

COMPUTATIONAL METHOD OF BINARY SEMANTIC SEGMENTATION OF BUILDING STRUCTURE DEFECTS BASED ON CONVOLUTIONAL NEURAL NETWORKS

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Abstract. The problem of automated diagnostics of defects in building structures is due to the high labor intensity and subjectivity of visual inspections. The paper presents a prototype computer vision system based on an architecture featuring a lightweight feature extraction encoder, designed for the binary semantic segmentation of cracks in building surface images. The new proposal is to adapt the specified architecture to the problem of detecting thin extended objects on a non-uniform background using a combined loss function that combines binary cross-entropy and the Dice coefficient. The paper provides the mathematical formulation of the problem, a formal description of the modified optimization criterion, a data preprocessing methodology that accounts for JPEG compression artifacts, and the results of computational experiments. Evaluated on an independent test set, the resulting metrics—specifically the Dice coefficient and Jaccard index (IoU)—validate the effectiveness of the proposed approach and outline directions for further technological improvements.

Keywords: computer vision, deep learning, semantic segmentation, defects of building structures, cracks, U Net, MobileNetV2, Dice loss function

ВЫЧИСЛИТЕЛЬНЫЙ МЕТОД БИНАРНОЙ СЕМАНТИЧЕСКОЙ СЕГМЕНТАЦИИ ДЕФЕКТОВ СТРОИТЕЛЬНЫХ КОНСТРУКЦИЙ НА ОСНОВЕ СВЕРТОЧНЫХ НЕЙРОННЫХ СЕТЕЙ

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Аннотация. Проблема автоматизированной диагностики дефектов строительных конструкций обусловлена высокой трудоемкостью и субъективностью визуальных обследований. В статье предложен прототип системы компьютерного зрения на основе архитектуры с облегченным блоком извлечения визуальных признаков (энкодером), предназначенный для бинарной семантической сегментации трещин на изображениях строительных поверхностей. Новое предложение заключается в адаптации указанной архитектуры к задаче выделения тонких протяженных объектов на неоднородном фоне с применением комбинированной функции потерь, объединяющей бинарную кросс-энтропию и коэффициент Дайса. Приведены математическая постановка задачи, формальное описание модифицированного критерия оптимизации, методика подготовки данных с учетом артефактов JPEG-сжатия, а также результаты вычислительных экспериментов. Полученные в работе на независимой тестовой выборке метрики значения коэффициента Дайса и индекса Жаккара (IoU) подтверждают работоспособность предложенного подхода и определяют направления дальнейшего совершенствования технологии.

Ключевые слова: компьютерное зрение, глубокое обучение, семантическая сегментация, дефекты строительных конструкций, трещины, архитектура U Net, энкодер MobileNetV2, функция потерь Дайса

1. INTRODUCTION

The methodological basis for technical examination of the condition of building structures is traditionally their visual inspection followed by an expert assessment of the degree of their damage [1-10]. This approach is characterized by high labor intensity, dependence on the specialist's qualifications, and the difficulty of achieving a sufficient level of reproducibility of results. At the same time, the development of remote sensing methods, including aerial photography from unmanned aerial vehicles, makes it possible to obtain high-resolution digital images suitable for automated analysis using deep learning algorithms. The key task of automation is the so-called semantic segmentation of cracks – identifying pixels in the image that contain defects and separating them from the background.

Initial approaches to automated crack detection relied on classical computer vision methods – thresholding, morphological operations, and gradient filtering. These methods were computationally efficient, but demonstrated low resistance to non-uniform backgrounds, shadows, and textures of materials, primarily concrete, due to their reliance on local brightness features without taking into account contextual information. The subsequent development of machine learning methods with manual feature construction partially compensated for these limitations, but transferred the problem to the vast area of subjectivity of feature selection by the developer. In parallel with the evolution of image processing algorithms, attempts were made to solve problems of construction flaw detection using expert systems designed to accumulate and formalize the knowledge of expert engineers for comprehensive damage diagnostics [13-28]. However, such symbolic approaches faced the classic "intellectual bottleneck" problem of knowledge extraction and required labor-intensive manual creation of rigid productive rule bases. They typically lacked built-in mechanisms for directly extracting features from raw image data, which

significantly limited their scalability and practical use. The use of convolutional neural networks, in particular their U-Net architecture [29], provides the ability to simultaneously extract hierarchical features and preserve spatial localization in end-to-end learning mode. However, the direct use of "heavy" models without taking into account the specifics of building surfaces – small crack widths (down to fractions of a pixel), noisy masks, high image resolution – led to a compromise between accuracy and computational efficiency: high-performance models prove unsuitable for mobile platforms, while lightweight architectures do not achieve sufficient localization accuracy for the aforementioned defects. Resolving this contradiction is the central objective of this study.

The objective of this work is to develop and experimentally verify a prototype of binary semantic segmentation of cracks based on the U Net architecture with the MobileNetV2 encoder, trained using a combined loss function that simultaneously optimizes pixel-by-pixel classification and spatial overlap measure. The article presents a formal statement of the problem, a description of the architecture, a data preparation methodology, and the results of computational experiments confirming the viability of the proposed approach. In order to accurately place this work within the overall structure of the field of research, it is necessary to critically examine the key results achieved by the global community in recent years.

2. PROBLEM AREA ANALYSIS

The evolution of methods for automatic analysis of defects in building structures is characterized by a consistent increase in the complexity of problem statements. The initial stage focused on the task of binary image classification, namely, based on the presence/absence of a crack. This approach, abstracting from the spatial characteristics of the defect, made it possible to achieve high accuracy rates. For example, a team

led by S. Siva Rama Krishnan, using the Inception V3 architecture, achieved an accuracy (Accuracy \approx) of 99.98% on a dataset of 40,000 images [30]. However, the classification approach does not provide spatial localization of the defect, which limits its applicability for quantitative damage assessment.

The next stage of development is associated with the transition to semantic segmentation. In 2020, S. Bhowmick et al. demonstrated the effectiveness of the U-Net architecture for crack detection in UAV videos followed by morphological post-processing to quantify geometric parameters [31]. In 2021, P. Kumar et al. implemented a real-time system based on YOLO-v3, achieving a detection accuracy of 94.24% with a frame processing time of 0.033 s [32]. In 2022, V. Gharehbaghi et al. proposed a 12-layer deep network, FastCrackNet, optimized for crack identification in noise and shadows [33].

The analysis of the above key works indicates the following limitations:

1. The contradiction between the accuracy of segmentation, assessed by the coefficient of geometric overlap of predicted and actual crack contours (mIoU $>$ 0.7), and the high computational complexity of such models.
2. Reduced segmentation quality due to training on limited datasets with JPEG compression artifacts and subjective labeling.
3. The limitations of the binary formulation of the problem, which does not allow classifying defects by type and degree of danger.

The current stage of research is characterized by the development of integrated approaches aimed at overcoming these limitations. On the one hand, multi-class and multi-modal systems are being developed – B. Gürer and M. E. Karslıgil (2024) obtained mIoU = 0.77 for damage segmentation using the OneFormer model and mIoU = 0.52 for damage level classification using the SegFormer model on data from the earthquake in Turkey [34]. On the other hand, lightweight architectures and combined loss functions are introduced to simultaneously optimize pixel-by-pixel accuracy and spatial connectivity. A significant factor in

the development of the field is the emergence of open multimodal datasets such as BRIGHT [35], which provide an objective basis for training and comparing algorithms. Additionally, work on damage assessment based on post-event SAR data [36], the use of visual language models for damage classification [37], and the rapid deployment of UAV-based AI systems in real-world conditions [38] are noted. As a result, the field is moving away from isolated classification and segmentation solutions towards end-to-end systems that integrate multimodality, post-processing, and deployment on onboard computing platforms. This work develops this direction. The prototype proposed in this paper retains the U-Net architecture with skip connections to preserve spatial details, but uses the lightweight MobileNetV2 encoder and a combined loss function (BCE + Dice). This choice is due to the need to ensure a compromise between the accuracy of fine crack detection and computational efficiency sufficient for integration into mobile platforms.

3. MATHEMATICAL STATEMENT OF THE PROBLEM

The problem is formulated as follows. Let a set of “image – true binary mask” pairs $\{X_i, Y_i\}_{i=1}^N$ be given, where $X_i \in \mathbb{R}^{H \times W \times 3}$ is a color image of the surface of a building structure, and $Y_i \in \mathbb{R}^{H \times W}$ is the corresponding mask (a pixel is equal to 1 if it belongs to a crack, and 0 otherwise). It is required to construct a parameterized mapping $f(\cdot; \theta): \mathbb{R}^{H \times W \times 3} \rightarrow [0, 1]^{H \times W}$ that associates with each pixel the probability of its belonging to the “crack” class. Thus, the binarized forecast \hat{Y}_i is obtained by applying the threshold $\tau=0.5$:

$$\hat{Y}_i(j) = \begin{cases} 1, & p_{i,j} \geq \tau, \\ 0, & p_{i,j} < \tau. \end{cases} \quad (1)$$

where each pixel $p_{i,j} = P_i(j)$ is interpreted as the probability of belonging to the “crack” class. The optimal parameters θ^* are calculated by minimizing the empirical risk:

$$\theta^* = \arg \min_{\theta} \frac{1}{N} \sum_{i=1}^N \mathcal{L}(f(X_i; \theta), Y_i). \quad (2)$$

The choice of the loss function \mathcal{L} is a critical aspect of the formulation. When using exclusively binary cross-entropy, where $M = H \times W$ is the total number of pixels in the image:

$$\mathcal{L}_{BCE} = -\frac{1}{M} \sum_{j=1}^M [y_j \log p_j + (1 - y_j) \log(1 - p_j)], \quad (3)$$

the model optimizes pixel-by-pixel classification, but does not take into account the spatial connectivity of objects. For thin cracks occupying a small fraction of the frame area, this leads to fragmentation of the forecast. When using a loss function based on the Dice coefficient:

$$\mathcal{L}_{Dice} = 1 - \frac{2 \sum_j p_j y_j + \varepsilon}{\sum_j p_j + \sum_j y_j + \varepsilon}, \varepsilon = 10^{-7}, \quad (4)$$

the model focuses on the measure of spatial overlap. This can result to blurring of boundaries and reduced pixel accuracy.

To balance between local accuracy and global shape, a combined loss function is used in this work:

$$\mathcal{L}(P, Y) = \mathcal{L}_{BCE}(P, Y) + \mathcal{L}_{Dice}(P, Y), \quad (5)$$

This formulation provides simultaneous optimization of pixel-wise classification and spatial integrity of segmented objects.

The quality of the trained model is assessed on an independent test sample using the Dice coefficient and the Jaccard index (IoU):

$$Dice = \frac{2 \sum_j \hat{y}_j y_j}{\sum_j \hat{y}_j + \sum_j y_j}, \quad (6)$$

$$IoU = \frac{\sum_j \hat{y}_j y_j}{\sum_j \hat{y}_j + \sum_j y_j - \sum_j \hat{y}_j y_j}. \quad (7)$$

4. NEURAL NETWORK ARCHITECTURE

The U-Net architecture [29] includes an analytical branch (encoder), which sequentially compresses the image to highlight the

characteristic features of the defect - its contrast, shape and texture, and a restoration branch (decoder). The latter one, based on these features, forms the final segmentation map with the original spatial resolution. Diagnostic bridges (skip connections) between symmetrical levels of the analytical and restorative branches ensure direct transfer of geometric details. This is critical for accurately detecting fine structures such as cracks a few pixels wide.

The classic implementation of U-Net with a full-size encoder is characterized by high computational complexity, which limits its applicability on mobile platforms. In this paper, MobileNetV2 [39], pre-trained on the ImageNet dataset, is used as the encoder. Using a pre-trained model ensures efficient initialization of low-level filters and accelerates convergence when training a neural network on a limited, specialized dataset.

The MobileNetV2 core block with expansion factor t and kernel of size $k \times k$ transforms the input tensor $x \in \mathbb{R}^{C_{in} \times H \times W}$ into the output $y \in \mathbb{R}^{C_{out} \times H' \times W'}$ via operator composition:

$$y = \text{LinearBottleneck}(x) = \text{BN} \left(\text{Conv}_{1 \times 1}^{C_{in} \rightarrow t C_{in}}(x) \right) \circ \text{ReLU6} \circ \text{BN} \left(\text{DWConv}_{k \times k}^{t C_{in}}(x) \right) \circ \text{ReLU6} \circ \text{BN} \left(\text{Conv}_{1 \times 1}^{C_{in} \rightarrow t C_{in}}(x) \right) + \text{skip}(x), \quad (8)$$

where Conv is a regular convolution, DWConv is a depthwise convolution, BN is a batch normalization, ReLU6 is an activation function, skip(x) is a residual connection (if the dimensions are consistent). Pretraining on ImageNet provides good initialization of low-level filters, which speeds up convergence when training on a small dataset. The decoding part of the architecture sequentially increases the spatial resolution of feature maps using bilinear interpolation or transposed convolutions and combines them with the corresponding encoder maps via skip connections. The final layer is a 1×1 convolution with sigmoid activation, forming a single-channel probability mask of the size of the original image (Fig. 1).

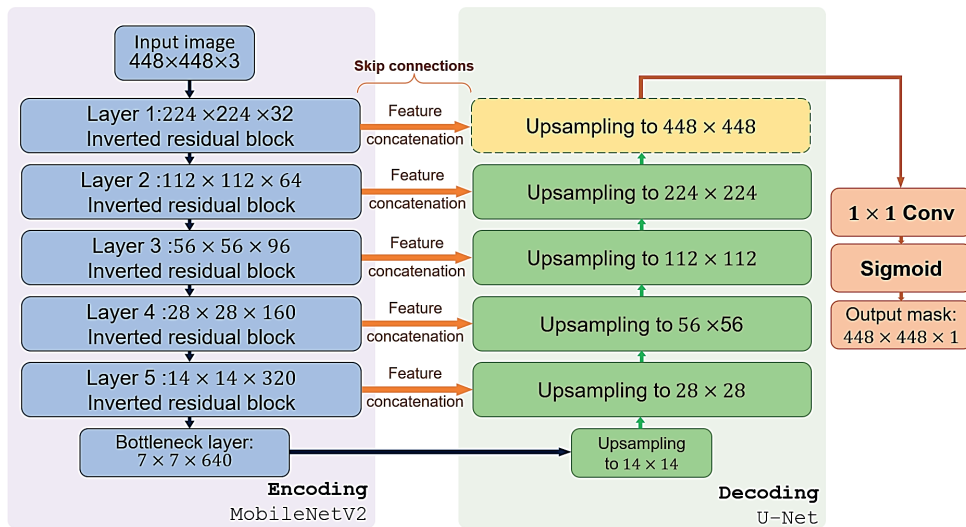


Figure 1. Architecture of the U-Net neural network with the MobileNetV2 encoder for binary crack segmentation: schematic representation of the encoding and decoding branches, skip connections, and the final sigmoid activation layer

The choice of MobileNetV2 as an encoder was driven by the requirements for computational efficiency for subsequent integration into mobile platforms and on-board systems of unmanned aerial vehicles.

5. DATA PREPARATION AND AUGMENTATION

The experiments were conducted on a specialized dataset [40] containing pairs of images of concrete surfaces and corresponding binary crack masks. The original masks were

saved in JPEG format, which introduced compression artifacts near the crack boundaries. To minimize the influence of artifacts, preliminary binarization of masks was performed with a threshold of 127: pixels with a value >127 were classified as belonging to a crack, the rest were classified as background. This operation reduced the noise level, but did not completely eliminate the blurring of edges caused by losses during JPEG compression. To increase the diversity of the training sample and improve the generalization ability of the model, augmentations were used: random horizontal and vertical reflections, rotations at angles multiples of 90°.

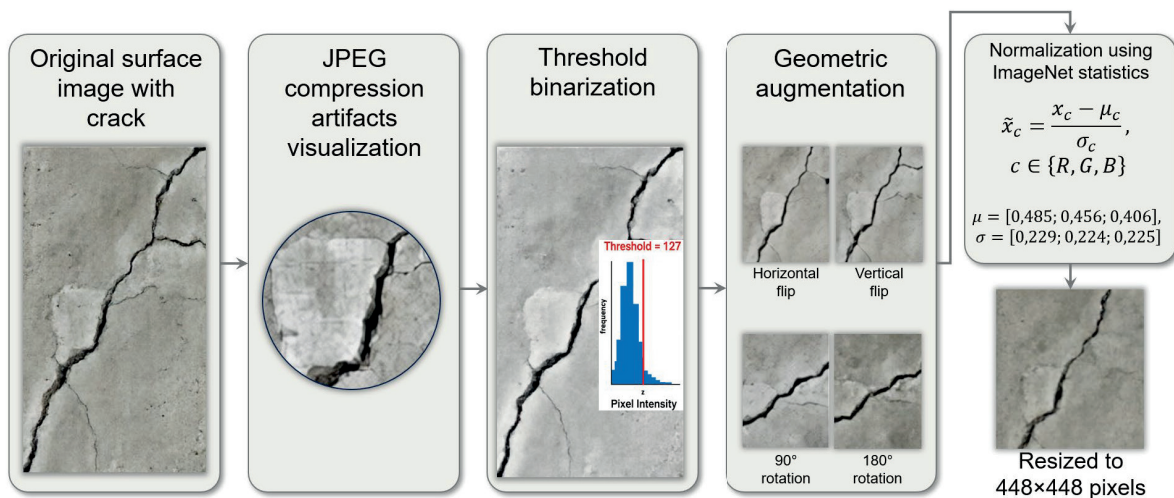


Figure 2. Schematic of the dataset preprocessing pipeline for crack detection

Geometric transformations were performed synchronously for images and masks using bilinear interpolation for images and the nearest neighbor method for masks. The input tensors were normalized based on RGB channel statistics computed from the ImageNet dataset (Fig. 2):

$$\tilde{x}_c = \frac{x_c - \mu_c}{\sigma_c}, c \in \{R, G, B\}, \quad (9)$$

where

$$\mu = [0,485; 0,456; 0,406], \sigma = [0,229; 0,224; 0,225].$$

All images and masks are resized to a fixed size of 448×448 pixels using bilinear interpolation (images) and nearest neighbor (masks). The final input tensor had dimensions 3×448×448, the output mask – 1×448×448.

6. TRAINING THE MODEL

Training was performed using the stochastic gradient descent method with the AdamW optimizer, combining adaptive learning rate adjustment with L2 regularization (weight decay). The learning rate is set to $1 \cdot 10^{-4}$, the mini-batch size is 4 images. The maximum number of training epochs is 30, with the best

model based on the Dice coefficient value on the validation set being preserved.

The learning rate is set to $1 \cdot 10^{-4}$ level, the mini-batch size is 4 images. The maximum number of training epochs is 30, with the best model based on the Dice coefficient value on the validation set being preserved.

The original dataset is randomly divided into training (80%) and validation (20%) subsamples. An independent test set, not involved in the training process, was used for the final metrics evaluation.

The dynamics of training demonstrates a monotonic decrease in the loss function and an increase in metrics during the first 10–15 epochs, after which a plateau is reached in the region of the Dice coefficient value: $\text{Dice} \approx 0,70$. The absence of a significant discrepancy between training and validation metrics indicates the adequacy of the chosen architecture and the absence of overfitting. The best model was recorded at the 24th epoch.

7. EXPERIMENTAL RESULTS AND DISCUSSION

The quantitative learning outcomes are presented in Table 1.

Table 1. Quality metrics for binary crack segmentation

Metrics	Validation set (at the best training epoch)	Test samples
Losses (BCE + Dice)	0,4984	0,4907
Dice coefficient (Dice)	0,7090	0,7118
Jaccard index (IoU)	0,584	0,5875

The comparability of validation and test values confirms the high generalization ability of the model. Visual analysis of the predicted masks on test images showed stable detection of main crack areas while correctly ignoring background textures, including concrete roughness, shadows, and local color changes.

However, the following limitations of the method were observed:

1. Blurring of boundaries in areas with a crack width of 1–2 pixels, caused by both the architectural limitations of the MobileNetV2 encoder (effective receptive size) and the original quality of the masks (JPEG compression artifacts) (Fig. 3). Fragmentation of extended cracks in cases of local decrease in contrast or intersection with shaded areas.

2. The achieved values: $\text{Dice} > 0.7$ confirm the viability of the proposed prototype as a basis for

further research. Increasing the accuracy to the level of $mIoU \geq 0.85$, necessary for an acceptable quality level of practical engineering diagnostics, involves solving the following problems:

- creation of a new data set with masks saved in PNG format without lossy compression, and with the involvement of expert markup from professional builders;

- transition to multi-class segmentation with classification of defects by type (cracks, chips, corrosion, etc.);

- use of more complex architectures (DeepLabV3+, HRNet, models with attention mechanisms) and specialized loss functions (Focal Loss, Tversky Loss);

- implementation of morphological post-processing, including skeletonization, closure, and false-positive filtering.

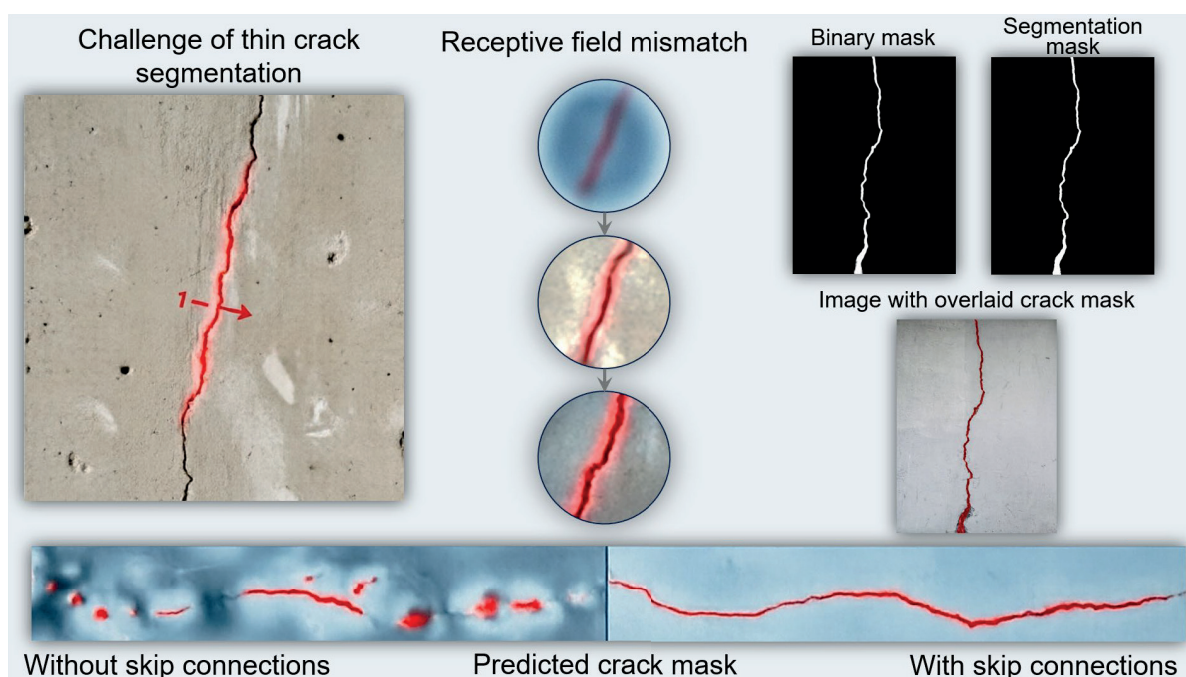


Figure 3. Visualization of the ultra-thin cracks segmentation problem: the influence of the encoder receptive field and the role of skip connections in maintaining spatial continuity of 1–2 pixel wide defects

8. CONCLUSION

The developed prototype of binary semantic segmentation of cracks on concrete surfaces based on U-Net with MobileNetV2 encoder, trained using a combined loss function (BCE + Dice), demonstrated robust ability to highlight defects in real images of building structures. An approach is proposed for adapting a lightweight architecture to the task of segmenting thin extended objects on noisy data, as well as for experimentally substantiating the influence of compression artifacts of the original masks on the quality of the model. The obtained metrics (Test

Dice = 0.7118, IoU = 0.5875) meet the requirements of the proof-of-concept stage and define the basic parameters for the development of a full-scale automated diagnostic system. Promising research areas include the formation of a representative dataset with high-quality masks, the implementation of a multi-class defect detector, and the integration of a prototype into a software package for processing aerial photography data. The practical result of this stage of research is the automatic generation of defect lists and damage cartograms in accordance with the requirements of GOST 31937–2024.

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