https://doi.org/10.33271/nvngu/2023-6/134

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AUTOMATED BUILDING DAMAGE DETECTION ON DIGITAL IMAGERY USING MACHINE LEARNING

Purpose. To develop an automated method based on machine learning for accurate detection of features of a damaged building on digital imagery.

Methodology. This article presents an approach that employs a combination of unsupervised machine learning techniques, specifically Principal Component Analysis (PCA), K-means clustering, and Density-Based Spatial Clustering of Applications with Noise (DBSCAN), to identify building damage resulting from military conflicts. The PCA method is utilized to identify principal vectors representing the directions of maximum variance in the data. Subsequently, the K-means method is applied to cluster the feature vector space, with the predefined number of clusters reflecting the number of principal vectors. Each cluster represents a group of similar blocks of image differences, which helps to identify significant features associated with fractures. Finally, the DBSCAN method is employed to identify areas where points with similar characteristics are located. Subsequently, a binary fracture mask is generated, with pixels exceeding the threshold being identified as fractures.

Findings. The introduced methodology attains an accuracy rate of 98.13 %, surpassing the performance of conventional methods such as DBSCAN, PCA, and K-means. Furthermore, the method exhibits a recall of 82.38 %, signifying its ability to effectively detect a substantial proportion of positive examples. Precision of 58.54 % underscores the methodology's capability to minimize false positives. The F1 Score of 70.90 % demonstrates a well-balanced performance between precision and recall.

Originality. DBSCAN, PCA and K-means methods have been further developed in the context of automated detection of building destruction in aerospace images. This allows us to significantly increase the accuracy and efficiency of monitoring territories, including those affected by the consequences of military aggression.

Practical value. The results obtained can be used to improve automated monitoring systems for urban development and can also serve as the basis for the development of effective strategies for the restoration and reconstruction of damaged infrastructure.

Keywords: *unsupervised machine learning, digital image, recognition, building damage, military conflicts*

Introduction. Every year, the world witnesses the devastation caused by natural disasters such as forest fires [1], earthquakes, floods, and hurricanes. In addition, military conflicts [2] and armed clashes cause significant economic damage and intangible losses [3]. The destruction of buildings during the war is a form of aggression that causes significant damage to civilians [4]. It is often used to force displacement of the populations and thus requires special attention. However, obtaining reliable data from war-affected areas is usually problematic, incomplete, and contradictory, even when such data is available. The lack of comprehensive data from conflict zones significantly hampers the media, humanitarian aid, human rights monitoring, recovery initiatives, and scientific research on military conflicts. A solution to this problem uses remote sensing data to detect destruction in digital imagery. This approach is becoming increasingly popular due to the availability of high-resolution imagery accessed each week or even daily. The latest advances in deep learning provide sophisticated tools to analyze these images and extract data efficiently.

Scientific studies have demonstrated the successful use of automatic classifiers for damage detection [5, 6]. However, there have been serious challenges, such as labeling problems, determining the contours of destroyed objects, and imbalance of classes in images of urban war zones. It has led to international organizations such as the United Nations and others using remote sensing with manual classification to conduct case studies on damage assessment. On the other hand, conflict data providers for academic research still rely heavily on news reports and eyewitness accounts, which leads to a significant delay in data publication and possible bias. Therefore, an automated classifier of building damage on digital imagery has a low false positive rate in unbalanced samples and allows for near real-time tracking of destruction on the ground, which would be extremely valuable for both the international community and academic researchers.

Literature review. Detecting controlled changes is a task that automated damage detection can handle. Previous research in this area showed the successful use of image segmentation to solve this problem. Assuming no structural patterns have changed, one can identify masks of structures in the pre-event images given a pair of images corresponding to the same set of coordinates before and after the hazard. Automated damage detection involves detecting controlled changes. Many researchers have used automatic image processing methods on remote sensing data to detect and analyze the effects of hostilities, such as damaged and destroyed building structures [7, 8]. In paper [9], the authors investigated the problem of detecting damage to buildings caused by the civil war in Syria using satellite images before and after the destruction. They developed a framework to identify patch-level changes to classify patches as destroyed or undamaged. Despite the successful binary classification by patch, the intensity and extent of damage could not be accurately determined using this approach. Several scientific studies have demonstrated the use of computer vision to analyze satellite images to detect various types of damage [10, 11]. In many cases, this damage was the result of natural disasters that are characterized by spatial concentration [12]. Even if the results presented in the literature are encouraging, they are limited to point-in-time estimates and the use/validation of datasets containing an equal number of damaged and undamaged images.

Urban areas are characterized by structural diversity and spectral variability, even when they have a homogeneous composition. Spectral methods, such as the use of distinction indices and supervised classification, which are used to define land classes and track their changes, assign each pixel a class based on its spectral reflectance, without considering spatial features. It becomes less effective because spectral information can exhibit heterogeneity due to different roof materials and the similar composition of buildings, roads, and open space. Methods based on spectrum analysis are not effective enough to identify spectrally heterogeneous but spatially land uses, making it difficult to obtain accurate and complete information about changes [13]. Lately, deep learning has made a big splash in automated building extraction methods. Deep learning methods avoid the subjectivity of manual feature selection. The fully convolutional pixel-to-pixel network (FCN) proposed by Long, et al. [14] has significantly improved the accuracy of building detection. Despite achieving high-quality object detection, CNNs have noticeable drawbacks [15]: training is multi-stage and often takes a long time to implement; it is difficult to optimize, as each stage needs to be trained separately. Huang, et al. [16] proposed a progressive residual refinement network (GRRNet) for building detection by combining high spatial resolution aerial images and LiDAR data. Although these methods have positive results and recognize buildings, some problems still need to be studied in more detail [17]. To tackle the problem of artifacts, one can employ additional image processing techniques, such as image smoothing methods or techniques for extracting geometric data. Some methods, such as the depth-based method, can use more information about the depth of objects to improve the quality of building extraction.

Purpose. This study aims to develop an efficient methodology for the automated detection and mapping of building damage in digital images. The focus is on leveraging unsupervised machine learning techniques to enhance the accuracy and speed of the damage identification process.

In this work, to achieve the set goal, the following tasks were formed and solved:

- to create a robust framework utilizing unsupervised machine learning techniques, specifically focusing on methods such as Principal Component Analysis (PCA), K-means clustering, and Density-Based Spatial Clustering of Applications with Noise (DBSCAN);
- to optimize image processing algorithms within the framework to enable precise identification and mapping of building damage features in digital images;
- to conduct comprehensive evaluations and comparisons of the proposed methodology against traditional methods, assessing factors such as accuracy, speed, and computational efficiency;
- to test the effectiveness and applicability of the developed methodology by applying it to real-world datasets, with a specific emphasis on images capturing building damage resulting from the 2022 Russian invasion of Ukraine.

Methods. The method algorithm is shown in Fig. 1 and consists of six steps. The first step is to upload digital images. In this study, we used images obtained from Google Earth. The dataset was preprocessed, including georeferencing and orthotransformation, to improve the accuracy and quality of the results before applying the clustering algorithms.

Since the focus of this study is to classify the observations into two main categories – damaged buildings and non-damaged buildings – using clustering algorithms, the measurements were filtered to improve the results. The pre-processing stage [18] involves assessing the total characteristics of the image. The assessment includes parameters such as noise, blur, background intensity variations, brightness, contrast, and the overall distribution of pixel values (histogram profile). Attention should also be paid to shaded areas to determine their detail, bright elements (or highlights), and areas of intermediate pixel intensity.

At this stage, a lookup table (LUT) is used for large images, which stores the intensity transformation function (mapping function). The is designed to calculate its output gray level values (I) as follows1

$$G = LUT(I),$$

where G is the output gray level value; LUT is lookup table (display function); I is the input value of the pixel intensity.

This lookup table allows changing the intensity of image pixels using a given transformation function, which can be useful for improving image quality and preparing data for further analysis and fracture detection.

The third step is the use of complex unsupervised machine learning methods. Recently, machine learning methods have become widespread in everyday life. These methods are also actively used to extract the necessary geophysical information from the data. The most suitable unsupervised machine learning method for building collapse detection is clustering, as it is part of a wide range of methods for identifying subgroups or clusters in a dataset. Clustering assigns a unique number to each observation that indicates which cluster the observation belongs to. Thus, clustering aims to identify the overall structure, including distinct clusters and homogeneous subgroups among the observations [15]. This study focuses on the following most well-known approaches clustering: PCA, K-means and DBSCAN.

PCA. Principal Component Analysis method is applied to improve data processing. PCA is a statistical method used to reduce the dimensionality of data while retaining the majority portion of its variance. In the context of clustering and analyzing geophysical data, PCA helps to identify influential variables and reduce the number of variables used for further analysis, reducing the impact of noise, and providing better interpretability of the results. First, the covariance matrix (**C**) is calculated for the original data set X, where X is a matrix with objects in the rows and features in the columns [19]

$$\mathbf{C} = \left(\frac{1}{n}\right) \cdot \mathbf{X}^T \cdot \mathbf{X},$$

where n is the number of observations (rows) in $\mathbf{X}$, $\mathbf{X}^T$ is the transposed matrix of $\mathbf{X}$.

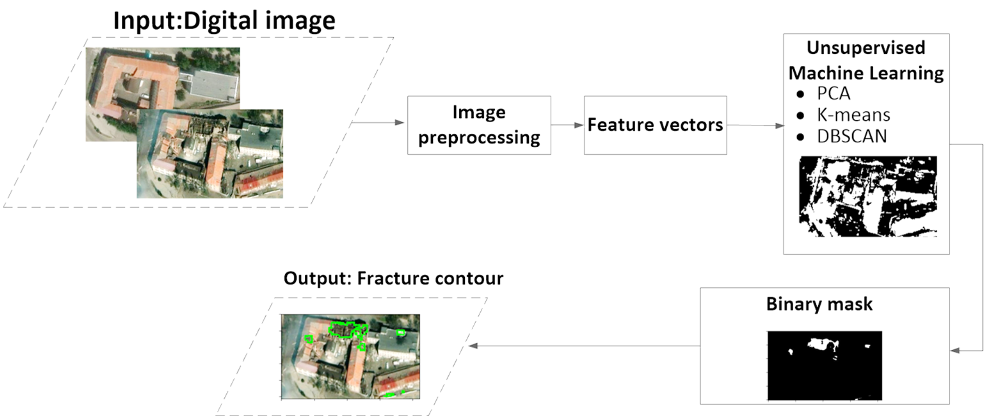


Fig. 1. Algorithm of the proposed method

Then, the singular value decomposition of the covariance matrix C is calculated, which allows us to decompose it into a set of principal components and their eigenvalues [19]

$$\mathbf{C} = \mathbf{V} \cdot \Lambda \cdot \mathbf{V}^T,$$

where $\mathbf{V}$ is an $m \times n$ column-orthonormal matrix of principal components (eigenvectors); $\Lambda = \mathrm{diag}(\sigma_1, \sigma_2, ..., \sigma_n)$ is a diagonal matrix, where the elements on the diagonal are eigenvalues; $\mathbf{V}^T$ is the transposed matrix of $\mathbf{V} = [v_{i,j}]$.

At this step, the PCA method identifies the principal vectors that represent the directions of maximum variance in the data. The eigenvalues obtained during this process are transformed into a new feature vector space. Each vector in this space indicates the importance of the corresponding principal vector. This procedure allows you to preserve the most common aspects of image changes and highlight them in new features. Using PCA in the context of geophysical data analysis helps to reduce the number of features, increase the robustness of clustering, and facilitate the interpretation of results. This method is usually applied after preprocessing and clustering to advance data analysis.

K-Means Clustering. Next, we use the K-means, one of the simplest and most popular algorithms for dividing a dataset into K separate non-overlapping clusters. The K-means algorithm is based on the number of clusters initially set to K. The basic idea behind K-means is that the ideal clustering is determined so that the within-cluster variance is as low as possible. The intra-cluster variance for a cluster C_k is calculated using the measure $W(C_k)$, which quantifies the degree of dissimilarity among the observations within the cluster.

Thus, we have the following problem statement [20]

$$\text{Minimize}\, W(C_1, C_2, ..., C_k) = \sum_{i=1}^{N} \left\| X_i - \mu_{k_i} \right\|^2,$$

where i belongs to C_k; $W(C_1, C_2, ..., C_k)$ is the total intra-cluster variance for all clusters $C_1, C_2, ..., C_k$; the vector μ_{k_i} represents the assignment of data point i; $\left\| X_i - \mu_{k_i} \right\|^2$ is the center of mass (mean value) of cluster C_k.

DBSCAN Clustering. Density-Based Spatial Clustering of Noisy Applications (DBSCAN) is commonly used in data mining and machine learning, as proposed in [20]. DBSCAN has several merits, including the absence of the need to determine the number of clusters a priori, which distinguishes it from K-means and agglomerative methods. It can detect clusters of different shapes and highlight points that do not belong to any cluster. DBSCAN clusters observations based on their relative position and use a distance measure (usually Euclidean distance) and a minimum number of points to define a cluster. It also marks points that are in low-density regions as outliers.

For DBSCAN to run correctly, two basic hyper parameters are set: ε and $N(p)$ (minimum number of points for a cluster). The ε parameter defines the radius around each point in which other points are considered to determine the neighborhood. Points that are within ε of each other are considered to be neighbors. The minimum number of points $N(p)$ defines the minimum number of neighbors required for a point to be considered a core point and to create a cluster. That is, if a point has at least $N(p)$ of neighbors within an ε radius, it is included in the cluster. Thus, DBSCAN defines a cluster as the maximum set of points that are mutually adjacent and connected by other points [21]

$$N_\varepsilon(p) = \{q \in D | \mathrm{dist}(p, q) \le \varepsilon\},$$

where $N_\varepsilon(p)$ is the set of points in the neighborhood of point p; q is another point in the data set; D is a data set; $\mathrm{dist}(p, q)$ is the distance between points p and q; ε is the radius of the neighborhood.

The main point (p) is a point for which the number of points in its neighborhood ($N(p)$). The point p is included in the cluster C if p is the main point.

The points that can be reached from other primary points are also included in cluster C.

The final step is to obtain a binary mask and further map the building damage on digital images. After preprocessing and clustering the data, obtaining, binary masking is an important step in identifying areas where building damage is located [21]

$$\begin{cases} 1, & \text{if the point } (x, y) \text{ belongs to the cluster of damages} \\ 0, & \text{otherwise} \end{cases}.$$

The binary mask can then be used to create a damage map on a digital image, where building damage is marked as separate areas or contours. This mapping process allows you to localize and determine the size and location of the damage in the image, which facilitates further analysis and interpretation of the results.

The binary mask is an image where pixels are defined as "damaged" or "non-damaged" depending on their presence in the clusters defined in the previous steps.

So, the PCA method identifies the principal vectors that present the directions of maximum variance in the data. The eigenvalues obtained during this process are transformed into a new feature vector space. After that, the K-means method is used to cluster the feature vector space. The number of clusters is predefined and can reflect the number of principal vectors. Each cluster represents a group of similar image difference blocks. Thus, K-means clustering helps to identify important groups of features, which facilitates further detection of damage in the image. The DBSCAN method is used to identify areas where points with similar characteristics are located. In the context of fracture detection, this allows you to identify areas in the image where the detected changes indicate potential fractures. After that, a binary fracture mask is generated, with pixels exceeding the threshold being identified as fractures.

Results. The use of open data and consideration of spatial resolution are fundamental aspects of our study. To this end, we chose to use imagery from Google Earth because of its nature as an open dataset that includes the destruction of buildings caused by the Russian invasion of Ukraine in 2022 year.

This work studied and compared the effectiveness of the proposed method with existing approaches for evaluating the recognition of building objects.

To evaluate the allocation of runes on building objects, we used a confusion matrix [22]

$$\begin{bmatrix} TN & FP \\ FN & TP \end{bmatrix}, \tag{1}$$

where True Positives (TP) is the number of pixels that have correctly been identified as "damaged"; false Positives *(FP)* are the number of pixels that have mistakenly been identified as "damaged"; True Negatives (TN) is the number of pixels that have correctly been identified as "non-damaged"; False Negatives (FN) are the number of pixels that have mistakenly been identified as "non-damaged" but are fractured.

The following metrics were calculated from this matrix (1):

Accuracy: $$\frac{TP + TN}{TP + TN + FP + FN}. \tag{2}$$

Recall: $$\frac{TP}{TP + FN}. \tag{3}$$

Specificity: $$\frac{TN}{TN + FP}. \tag{4}$$

Precision: $$\frac{TP}{TP + FP}. \tag{5}$$

F1 Score: $$\frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{6}$$

Data analysis and implementation of the developed algorithm were performed using the Python 3.11 programming language. The tests were conducted on digital images of Google Earth after the Russian invasion. Fig. 2 shows a fragment of the image of Mariupol city. Fig. 3, *a* shows the result of Agglomerative Clustering. This method groups similar areas into large clusters. It allows you to create a hierarchy of clusters, which makes you consider different levels of detail (requires a lot of resources). Fig. 3, *b* shows the result of Density-Based Clustering based on finding high-density areas in the vector data space. It helps to separate destruction from the surrounding background if they form high-density areas in the image. The main advantages of DBSCAN are that it does not require an a priori number of clusters, unlike K-means and agglomerative methods, and it can cover clusters of complex shapes and identify points that do not belong to any cluster.

Fig. 4 shows the result of the algorithm proposed in this paper based on machine learning without a teacher, which allowed us to find and highlight destruction at buildings.

At this stage of the visual analysis, it was found that the proposed binary mask more accurately identifies and maps building damage compared to the masks obtained using PCA (Fig. 5, *a*), K-means (Fig. 5, *b*) and DBSCAN (Fig. 5, *c*). This indicates the higher efficiency of the proposed fracture recognition method in this context.

After the visual analysis, the proposed method is evaluated and compared with existing approaches to recognize building damage using an error matrix and metrics (2–6): Accuracy, Recall, Specificity, Precision and F1 Score (Table 1).

Fig. 6 shows the graphical result of the confusion matrix to represent the validation results of the different methods. The main diagonal of the confusion matrix consists of the number of observations that were correctly clustered.

Analyzing the matrices in Table 1, we can conclude that the proposed algorithm has a significant number of correctly classified cases (TP and TN) compared to other methods, which indicates its higher efficiency in determining the damage to buildings. Table 2 shows the results of the Accuracy, Recall, Specificity, and Precision metrics, F1 Score.

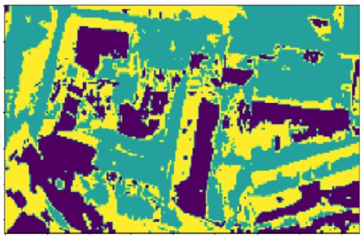
Examining the outcomes presented in Table 2 reveals that the proposed method demonstrates an accuracy of 98.13 %. It is a high rate and indicates the overall effectiveness of the method. DBSCAN, PCA, and K-means have very low accuracy. Recall is 82.38 % for the proposed method. It indicates the ability of the method to detect all positive examples. The proposed method detects more than 80 % of the true positives. Precision is 58.54 % for the proposed method. The F1 Score is 70.90 % for the proposed method, which indicates a good balance between these two aspects. Thus, DBSCAN, PCA, and K-means have very low accuracy, sensitivity, precision, and F1 Scores and are not useful in detecting damage to buildings.

a

b

Fig. 2. Digital images of Mariupol city:

a — before the Russian invasion; b — after the Russian invasion

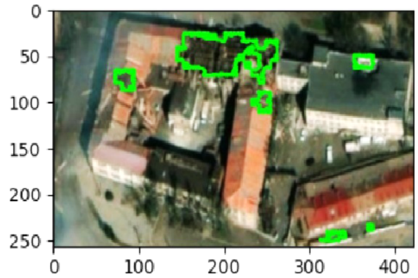


a

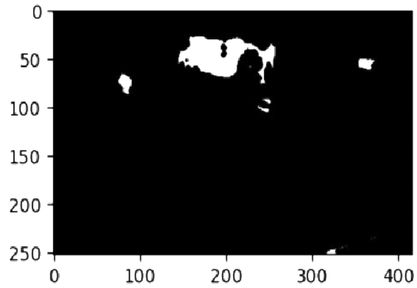
b

Fig. 3. Results:

a — Agglomerative Clustering; b —Density-Based Clustering



a



b

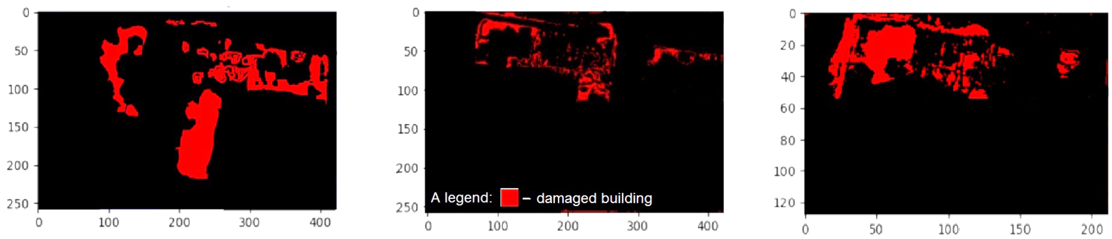
Fig. 4. Results of the proposed algorithm:

a — mapping destruction at buildings; b — binary mask

The next stage of our research is to analyze the recognition of fracture boundaries on building damage using the IoU metric (Fig. 6).

The results of comparing different methods, such as Baseline, PCA, K-means, DBSCAN, and our proposed method, provide valuable insights into the effectiveness of each method in extracting fracture contours on buildings.

According to the results in Fig. 6, the Baseline method demonstrates an IoU value up to 80.0 %, while DBSCAN, K-



a *b* *c*

Fig. 5. A binary mask:
a – PCA; b – K-means; c – DBSCAN

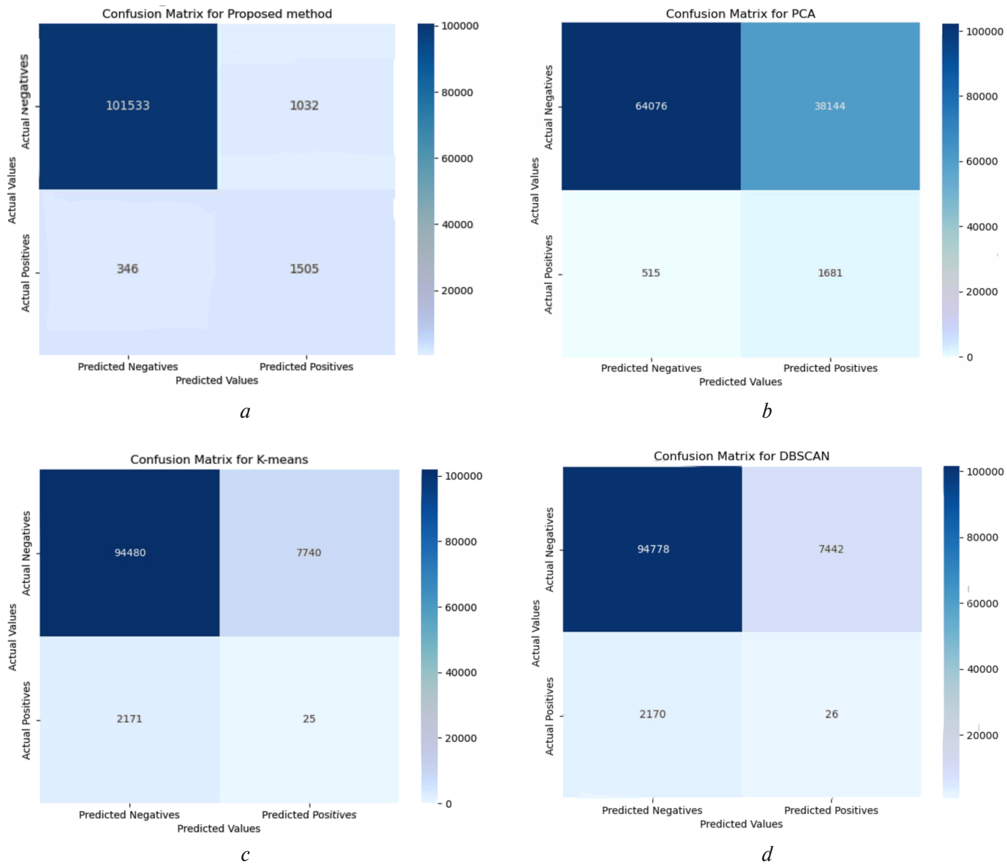


Fig. 6. Confusion matrix for:
a – proposed method; b – PCA; c – K-means; d – DBSCAN

Table 1

Evaluation Metrics of Confusion Matrix

Method	TP	TN	FP	FN
PCA	1681	64076	38,144	515
K-means	25	94480	7740	2171
DBSCAN	26	94778	7442	2170
Proposed	1505	101,533	1032	346

Table 2

Effectiveness of building damage mapping methods

Method	Accuracy	Recall	Precision	F1 Score
PCA	0.58	0.81	0.04	0.08
K-means	0.91	0.01	0.00	0.01
DBSCAN	0.91	0.01	0.00	0.01
Proposed	0.98	0.82	0.59	0.71

means, and PCA score of above 45.5, 37.0 and 24.7 %, respectively. The highest IoU, namely 89.0 %, is observed in the case of our proposed method. It indicates exceptional effectiveness in identifying fracture contours on buildings compared to other methods.

Conclusions. This paper proposes a new method for automated building damage detection in conflict zones using unsupervised machine learning on digital imagery. The proposed method achieves an accuracy value up to 98.13 %, which indicates its overall effectiveness. In contrast, traditional methods such as DBSCAN, PCA, and K-means demonstrate significantly lower accuracy rates. In addition, the proposed method shows a recall of up to 82.38 %, which indicates its ability to detect a significant proportion of positive examples. The precision measured at 58.54 % emphasizes the method's ability to minimize false positives. The F1 Score takes the values of 70.90 %, which illustrates a well-balanced relationship between accuracy and recall. In the case of DBSCAN, PCA, and K-means, on the other hand, they show noticeable shortcomings in accuracy, sensitivity, precision, and F1 score, making them less effective in detecting building

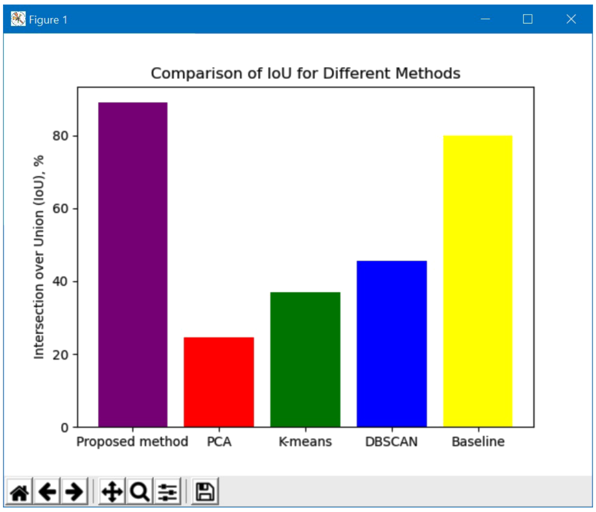


Fig. 7. IoU metric result

damage. The proposed method, with its high accuracy and balanced performance, is a valuable tool for tracking damage in the field in real-time, which will benefit both the international community and academic researchers. This research underscores the significance of utilizing open data and considering spatial resolution in the analysis of conflict zones, providing a foundation for ongoing advancements in the advancement of automated classifiers for evaluating building damage.

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Автоматизоване виявлення руйнувань будівель на цифрових зображеннях за допомогою машинного навчання

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Мета. Розробка автоматизованого методу на основі машинного навчання для точного виявлення ознак руйнувань будівель на цифрових знімках.

Методика. Представлено підхід, що використовує комбінацію методів неконтрольованого машинного навчання, зокрема, аналіз головних компонент (PCA), кластеризацію за методом K-середніх і DBSCAN метод, для виявлення руйнувань будівель, спричинених військовими конфліктами. Метод PCA використовується для визначення головних векторів, що представляють напрямки максимальної дисперсії в даних. Потім, застосовується метод K-середніх для кластеризації простору векторів ознак із заздалегідь визначеною кількістю кластерів, що відображає кількість головних векторів. Кожен кластер представляє групу схожих блоків відмінностей зображення, що допомагає ідентифікувати значущі ознаки, пов'язані із руйнуваннями. Наостанок, використовується метод DBSCAN для виявлення областей, де розташовані точки зі схожими характеристиками. Після цього генерується бінарна маска, де пікселі, що перевищують поріг, ідентифікуються як руйнування.

Результати. Запропонований метод досягає точності 98,13 %, перевершуючи показники окремого застосування традиційних методів, таких як DBSCAN, PCA та K-середніх. Крім того, метод демонструє повноту 82,38 %, що свідчить про його здатність ефективно виявляти значну частку позитивних прикладів. Точність 58,54 % підкреслює здатність методу мінімізувати помилкові спрацьовування. Розрахований показник F1, що становить 70,90 %, демонструє добре збалансоване співвідношення між точністю й повнотою.

Наукова новизна. Методи DBSCAN, PCA та K-середніх отримали подальший розвиток у контексті автоматизованого виявлення на аерокосмічних зображеннях руйнувань будівель. Це дозволяє значно підвищити точність і оперативність моніторингу територій, зокрема постраждалих від наслідків військової агресії.

Практична значимість. Отримані результати можуть бути використані для удосконалення систем автоматизованого моніторингу об'єктів забудови, а також послужити основою для розробки ефективних стратегій відновлення й реконструкції пошкодженої інфраструктури.

Ключові слова: *неконтрольоване машинне навчання, цифрове зображення, розпізнавання, руйнування будівель, військові конфлікти*

The manuscript was submitted 16.06.23.