INVESTIGATION OF AUGMENTATION IMPACT OF FIBERS MACRO-IMAGES SET ON THE NEURAL NETWORK CLASSIFICATION ACCURACY

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The development of intelligent methods for recognizing textile materials by visual characteristics is relevant for automated sorting, recycling technologies and circular economy processes, since the efficiency of textile waste processing depends on accurate identification of fiber composition. In real conditions, manual recognition is time-consuming and subjective, while laboratory methods are not always suitable for rapid decision-making systems. Therefore, computer vision [1] and neural network classification [2, 3] of Fibers Macro-Images are promising tools for automated textile material analysis. However, this task is more complex than traditional object recognition because the model must rely not on stable object contours [4], but on local texture [5], fiber arrangement, structural density and subtle visual differences between classes [6]. Since specialized Fibers Macro-Images datasets are usually limited, neural networks may overfit to accidental image properties; thus, augmentation is used to increase training variability, although its effect must be experimentally verified because some transformations may improve one class while distorting important features of another [7, 8].

Convolutional neural networks remain one of the key instruments of modern computer vision because they are able to learn hierarchical visual representations directly from image data [9]. Recent reviews emphasize that CNN-based models are widely used in image classification, object detection, segmentation and visual prediction tasks due to their ability to extract spatial features from original input images and gradually transform them into higher-level representations [10]. This property is especially important for textile image analysis [11], where handcrafted features may be insufficient to describe complex fiber structures, variable texture patterns and local visual differences between material classes [12].

The relevance of CNN-based textile recognition is also confirmed by recent studies in textile and fabric analysis. Deep learning approaches were actively used for fabric texture recognition, fabric defect detection, ancient textile image classification and waste textile identification. For example, Li et al. [13] showed the practical significance of CNN-based models for waste textile classification, where accurate recognition of fiber composition is necessary for efficient recycling. Yang and Zheng [14] also demonstrated the relevance of combining image processing and neural classification for intelligent fabric texture recognition in automated textile systems.

The aim of the work is to experimentally investigate the impact of image augmentation of the Fibers Macro-Images Set on the neural network classification accuracy and to determine which augmentation transformations provide the most effective and stable improvement of classification quality under a fixed training and testing protocol.

The experimental study was organized as a controlled comparison of several augmentation strategies applied to the same neural network classifier. The initial dataset contained 756 labeled Fibers Macro-Images distributed among three fiber composition classes: “30–50”, “50–70” and “70–100”. The class distribution was close to uniform, which made it possible to analyze augmentation effects without a strong imbalance in favor of one class. The use of three related classes made the task methodologically meaningful, since the model had to distinguish not only clearly separated visual categories, but also transitional differences in fiber composition based on texture and structural features.

To ensure the comparability of results, a fixed data splitting protocol was used. Fifty percent of the images were allocated to the independent test subset, forty percent to the training subset and ten percent to the validation subset. The same split was preserved for all experimental variants. This made it possible to interpret differences in classification metrics as the result of the applied augmentation transformations rather than as the consequence of random changes in the composition of training or test data.

Such a protocol is important for small and medium-sized image datasets, where even minor changes in the data split may noticeably affect the final quality indicators.

A compact neural network classifier based on MobileNetV2 was used as the basic model. The model was applied as a convolutional feature extractor with weights pre-trained on ImageNet. In the experiment, the feature extraction part was frozen, which reduced the influence of additional training variability and allowed the study to focus on the augmentation factor. The input images were resized to 224 × 224 pixels and preprocessed according to the standard input requirements of the model. Above the frozen feature extractor, a lightweight classification head was used, consisting of a Dropout layer with a coefficient of 0.2 and a Dense output layer with three neurons and softmax activation. The model was trained for 3 epochs using the Adam optimizer.

The short training mode was selected deliberately because the aim of the study was not to obtain the maximum possible accuracy by extensive fine-tuning, but to compare the relative effect of selected augmentation techniques under identical experimental conditions. This design made it possible to evaluate how the model reacts to different transformations of the training images when the architecture, optimizer, number of epochs and data split remain unchanged. Such an approach provides a clearer interpretation of augmentation impact and reduces the risk of attributing performance changes to uncontrolled experimental factors.

Five types of augmentation were compared with the baseline configuration without augmentation. Horizontal flipping was used to simulate mirrored representation of image fragments. Rotation reflected possible angular changes in the position of fibers within the frame. Zoom augmentation modeled changes in scale and distance during image acquisition. Contrast transformation represented differences in illumination and optical conditions. Translation simulated displacement of the analyzed fragment inside the image. Each augmentation type was tested separately, while the test subset remained unchanged and was not augmented. This ensured the correctness of direct comparison between the obtained results.

Classification quality was evaluated using accuracy, macro-Precision, macro-Recall and macro-F1. Accuracy was considered as a general indicator of the proportion of correctly classified images. However, for the considered task, accuracy alone is insufficient because it may hide differences in the quality of recognition between separate classes. Therefore, macro-averaged metrics were used to assess the balance of classification quality across all fiber composition classes. In addition, the class-specific F1-score was analyzed for each augmentation type. The effect of augmentation was estimated through ΔF1, defined as the difference between the F1-score of the augmented model and the F1-score of the baseline model without augmentation for the same class.

Translation also demonstrated a positive effect. The test macro-F1 score for translation reached 0.7944, which was close to the zoom result and higher than the baseline value. This suggests that displacement of image fragments during training can reduce the model’s dependence on the exact position of fiber structures in the frame. Such a result is practically reasonable because in real image acquisition conditions the analyzed material fragment may not always be centered or positioned in the same way.

Therefore, translation augmentation may increase the robustness of the classifier to positional variability.

Contrast augmentation achieved the highest validation result but did not provide the best generalization on the independent test subset. Its validation macro-F1 was 0.7842, while the test macro-F1 was 0.7878. This discrepancy indicates that the best result on the validation subset does not always correspond to the best result on independent data. In small image datasets, the validation subset may reflect only part of the possible visual variability, while the test subset provides a stricter estimate of generalization. Therefore, the selection of augmentation policy should be based primarily on independent test performance and supported by class-specific analysis.

Horizontal flipping and rotation produced weaker integral improvements. Horizontal flipping achieved a test macro-F1 of 0.7853, and rotation achieved 0.7874. Both values were slightly higher than the baseline, but the improvement was less pronounced than for zoom and translation. This means that simple geometric transformations may support generalization, but their effectiveness depends on whether they preserve class-relevant texture properties. In the case of Fibers Macro-Images, some spatial transformations may be useful, while others may partially distort features related to fiber structure and visual density.

The class-specific analysis revealed a more detailed and important pattern. For the class “30–50”, the strongest positive effect was observed for zoom augmentation, which increased F1-score by 0.067 compared with the baseline. Translation also improved this class, with ΔF1 equal to 0.048, and rotation provided a positive change of 0.042. These results indicate that the recognition of the “30–50” class benefits from transformations that modify scale, position and orientation of the image fragment. A possible explanation is that the relevant visual features of this class remain stable under moderate geometric transformations and become more reliably represented during training.

For the class “50–70”, the effect of augmentation was almost neutral. The values of ΔF1 were close to zero for all tested transformations. This may be explained by the intermediate nature of this class, which can share visual characteristics with both neighboring classes. As a result, simple augmentation transformations may not substantially change the decision boundary for this group. Another possible interpretation is that the baseline model already captured the most stable visual features of this class, while additional transformations did not provide a meaningful improvement.

For the class “70–100”, some augmentation techniques had a negative effect. Rotation reduced the F1-score by 0.025, and zoom reduced it by 0.023 compared with the baseline. Translation also caused a decrease of 0.014. At the same time, horizontal flipping and contrast change had only weakly positive effects. This result is particularly important because it demonstrates that the augmentation method with the best integral macro-F1 may simultaneously reduce recognition quality for one of the classes. Therefore, augmentation selection should not be based only on the overall metric, even when this metric is macro-averaged.

The obtained results confirm that augmentation of Fibers Macro-Images should be considered a controlled experimental factor rather than a universal preprocessing operation. In texture-based classification tasks, class-defining information may be embedded in local density, spatial structure, contrast transitions and orientation of fiber elements. Transformations such as zoom or rotation can improve recognition when these features are invariant to scale or orientation, but they can also reduce accuracy when the transformed image changes visually meaningful structural proportions. This explains why the effect of augmentation is different for different fiber composition classes.

Repeated experimental runs supported the stability of the main conclusion for zoom augmentation. For this configuration, the test macro-F1 reached 0.8047 ± 0.0052. This confirms that the positive effect of zoom is not only the result of a single random training procedure. At the same time, the differences between several augmentation variants were relatively small, so the results should be interpreted within the limits of the selected dataset, model architecture and training regime. Further experiments with larger datasets, external test samples and partial model fine-tuning are needed to generalize the conclusions.

Thus, the study experimentally investigated the impact of augmentation of the Fibers Macro-Images Set on the neural network classification accuracy. The experiment was carried out under a fixed protocol using 756 labeled Macro-Images of three fiber composition classes. The data were divided into training, validation and independent test subsets in the proportion of 40%, 10% and 50%. The same neural network architecture, training settings and test subset were used for all augmentation variants, which ensured the comparability of the obtained results.

The best integral result on the independent test subset was obtained for zoom augmentation, which achieved test macro-F1 = 0.7968 compared with 0.7814 for the baseline model without augmentation. Translation also demonstrated a positive effect, with test macro-F1 = 0.7944. Contrast augmentation provided the best validation result, but its test performance was lower than that of zoom and translation. This confirms that the effectiveness of augmentation should be evaluated on an independent test subset rather than only on validation metrics.

The class-specific analysis showed that augmentation effects are heterogeneous. Zoom augmentation substantially improved the recognition of the “30–50” class, where ΔF1 reached +0.067, but reduced F1-score for “70–100” class by −0.023. Rotation also improved “30–50” class but decreased “70–100” class by −0.025. Therefore, the choice of augmentation policy should consider not only integral accuracy or macro-F1, but also the balance of recognition quality between classes.

References

1. Malaydakh, V., Molchanova, M., Shevchuk, P., & Mazurets, O. (2025). Deep learning neural network architecture for determining sunflower growth stage from visual data. In Modern scientific research: Theoretical and practical aspects (Proceedings of the II International Scientific and Practical Conference, May 26–28, 2025, Riga, Latvia) (pp. 143–148).

2. Didur, V. O., Molchanova, M. O., Tyschenko, O. O., & Mazurets, O. V. (2025). Approach for comparative analysis of effectiveness of using MobileNetV3 and ViT neural network models for graphical localization of destroyed buildings remains areas. In Formation of innovative potential of world science (Proceedings of the IX International Scientific and Practical Conference, May 16, 2025, Waterford, Ireland) (pp. 94–97).

3. Mazurets, O., Molchanova, M., Shurypa, M., & Sobko, O. (2026). Devising a neural-network method for assessing the condition of destroyed buildings using images from unmanned aerial vehicles. Eastern-European Journal of Enterprise Technologies, 1(2(139)), 6–16.

4. Dydo, R., Sobko, O., Molchanova, M., & Mazurets, O. (2025). Analysis of precision of finding the destroyed remains buildings on photos using MobileNetV3 and ViT neural networks. In Science and technology: New horizons of development (Proceedings of the I International Scientific and Practical Conference, May 14–16, 2025, Prague, Czech Republic) (pp. 208–214).

5. Mazurets, O., Sobko, O., Dydo, R., Zalutska, O., & Molchanova, M. (2025). Augmented reality audiostream creation using CNN: Boosting inclusion and safety for visually impaired people. CEUR Workshop Proceedings, 4004, 347–361.

6. Molchanova, M., Didur, V., Mazurets, O., Sobko, O., & Zakharkevich, O. (2025). Method for construction and demolition waste classification using two-factor neural network image analysis. CEUR Workshop Proceedings, 3970, 168–182.

7. Didur, V., Molchanova, M., & Mazurets, O. (2025). Research on the effectiveness of neural network detection of plots with the destroyed buildings remains. In Modern technologies and science: Problems, new and relevant developments (Proceedings of the XXI International Scientific and Practical Conference, May 26, 2025, Zaragoza, Spain) (pp. 245–251).

8. Hladun, O., Zalutska, O., Klimenko, V., & Mazurets, O. (2025). Research on the effectiveness of classifying the remains of destroyed buildings using MobileNetV3 neural network architecture. In Innovations in science: From theoretical foundations to practical impact (Proceedings of the 1st International Scientific and Practical Conference, May 12–14, 2025, Antwerp, Belgium) (pp. 158–162).

9. Vit, R., Molchanova, M., & Mazurets, O. (2025). Representative samples forming of urban aerial and satellite imagery for building footprint segmentation. In Modern perspectives on global scientific solutions (Proceedings of the 6th International Scientific and Practical Conference, December 29–31, 2025, Bergen, Norway) (pp. 193–203).

10. Ahmad, H., Banjar, A., Alzahrani, A. O., Ahmad, I., & Naeem, M. S. (2024). Image synthesis of apparel stitching defects using deep convolutional generative adversarial networks. Heliyon, 10(4).

11. Zalutska, O., Mazurets, O., & Molchanova, M. (2025). Efficiency analysis of wrecking waste classification using neural network. In Information technology and implementation (Satellite) (Proceedings of the 12th International Conference, November 21, 2025, Kyiv, Ukraine) (pp. 142–143).

12. Mushtyn, O., Sobko, O., Molchanova, M., & Mazurets, O. (2025). Convolutional neural network architecture for image-based architectural style recognition. In Evolving science: Theories, discoveries and practical outcomes (Proceedings of the 4th International Scientific and Practical Conference, June 9–11, 2025, Zurich, Switzerland) (pp. 130–143).
13. Li, J., Liu, Q., Niu, H., & Wang, X. (2025). Identification of textile fiber composition in waste textiles using improved CNN and near-infrared spectroscopy. Journal of Industrial Textiles, 55, 15280837251359681.
14. Yang, Y., & Zheng, R. (2026). Research on intelligent fabric texture classification based on mathematical modeling and image processing. Textile & Leather Review, 9, 291–306.