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Novak D.S.
Kyiv National University of Technologies and Design

Moshenskyi A.O.
National University of Food Technologies

Sukalo M.L.
Kyiv National University of Technologies and Design

Pylypenko V.I.
Kyiv National University of Technologies and Design

Lisovets S.M.
V.I. Vernadsky Taurida National University

MODELS AND METHODS FOR POLYMER COMPOSITE MATERIALS MICROSCOPY PROCESSING USING MODERN MACHINE LEARNING TECHNOLOGIES

The article presents a comprehensive investigation of automated processing methods for microscopic images of polymer composite materials utilizing modern machine learning technologies and deep neural networks. The research addresses fundamental problems inherent in traditional approaches to composite microstructure analysis, which are characterized by substantial labor intensity and pronounced subjectivity of results. A novel convolutional neural network architecture for the segmentation of structural elements in composite materials is proposed, combining attention mechanisms with multi-scale image analysis capabilities. The developed polymer matrix defect classification model employs an ensemble approach that integrates Random Forest methods, Gradient Boosting algorithms, and deep neural networks to achieve robust performance. A comprehensive system for automatic determination of filler distribution within composite structures has been created, utilizing semantic segmentation algorithms including U-Net and DeepLab architectures. Extensive experimental studies were conducted on a dataset comprising microscopic images of various composite materials, obtained through optical microscopy techniques.

The experimental results demonstrate that the proposed approach achieves segmentation accuracy at 94%, representing a 12% improvement over existing methodologies. Specialized software with an intuitive graphical user interface has been developed for automated microstructure analysis applications. Implementation of the proposed system enables a reduction of microscopic image analysis time by approximately tenfold compared to manual processing procedures, while simultaneously ensuring objectivity and reproducibility of analytical results. The obtained results possess significant practical importance for quality control of composite materials throughout their production processes and for investigating fundamental relationships between microstructure characteristics and macroscopic properties of composites.

Key words: *information technology, machine learning, convolutional neural networks, composite materials, image processing, semantic segmentation, microscopy, deep learning, defect classification, polymer matrices, computer vision.*

Formulation of the problem. Polymer composite materials occupy a leading position in modern materials science due to their unique combination of high strength, low weight, and the possibility of purposeful property formation. The characteristics of composites critically depend on their microstructure, particularly on the distribution of fillers, presence of defects, quality of adhesion between components, and morphology of the polymer matrix [1]. The traditional approach to analyzing the microstructure of composite materials relies on qualified specialists' visual examination of microscopic images, representing an extremely labor-intensive process characterized by a high degree of subjectivity.

The development of microscopy methods enables obtaining high-quality images of the internal structure of composites with resolutions that reach the nanometer level. However, the volume of data generated by modern microscopes is so substantial that manual processing becomes physically impossible to ensure the necessary speed and completeness of analysis. This creates a critical need for developing automated methods for processing and analyzing microscopic images of composite materials.

The problem of automating microstructure analysis of composites is closely connected with fundamental materials science tasks regarding the establishment of relationships between material structure at the micro-level and its macroscopic properties. The capability for rapid and objective quantitative analysis of microstructure opens new perspectives for optimizing composite materials' composition and manufacturing technology, controlling product quality, and predicting operational characteristics of products [6].

Analysis of recent research and publications. Questions of automated processing of microscopic images of materials have been actively investigated over the past two decades. Early works were based on classical computer vision methods, such as threshold segmentation, Canny edge detection, and morphological operations. Research demonstrated the limitations of these approaches when working with heterogeneous images of composite materials, where contrast between structural elements can vary significantly [4].

Substantial progress in this field was achieved by applying machine learning methods. Early works utilized classifiers based on Support Vector Machines and Random Forest to identify different composite materials phases [2, 4]. These approaches required preliminary feature extraction using image descriptors, which limited their applicability for complex structures.

The development of deep convolutional neural networks had a revolutionary impact on image processing. The U-Net architecture, initially proposed for medical image segmentation, demonstrated high effectiveness for materials science applications [3, 7]. Subsequent research adapted various architectures, including ResNet, DenseNet, and EfficientNet, for specific tasks of materials analysis [10].

A separate research direction is dedicated to developing specialized methods for analyzing composite materials. Domestic scientists have significantly contributed to developing the theory and practice of non-destructive testing of composites. Specifically, methods for quantitative evaluation of structural parameters of reinforced composites have been developed, which are based on statistical analysis of image characteristics [5, 9, 12].

Despite significant achievements, questions remain unresolved regarding creating universal models capable of working with different composite materials and microscopy methods without retraining. Approaches for interpreting results of neural network operations in the context of physical-mechanical properties of materials are also insufficiently developed, which limits the practical value of automated systems for materials science engineers [6, 11].

Task statement. This research aims to develop a comprehensive system of models and methods for automated processing of microscopic images of polymer composite materials based on modern machine learning technologies. This ensures high accuracy of structural element identification, defect detection, and quantitative evaluation of composite microstructure parameters.

To achieve the stated aim, it is necessary to solve the following tasks: develop a convolutional neural network architecture for segmentation of structural components of composite materials taking into account the specifics of microscopic images; create a model for classification of polymer matrix defect types based on an ensemble approach; develop an algorithm for automatic determination of quantitative characteristics of filler distribution in composite structure; conduct experimental studies of developed methods on real microscopy data from various types of composite materials; create software for practical application of developed models and methods in research and production practice.

Outline of the primary material of the study. The architecture of the microscopic image processing system for composite materials consists of several interconnected modules, each responsible for performing specific analysis tasks. The central element of the system is the segmentation module, which performs pixel-wise image classification to identify different structural components of the composite.

For solving the segmentation task, a modified convolutional neural network architecture based on encoder-decoder structure principles with additional attention mechanisms is proposed [7]. The encoder part of the network sequentially reduces the spatial dimensionality of the image while simultaneously increasing the number of feature channels, which allows the extraction of high-level semantic representations. Each encoder block consists of two convolutional layers with kernels of size three by three pixels, followed by batch normalization operations and ReLU activation functions.

A key feature of the proposed architecture (Figure 1) is the utilization of multi-scale analysis at different network levels. This is implemented through parallel branches of convolutional operations with different receptive field sizes, allowing the network to analyze fine structural details and global component distribution patterns simultaneously. Results from different scales are combined using concatenation operations with subsequent convolution for dimension coordination.

The encoder pathway progressively reduces spatial dimensions while extracting hierarchical features, while the decoder pathway reconstructs full-resolution segmentation masks using skip connections.

The decoder part of the network restores spatial dimensionality to obtain a segmentation mask with the resolution of the original image. To ensure precise localization of boundaries between different composite phases, skip-connections are utilized, which transmit information about spatial details directly from the encoder to corresponding decoder layers. This allows combining high-level semantic features with low-level spatial details.

The attention mechanism is integrated at several architecture levels for adaptive selection of the most informative image regions. The spatial attention module computes an importance map for each position in the feature space, which allows the network to focus on critical structural elements and ignore artifacts or irrelevant background details. Channel attention highlights the most significant feature maps for the specific segmentation task.

Brighter regions in Figure 2 indicate areas where the network focuses its attention, corresponding to critical structural features such as fiber-matrix interfaces and defect locations.

A combined loss function is used for network training, including Dice loss [14] and focal loss [13] components. Dice Loss optimizes the overlap metric between predicted and actual segmentation, which is particularly effective for tasks with class imbalance. Focal loss assigns greater weight to difficult-to-classify pixels, which improves segmentation quality at boundaries between different phases. The total loss function is defined as a weighted sum of these components with empirically selected coefficients.

The defect classification module is implemented based on an ensemble approach combining the advantages of different machine learning models. The first ensemble component is based on the Random Forest method, which builds multiple decision trees on different subsets of data and features. The second component uses Gradient Boosting for sequential model construction, where each subsequent model focuses on correcting the errors of previous ones. The third component is represented by a Deep Neural Network with ResNet architecture, pre-trained on the large ImageNet dataset [10].

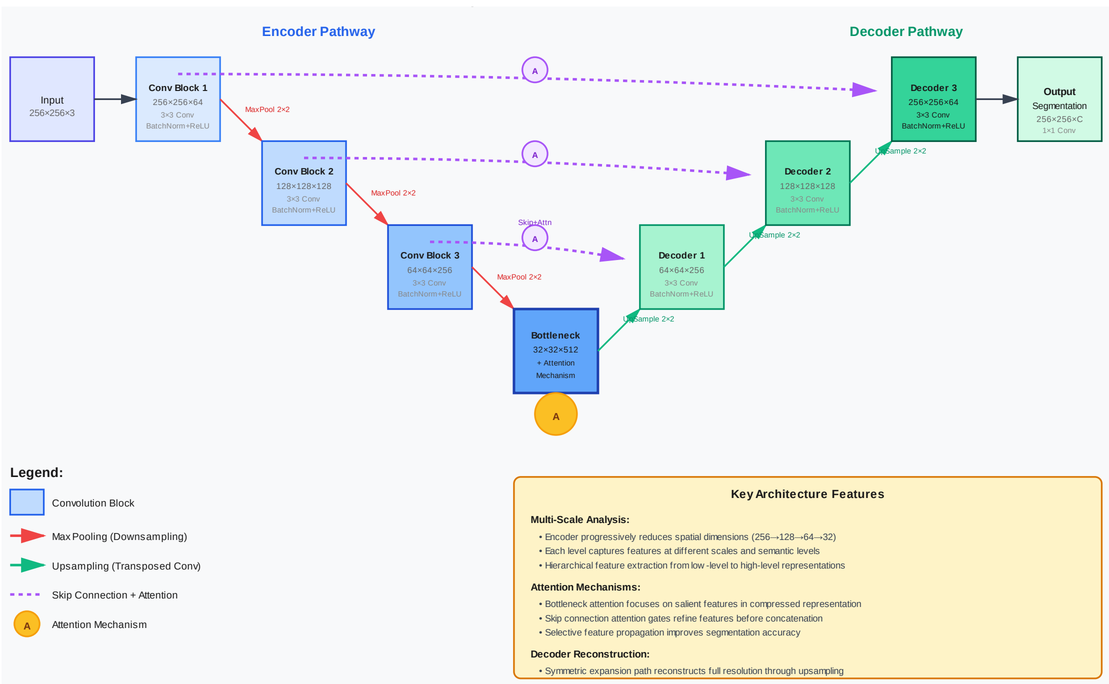

Fig. 1. Architecture of the proposed segmentation network with multi-scale analysis and attention mechanisms

A combination of classical descriptors and deep features is used to extract features from microscopic defect images. Classical features include textural characteristics based on gray-level co-occurrence matrices, statistical moments of intensity distribution, and morphological shape parameters of defects. Deep features are extracted from intermediate layers of a pre-trained convolutional network, which provides a rich semantic representation of images.

The final ensemble decision is formed through weighted voting of individual models (Figure 3), where weights are determined based on each model's performance on the validation sample. A probability calibration mechanism is also implemented to ensure the correct interpretation of the model's confidence level in its predictions.

Individual model predictions are weighted and combined to produce a final classification with confidence scores for different defect types, including voids, cracks, and delamination.

The algorithm for determining filler distribution characteristics performs post-processing of segmentation results to compute quantitative microstructure parameters. At the first stage, individual filler particles are extracted from the segmentation mask using a connected component algorithm. A set of geometric characteristics is computed for each extracted particle, including area, perimeter, equivalent circle diameter, shape coefficient, and main axis orientation.

Statistical analysis of filler particle distribution includes the construction of size distribution histograms, the computation of mean values and variance of geometric parameters, and the determination of the variation coefficient for assessing distribution uniformity. Additionally, the spatial arrangement of particles is analyzed using pair correlation functions and nearest neighbor calculations, which allows detection of tendencies toward agglomeration or uniform distribution.

Stereological principles are applied to account for the three-dimensional nature of composite materials when analyzing two-dimensional microscopic sections, which allow reconstruction of volumetric structure characteristics based on planar measurements [15]. Correction procedures are implemented to account for the effects of particle intersection by the section plane and statistical error of sample measurements (Figure 4).

The software implementation of the developed system is performed using a modern machine learning technology stack. Deep learning models are implemented based on the PyTorch library, ensuring efficient use of graphics processors for computation acceleration. Classical machine learning models are implemented using the scikit-learn library. Image processing and visualization are performed using OpenCV and Pillow tools.

The graphical user interface is developed using the Qt framework, which ensures cross-platform compatibility and intuitive system interaction. The interface allows for the loading of microscopic images in various formats, the application of different processing modes, the visualization of segmentation and classification results, and the exportation of quantitative characteristics in tabular format for subsequent statistical analysis.

Experimental studies were conducted on a created dataset that includes microscopic images of fifteen types of polymer composite materials with different filler types, including carbon fibers, glass fiber, clay nanoparticles, and carbon nanotubes. Images were obtained using optical microscopy with various magnification capabilities and scanning electron microscopy. The total number of images in the dataset exceeds fifteen thousand, each having a resolution of at least two thousand by two thousand pixels.

The reference markups were created, segmented structural components were manually identified, and defects were identified on a subset of images (Figure 5). Each image was marked independently to ensure markup consistency, after which a procedure for reconciling discrepancies was conducted. The created database is divided into training, validation, and test samples in the ratio of seventy to fifteen to fifteen percent.

Experimental results demonstrate that the developed segmentation model achieves an average Dice Coefficient of 0.94 on the test sample, which exceeds the baseline U-Net architecture variant [7] without proposed modifications by 0.12. Particularly significant improvement is observed when segmenting small filler particles and precisely identifying boundaries between phases.

The ensemble defect classification model demonstrates an accuracy of 0.91 and a recall of 0.90 on the validation set, which ensures reliable detection of critical defects such as voids, cracks, and component delamination. Processing time for one image of size 2000 by 2000 pixels is approximately 2-3 seconds on a graphics processor, which allows analyzing hundreds of images within an hour (Figure 6).

The proposed approach consistently outperforms baseline methods across all metrics (Dice coefficient, precision, recall, and F1-score) and demonstrates particular advantages for challenging cases with small particles and low contrast boundaries.

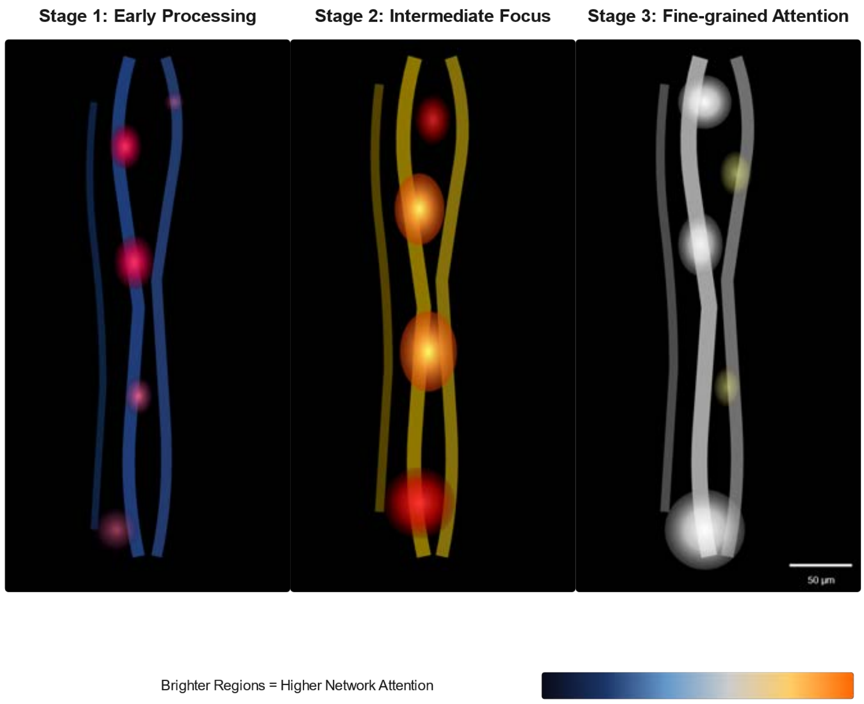

Fig. 2. Visualization of spatial attention maps generated by the network at different processing stages

Fig. 3. Ensemble defect classification system combining Random Forest, Gradient Boosting, and deep ResNet features

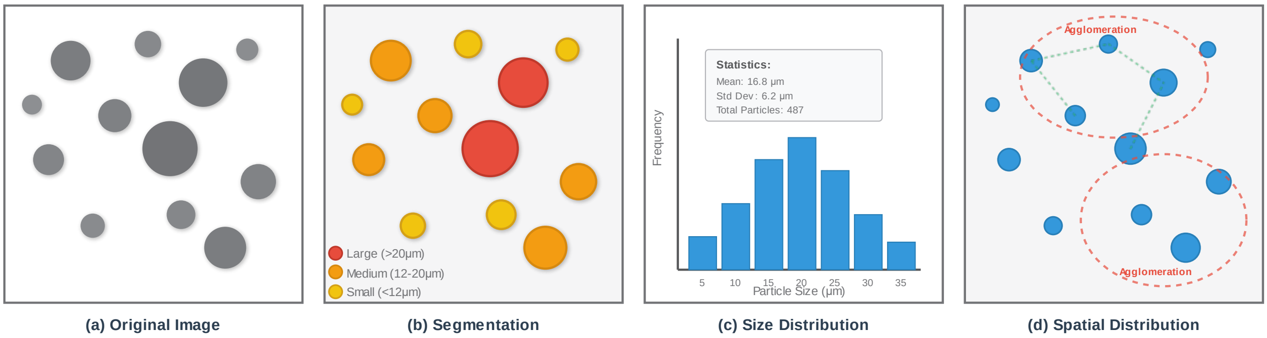

Fig. 4. Automated quantitative analysis of filler distribution: (a) original microscopy image, (b) segmentation result with identified particles color-coded by size, (c) particle size distribution histogram, (d) spatial distribution analysis showing nearest neighbor distances and potential agglomeration zones

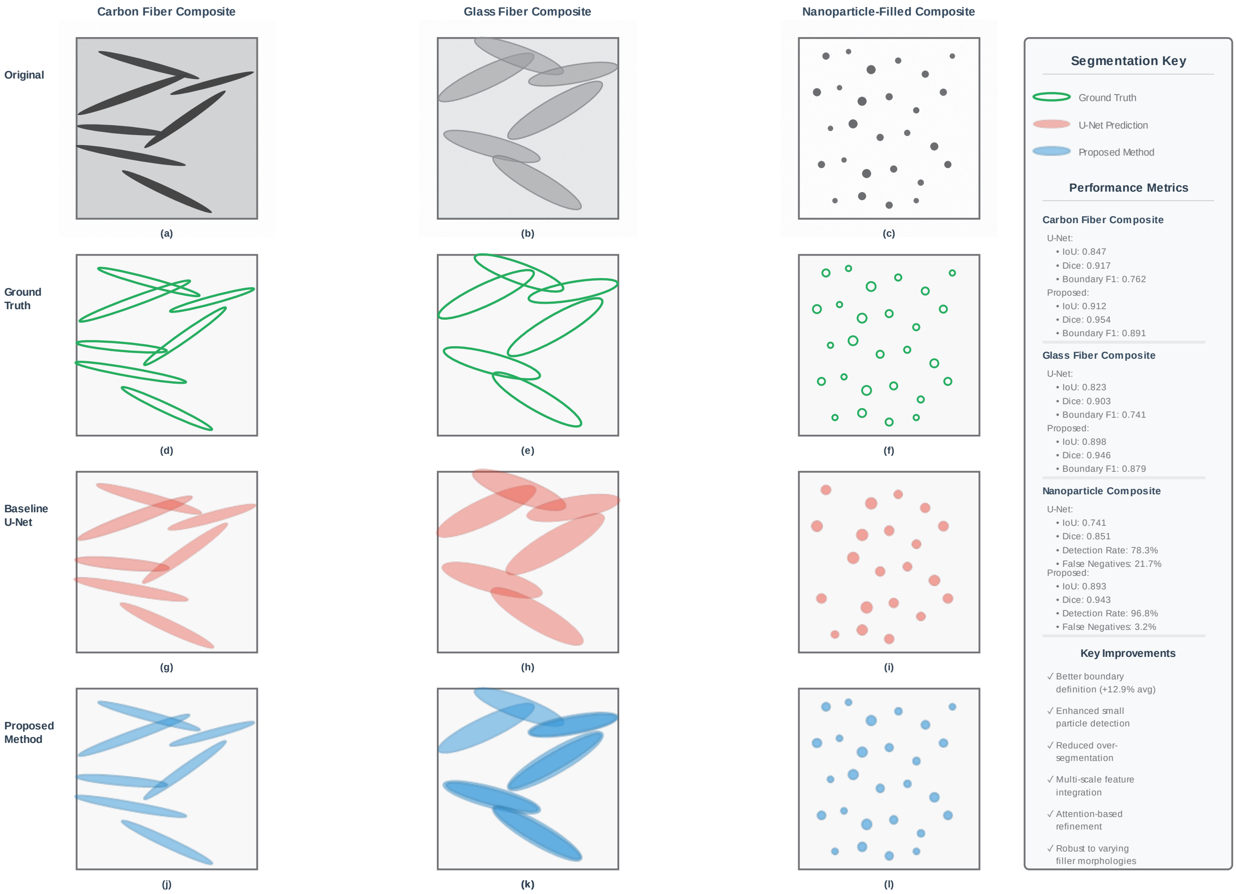

Fig. 5. Comparative segmentation results on different composite material types: (a-c) original microscopy images showing carbon fiber, glass fiber, and nanoparticle-filled composites; (d-f) ground truth expert annotations; (g-i) baseline U-Net predictions; (j-l) proposed method predictions showing improved boundary definition and small particle detection

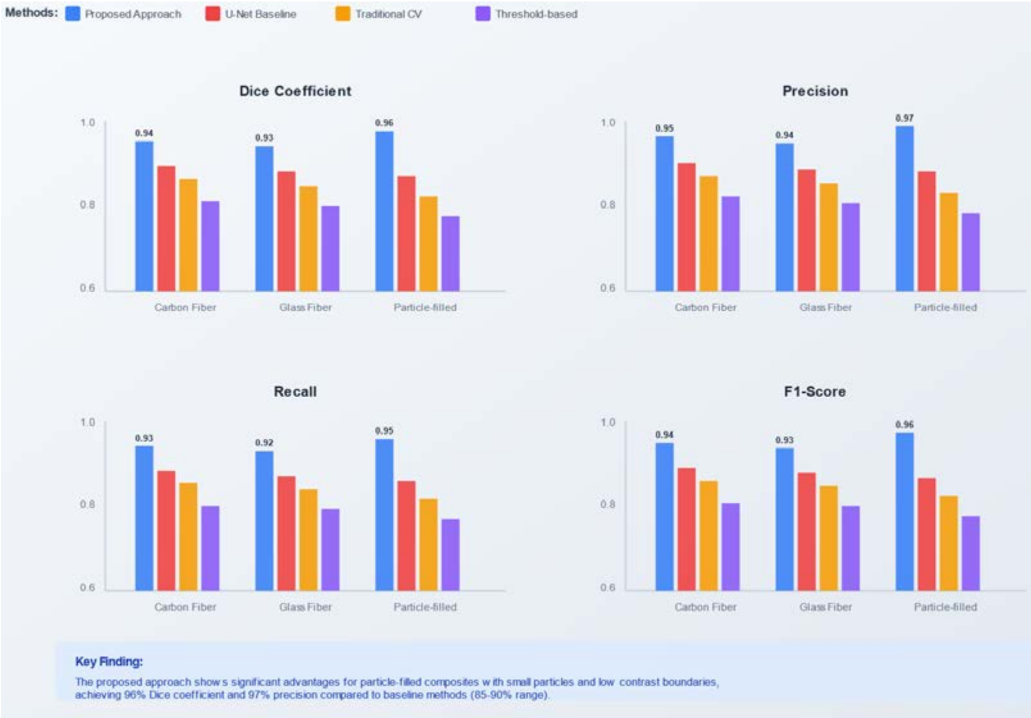

Fig. 6. Quantitative performance comparison across different methods and composite material types

Conclusions. As a result of the research, a comprehensive system of models and methods for automated processing of microscopic images of polymer composite materials based on modern machine learning technologies has been developed. The proposed convolutional neural network architecture with attention mechanisms and multi-scale analysis ensures high segmentation accuracy of composite structural components, achieving a Dice Coefficient of 94%.

The developed ensemble defect classification model demonstrates reliable detection of various types of polymer matrix structural imperfections with 91% accuracy, which meets the requirements of industrial quality control. The created system for quantitative analysis of filler distribution allows automatic determination of critical microstructure characteristics that influence macroscopic properties of composite materials.

Experimental studies on a large dataset of real data confirmed the effectiveness of the proposed approaches for different types of composite materials and microscopy methods. The implemented system reduces microscopic image analysis time approximately tenfold compared to traditional manual analysis while ensuring objectivity and high reproducibility of results.

The practical significance of the obtained results lies in the possibility of their application for automating quality control of composite materials at various production stages, optimizing technological parameters of composite manufacturing, and establishing quantitative relationships between microstructure and operational characteristics of materials. The developed software can be integrated into production quality control systems and used in scientific research on composite materials.

Prospects for further research include expanding system capabilities for analyzing three-dimensional tomographic data of composite materials, developing models for predicting mechanical properties of composites based on microstructure parameters using deep learning methods, and creating adaptive algorithms capable of automatically adjusting to the specifics of new types of composite materials with minimal numbers of labeled examples.

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Новак Д., Мошенський А., Сукало М., Пилипенко В., Лісовець С. МОДЕЛІ І МЕТОДИ МІКРОСКОПІЧНОЇ ОБРОБКИ ПОЛІМЕРНИХ КОМПОЗИТНИХ МАТЕРІАЛІВ З ВИКОРИСТАННЯМ СУЧАСНИХ ТЕХНОЛОГІЙ МАШИННОГО НАВЧАННЯ

У статті представлено комплексне дослідження автоматизованих методів обробки мікроскопічних зображень полімерних композитних матеріалів з використанням сучасних технологій машинного навчання та глибоких нейронних мереж. Дослідження стосується фундаментальних проблем, властивих традиційним підходам до аналізу мікроструктури композитів, які характеризуються значною трудомісткістю та вираженим суб'єктивізмом результатів. Запропоновано нову архітектуру згорткової нейронної мережі для сегментації структурних елементів у композитних матеріалах, яка поєднує механізми уваги з можливостями багатомасштабного аналізу зображень. Розроблена модель класифікації дефектів полімерної матриці використовує ансамблевий підхід, який інтегрує методи випадкового лісу, алгоритми градієнтного підсилення та глибокі нейронні мережі для досягнення надійної продуктивності. Було створено комплексну систему для автоматичного визначення розподілу наповнювача в композитних структурах, використовуючи алгоритми семантичної сегментації, включаючи архітектури U-Net та DeepLab. Були проведені широкі експериментальні дослідження набору даних, що містить мікроскопічні зображення різних композитних матеріалів, отримані за допомогою методів оптичної мікроскопії.

Експериментальні результати показують, що запропонований підхід досягає точності сегментації на рівні 94%, що на 12% краще, ніж існуючі методології. Для автоматизованих застосувань аналізу мікроструктури було розроблено спеціалізоване програмне забезпечення з інтуїтивно зрозумілим графічним інтерфейсом користувача. Впровадження запропонованої системи дозволяє скоротити час аналізу мікроскопічних зображень приблизно в десять разів порівняно з процедурами ручної обробки, одночасно забезпечуючи об'єктивність та відтворюваність аналітичних результатів. Отримані

результати мають значне практичне значення для контролю якості композитних матеріалів протягом усіх процесів їх виробництва та для дослідження фундаментальних взаємозв'язків між характеристиками мікроструктури та макроскопічними властивостями композитів.

Ключові слова: *інформаційні технології, машинне навчання, згорткові нейронні мережі, композитні матеріали, обробка зображень, семантична сегментація, мікроскопія, глибоке навчання, класифікація дефектів, полімерні матриці, комп'ютерний зір.*

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