentation densifies the neighborhood of observed conditions but does not substitute for missing domains. If UAV imagery is scarce, it must be treated as a domain that requires explicit coverage through data collection or targeted adaptation rather than through aggressive synthetic transformations alone.

Training configuration and optimization rationale. The pipeline contains two trainable components, and each presents distinct optimization issues. The segmentation component must learn to identify buildings in dense urban textures and under occlusion. Its quality is often measured with mean average precision for bounding boxes and masks.

The classification component must map building crops to damage levels while respecting severe class imbalance and the ordinal nature of labels. For this reason, macro averaged metrics are preferred because they avoid dominance by the most frequent class and better reflect performance on minority categories.

Transfer learning is essential for both components. Remote sensing datasets, even when large, may not cover the full spectrum of textures and lighting conditions encountered in real deployments. Initialization from large scale pretraining can stabilize optimization, reduce sensitivity to hyperparameters, and improve generalization. For the classifier, transformer based backbones can be particularly effective because they can integrate dispersed cues across a crop, capturing both localized damage evidence and broader context.

Class imbalance requires explicit handling. In damage datasets, extreme categories can be visually distinctive but not always balanced in frequency. Minor damage and major damage can also be underrepresented and are harder to learn. A robust training strategy typically involves class weighting or sampling strategies that encourage the model to attend to minority categories without collapsing calibration. Importantly, such interventions must be validated with macro metrics and confusion analysis, since improvements in macro F1 may come at the cost of increased severe misclassifications if the model becomes overly aggressive.

Evaluation design and metrics interpretation. Evaluation procedures must be explicitly aligned with the intended operational use of the system rather than relying on generic performance indicators. In the context of building damage assessment, segmentation quality plays a foundational role, as all subsequent classification decisions depend on the correctness of the spatial regions extracted for analysis. For this reason, it is essential to report both bounding-box–based and pixel-level mask metrics when evaluating segmentation performance. Mask-level indicators capture the accuracy of building contour delineation, while box-level metrics reflect the reliability of object localization. Inaccuracies at either level may propagate downstream, directly affecting the quality of damage classification by including irrelevant background pixels or excluding structurally important parts of the building.

For the damage classification task, overall accuracy is insufficient as a primary metric, particularly under class imbalance, which is typical for real-world damage distributions where moderately damaged buildings dominate. Instead, macro-averaged precision, macro-averaged recall, and macro-averaged F_1 score provide a more informative and fair assessment, as they weight all damage classes equally and reflect performance on rare but operationally critical categories. These metrics better align with decision-making scenarios in which overlooking severely damaged structures or misclassifying intact buildings may have significant consequences.

Beyond aggregate numerical scores, an in-depth analysis of confusion matrices is required to assess whether the model captures the ordinal nature of damage severity.

Building damage levels form a natural progression, and a desirable error structure is one in which most misclassifications occur between neighboring categories, such as between "damaged" and "severely damaged," while confusions between extreme states, such as "no damage" and "destroyed," remain rare. Such a pattern indicates that the model internalizes a monotonic notion of damage progression and that its uncertainty concentrates in regions where visual boundaries are inherently ambiguous, even for human experts.

Robustness evaluation represents another critical dimension of model assessment. Real-world deployment scenarios frequently involve complex scene conditions, including heavy debris accumulation, partial occlusions by surrounding structures or vegetation, strong cast shadows, and substantial illumination variability caused by weather or time of day. In addition, robustness testing should explicitly consider sensor shift, particularly in pipelines where satellite imagery is used for pretraining and UAV imagery is employed for fine-tuning or operational inference. Differences in spatial resolution, viewing geometry, noise characteristics, and radiometric properties can substantially alter the visual statistics of the input data.

These robustness tests are directly linked to the broader issues of representativeness and domain shift. If model performance degrades sharply under sensor shift, this does not automatically invalidate the approach; rather, it indicates that the system may be reliable within a specific acquisition domain but requires further adaptation for heterogeneous sensor deployment. Explicitly identifying such limitations is crucial for responsible application and for guiding future data collection strategies.

Experimental results and their implications. The reported experimental configuration, which combines YOLO-based segmentation with Vision Transformer–based damage classification, demonstrates strong performance at the macro level of evaluation. The obtained macro-averaged precision, recall, and F1 scores exceed approximately 0.90, indicating a high degree of balance across damage categories. In particular, the extreme classes corresponding to "no damage" and "destroyed" achieve F_1 values close to 0.92, reflecting the model's ability to reliably distinguish between structurally intact and catastrophically damaged buildings.

This performance profile has a clear operational interpretation. High reliability on extreme categories supports rapid triage and prioritization in post-disaster or post-conflict settings, where identifying the most critical objects is essential for effective allocation of inspection and reconstruction resources. Moreover, strong macro-level performance suggests that the model is not merely optimizing for the majority class but is learning meaningful representations that allow separation of intermediate damage states to a practically useful extent.

At the same time, these results should be interpreted with methodological caution. High macro-averaged metrics can mask systematic weaknesses if the evaluation protocol is insufficiently strict, for example due to geographic leakage between training and test sets or implicit learning of location-specific visual signatures. Although the benchmark design with multiple events and spatial splits mitigates these risks, real-world deployment will inevitably expose the system to new cities, architectural styles, construction materials, and sensor configurations that were not represented in the training data.

Consequently, the scientific value of the reported results is maximized when aggregate metrics are complemented by detailed error analysis and explicit domain shift evaluation. Such analyses provide insight into failure modes and help distinguish between genuine generalization and performance driven by dataset-specific correlations.

Domain shift as a central explanatory factor. A persistent challenge in remote sensing–based damage assessment is the domain shift between satellite imagery and UAV imagery. UAV data typically offer higher spatial resolution, but also introduce different noise characteristics, non-nadir viewing angles, motion blur, and stronger local illumination gradients. These factors significantly alter the texture and appearance of damaged structures compared to satellite images.

When a model is pretrained or predominantly tuned on satellite data and subsequently applied to UAV imagery, performance degradation may occur if the learned representations overfit to satellite-specific spatial patterns or texture statistics. Conversely, aggressive fine-tuning on UAV imagery can reduce performance on satellite data by emphasizing UAV-specific artifacts, leading to a trade-off between domains.

The methodological position adopted in this work is that domain shift should not be obscured or averaged away. Instead, it should be explicitly surfaced through careful validation design and treated as a source of diagnostic information. From this perspective, the model functions not only as a predictive tool but also as an instrument for assessing dataset representativeness. Systematic failures on UAV scenes indicate insufficient coverage of the UAV acquisition regime in the training distribution and point directly to the need for targeted data augmentation, additional sampling, or domain adaptation techniques.

This approach is scientifically more informative than reporting a single performance number that conflates heterogeneous conditions without explanation. By explicitly analyzing domain shift effects, the evaluation framework supports both more reliable deployment and a deeper understanding of the limits and capabilities of neural network–based damage assessment systems.

Error analysis and qualitative interpretation. Quantitative metrics explain how well the classifier performs, but they do not explain why it fails. For damage classification, the most informative error analyses relate predictions to visual evidence. Intermediate category errors often arise when damage cues are subtle, when roofs are partially occluded by vegetation, or when debris patterns resemble roof textures. Shadows can also mimic structural changes, especially in dense urban blocks. These errors are not purely model limitations. They reflect the intrinsic ambiguity of the visual evidence and the label noise inherent in overhead imagery. The goal of the system is not to eliminate ambiguity but to manage it through calibrated confidence and through systematic identification of cases that require human review.

In an object centered pipeline, segmentation errors can propagate into classification. A crop that includes too much background can introduce confounders, while a crop that truncates the building can remove crucial evidence. Therefore, end to end analysis should trace misclassifications back to segmentation quality. In practical deployments, this traceability supports iterative improvement, where segmentation thresholds and crop margins are tuned to reduce failure modes associated with clutter and adjacency.

Practical integration and deliverables. A damage classification system becomes operationally valuable when its outputs are GIS ready and interpretable. The dataset structure that links imagery and building polygons supports outputs that are naturally mapped to building geometries.

In a typical deployment, predicted damage labels can be attached to building footprints and exported as vector layers, enabling aggregation by administrative boundaries and supporting prioritization dashboards. Confidence scores should accompany labels to support thresholding policies. For example, a conservative policy may automatically accept only high confidence extreme class predictions while routing uncertain intermediate predictions for review.

Change monitoring is also a natural extension when multi temporal imagery is available. In such settings, the system can track transitions across damage levels over time, which is relevant for reconstruction monitoring. Even when the model is trained on event based datasets, its value can be extended to longitudinal settings if domain shift is managed and if temporal consistency checks are incorporated at the application layer.

Limitations and scientific caveats. Several limitations are fundamental to the problem. First, damage labels derived from remote sensing cues may not match structural integrity. This implies that model outputs should be interpreted as visual damage assessments rather than engineering certifications. Second, generalization across cities and sensors remains a central risk. UAV and satellite domain shifts require explicit handling, and evaluation must reflect the intended deployment regime.

Third, intermediate class ambiguity is an inherent limitation, and models may converge to decision boundaries that are sensitive to minor changes in illumination or viewpoint.

These limitations do not diminish the value of the approach. They motivate a deployment posture that incorporates human oversight, uncertainty reporting, and conservative thresholding policies for high impact decisions. From a research standpoint, they motivate ordinal aware objectives, domain adaptation strategies, and improved calibration techniques that align confidence with correctness.

Future improvements should focus on robustness, ordinality, and measurable uncertainty. Ordinal aware learning objectives can reduce severe misclassifications by encoding higher penalties for far distance confusions. Domain adaptation and domain generalization techniques can mitigate satellite to UAV shift by aligning feature distributions or by enabling test time adaptation. Semi supervised learning can exploit large volumes of unlabeled UAV imagery, which is often available earlier than curated labels in new events. Finally, uncertainty quantification can make the system safer and more useful by identifying cases where predictions are unreliable and should be reviewed.

This work demonstrates that neural network classification of building damage levels from Earth remote sensing data can achieve strong macro averaged performance when formulated as an object centered pipeline that combines building localization or segmentation with a high capacity classifier. The benchmark scale dataset with polygon footprints and a four level ordinal damage taxonomy enables reproducible evaluation and supports strong performance on extreme categories that are critical for triage.

Reported results indicate macro precision, macro recall, and macro F1 above approximately 0.90 and strong F1 for no damage and destroyed, supporting the practical viability of the approach for rapid mapping and decision support.

The central scientific message is that domain shift and representativeness must be treated explicitly rather than averaged away. By using validation as a diagnostic tool, the model can guide iterative dataset refinement and targeted fine tuning, enabling more trustworthy deployment across heterogeneous urban environments and sensor regimes.

References

1. Kazmi R., Chakraborty M. Use of different forms of waste promoting a circular economy in the construction industry: A systematic literature review // International Conference on Environmental Geotechnology, Recycled Waste Materials and Sustainable Engineering. – Singapore : Springer, 2025. – P. 193–204. – DOI: 10.1007/978-981-97-9777-6_17.
2. Jha S., Nanda S., Zapata O., Acharya B., Dalai A. K. A review of systems thinking perspectives on sustainability in bioresource waste management and circular economy // Sustainability. – 2024. – Vol. 16. – Article 10157. – DOI: 10.3390/su162310157.
3. Sayem F. R., Islam M. S. B., Naznine M., Nashbat M., Hasan-Zia M., Kunju A. K. A., Chowdhury M. E. Enhancing waste sorting and recycling efficiency: Robust deep learning-based approach for classification and detection // Neural Computing and Applications. – 2024. – P. 1–17. – DOI: 10.1007/s00521-024-10855-2.
4. Mazurets O., Molchanova M., Klimenko V., Klopotivskyi D. Datalogic model for image recognition by convolutional neural network using cloud services // Modern Scientific Research: Theoretical and Practical Aspects : proceedings of the XXII Int. Sci. and Pract. Conf. (Oslo, Norway, May 8–10, 2024). – Oslo, 2024. – P. 64–68.
5. Pokhytun A., Mazurets O., Molchanova M., Tyschenko O. Method for neural network detecting changed images of people's faces using CNN // New Horizons in Scientific Research: Challenges and Solutions : proceedings of the 1st Int. Sci. and Pract. Conf. (Marseille, France, Oct. 21–23, 2024). – Marseille, 2024. – P. 35–40.

6. Kharysh I., Sobko O., Mazurets O. Designing CNN neural network model for detecting fractures of lower extremities by X-ray images // The Impact of Scientific Research on the Development of the Modern World : proceedings of the XLIV Int. Sci. and Pract. Conf. (Dubrovnik, Croatia, Oct. 23–25, 2024). – Dubrovnik, 2024. – P. 91–96.
7. Zharnovskyi O., Mazurets O., Sobko O. Approach to identification of artificial intelligence-generated people images by means of machine learning // Key Aspects of the Development of Scientific Research in Modern Conditions : proceedings of the XLV Int. Sci. and Pract. Conf. (Constanta, Romania, Oct. 30 – Nov. 1, 2024). – Constanta, 2024. – P. 69–73.
8. Mazurets O., Zalutska O., Tyschenko O., Bohdanova A. An approach to using MobileNet CNN-model for gesture recognition // Problems of Science and Technology: the Search for Innovative Solutions : proceedings of the XXIII Int. Sci. and Pract. Conf. (Munich, Germany, May 15–17, 2024). – Munich, 2024. – P. 59–64.
9. Molchanova M., Mazurets O., Klimenko V., Kuflevsky E. Object-oriented model for neural network damage detection of mail packages // Solving Scientific Problems Using Innovative Concepts : proceedings of the XIV Int. Sci. and Pract. Conf. (Copenhagen, Denmark, Mar. 13–15, 2024). – Copenhagen, 2024. – P. 58–62.
10. Novak Y., Mazurets O. Practical application of method of automated personal identification by fingerprints using convolution neural networks // Modern Strategies of Global Scientific Solutions : proceedings of the V Int. Sci. and Pract. Conf. (Stockholm, Sweden, Dec. 27–29, 2023). – Stockholm, 2023. – P. 136–140.
11. Bohdanova A., Mazurets O., Sobko O. Gesture recognition using a neural network in real time // Black Sea Science 2023 : proceedings of the International Competition of Student Scientific Works. – Odesa : Odesa National University of Technology, 2023. – P. 556–566.
12. Krak I., Mazurets O., Zalutska O., Molchanova M., Barmak O. Approach for postural disorders recognizing from visual data using deep neural network // CEUR Workshop Proceedings. – 2025. – Vol. 4049. – P. 244–255.
13. Mazurets O., Sobko O., Dydo R., Zalutska O., Molchanova M. Augmented reality audiostream creation using CNN: Boosting inclusion and safety for visually impaired people // CEUR Workshop Proceedings. – 2025. – Vol. 4004. – P. 347–361.
14. Mazurets O. V., Klimenko V. I., Shurypa M. O. Neural network assessment of buildings condition based on visual data // Innovations of Modern Science and Education : proceedings of the IV Int. Sci. and Pract. Conf. (Vancouver, Canada, Dec. 25–27, 2025). – Vancouver, 2025. – P. 120–129.
15. Derzhak V. V., Mazurets O. V. Approach to image preprocessing for household waste classification in circular economy // Resource-Saving Technologies of Apparel, Textile & Food Industry : proceedings of the Int. Sci. and Pract. Conf. (Khmelnytskyi, Ukraine, Nov. 20, 2025). – Khmelnytskyi, 2025. – P. 319–323.
16. Mazurets O., Ovcharuk O., Vit R. Investigation of neural network detecting of construction waste by photos // Information Technology and Implementation (Satellite)

: proceedings of the 12th Int. Conf. (Kyiv, Ukraine, Nov. 21, 2025). – Kyiv, 2025. – P. 96–97.
17. Molchanova M., Didur V., Mazurets O., Sobko O., Zakharkevich O. Method for construction and demolition waste classification using two-factor neural network image analysis // CEUR Workshop Proceedings. – 2025. – Vol. 3970. – P. 168–182.

ПОРІВНЯЛЬНИЙ АНАЛІЗ ПЛАТФОРМ ДЛЯ РЕАЛІЗАЦІЇ АДАПТИВНИХ КЛІТИННИХ АВТОМАТІВ

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Анотація. У роботі проведено порівняльний аналіз програмних платформ NetLogo, Golly, CompuCell3D та AnyLogic для реалізації адаптивних клітинних автоматів. Розглянуто методику побудови моделей із адаптивними правилами та проведено серію експериментів із оцінкою простоти реалізації, продуктивності симуляцій, гнучкості налаштувань та можливостей візуалізації. Результати дослідження дозволяють виділити переваги та обмеження кожної платформи та сформулювати рекомендації щодо їх використання залежно від конкретних задач моделювання.

Ключові слова: клітинні автомати, адаптивні моделі, адаптивні клітинні автомати, NetLogo, Golly, CompuCell3D, AnyLogic, порівняльний аналіз, симуляції, програмні платформи.

Введення. Клітинні автомати є одним із ефективних математичних та обчислювальних інструментів для моделювання складних динамічних систем, що складаються з великої кількості простих елементів та локальних правил взаємодії. Вони широко застосовуються у таких галузях, як моделювання фізичних процесів, дослідження біологічних систем, аналіз поширення інформації, розробка алгоритмів штучного інтелекту, а також у комп’ютерній графіці та ігровому програмуванні. Особливий інтерес становлять адаптивні клітинні автомати, у яких правила переходів можуть змінюватися залежно від стану системи або зовнішніх умов, що дозволяє більш точно відтворювати поведінку реальних складних систем. У процесі реалізації таких моделей важливу роль відіграє вибір програмної платформи, оскільки від неї залежать продуктивність обчислень, масштабованість, зручність розробки, можливості візуалізації та подальшого аналізу результатів. У цьому дослідженні