Deep neural network-based classification of textile macrostructures by synthetic-to-natural fiber ratio

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Abstract

The paper is devoted to the creation and approbation of the approach to using deep neural networks for highly accurate determination of the percentage composition of fabrics from images of their macrostructure, as an alternative to traditional expensive methods of spectral analysis. It is shown that images with macro-level detail of fabrics contain a sufficient set of visual features that can be used for automated neural network classification of fabrics by the level of the synthetic component in certain intervals (30-50%, 50-70%, more than 70%). The proposed approach based on information technology includes the formation of a dataset, pre-processing of images, selection of deep learning architectures and evaluation of their effectiveness on a validation sample. For comparison, ViT-B/16, EfficientNet-B0 and ConvNeXt-Tiny were used, and the transformer model demonstrated the highest results (Accuracy 98.2 % and F_1-score 98.5 %), surpassing convolutional networks and published analogues based on CNN or spectral analysis. The classification of samples by three intervals of the synthetic component provides the practical applicability of the method for sorting tasks, marking control and assessment of recyclability. The results obtained form the basis for integrating the model into production systems for textile sorting and further expansion in the direction of working with heterogeneous structures, worn materials and variable operating conditions.

Keywords

deep neural network, synthetic-to-natural fiber ratio, textiles macrovisual characteristics

1. Introduction

The textile industry is one of the leading sectors of the global economy, but it also poses significant environmental challenges due to the complexity of production processes and material recycling [1]. One of the key prerequisites for the effective recycling and reuse of textile products is the accurate determination of the ratio of synthetic and natural fibers in the fabric composition [2]. It is this ratio that largely determines the suitability of a material for recycling: synthetic components provide elasticity and wear resistance, but complicate environmentally friendly recycling and create barriers to the development of a circular economy [3].

Traditional methods for analyzing fiber composition, such as chemical solubility tests or infrared spectroscopy, remain reliable, but are laborious, expensive and often destructive to samples [4]. This leads to a growing need for the implementation of intelligent, non-invasive and efficient approaches to determining the textiles material composition [5].

The intensive progress in the field of artificial intelligence and computer vision has proven its effectiveness for the analysis of heterogeneous structures, such as construction waste in the context of recycling [6], which opens up new opportunities for the study of textile materials. Deep learning models, in particular convolutional and transformative architectures, have demonstrated the ability

CS&SE@SW 2025: 8th Workshop for Young Scientists in Computer Science & Software Engineering, November 21, 2025, Kryvyi Rih, Ukraine
https://doi.org/10.55056/cssesw2025/paper26
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to recognize textures, detect defects and classify fabric types [7]. At the same time, the quantitative assessment of fiber ratios, in particular the percentage of synthetic components in blended fabrics based on images with macro-level detail of fabrics, still remains insufficiently studied.

The hypothesis of the study is the assumption that images with macro-level tissue detail contain a sufficient set of visual features that can be used for automated neural network classification of fabrics by the level of the synthetic component in certain intervals (30-50%, 50-70%, over 70%).

The paper aim is to confirm the possibility of using deep neural networks for highly accurate determination of the percentage composition of fabrics from images of their macrostructure, as an alternative to traditional expensive spectral analysis methods; development and experimental study of the corresponding approach.

The main contribution of the work is the development and experimental verification of a method that provides classification of fabrics by the synthetic component with an accuracy of over 98%.

2. Related works

In the study [8], a model for classifying cotton and linen fibers was proposed, which combines transfer learning methods and spatial fusion of deep features. The aim of the work was to improve the accuracy of fiber classification by integrating features obtained from different deep neural networks.

To achieve this goal, the authors used pre-trained VGG16 [9] and InceptionV3 [10] models to extract deep features from images of cotton and linen fibers. Then, they applied a spatial fusion algorithm that allows for efficient combination of information from different sources, reducing information loss and improving the overall efficiency of the model.

The results of experiments on a test set of 4008 images showed that the proposed model achieves 97.8% accuracy, 96.9% sensitivity, and 98.5% specificity. These indicators indicate the high efficiency of the proposed approach in the fiber classification problem.

The work demonstrates that the combination of transfer learning and spatial feature fusion methods can significantly improve classification results in tasks where it is important to accurately determine the types of fibers. This approach can be useful for automating the sorting processes of textile materials and product quality control in the textile industry.

In the considered work [11], a method for automated sorting of textile materials based on infrared Raman spectroscopy [12] in combination with machine and deep learning methods is proposed. The relevance of the study is due to the increase in the amount of textile waste and the need to implement effective recycling technologies that meet the goals of sustainable development, in particular, ensuring responsible consumption and production (SDG #12).

The research methodology involved obtaining spectral characteristics of fabrics using Raman spectroscopy [13], which reflect the molecular structure of fibers. The obtained data were used as input parameters for artificial intelligence models, including principal component analysis, nearest neighbor method, support vector method, random forest, artificial neural networks and convolutional neural networks. By combining spectroscopic analysis with machine learning algorithms, a textile classification system into six groups depending on the fiber composition was implemented.

The obtained results demonstrated the effectiveness of the proposed approach: the classification accuracy exceeded 95%, and the system speed was about one sample per second, which makes it suitable for large-scale industrial applications. An important advantage is the ability of the model to recognize even complex mixed fabrics containing several fiber types.

In the study [14], a system for automatic recognition of textile fiber types based on surface images of the fabric without the use of chemical or microscopic methods was proposed. The aim of the work was to create a fast and non-invasive approach to fiber classification, which allows to simplify the identification of fabric composition and improve the efficiency of quality control in the textile industry.

To solve the problem, the authors used an ensemble architecture based on several pre-trained CNN models – Inception, ResNet, VGG, MobileNet, DenseNet and Xception. Each of these models specialized in extracting certain features of the tissue, and their combination allowed to reduce the probability of errors of individual models and increase the accuracy of predictions. Training was carried out using surface images of tissues, which avoids sample destruction and simplifies data collection. The models were pre-trained on a large data set and additionally fine-tuned to the specifics of fiber classification.

The results showed an accuracy on the test set of about 84% and an F_1-score in the region of 90%, which exceeds the efficiency of individual CNN models. The main advantages of the approach are non-invasiveness, the ability to work with a large number of fiber types and the potential for scaling.

Although spectroscopic methods are traditionally considered highly accurate for determining tissue composition, their practical application is limited by the high cost of equipment and the complexity of setting up experimental conditions at scale. In contrast, computer vision methods are rapidly developing and show significant potential in the field of materials analysis, offering a more accessible and technologically flexible alternative. In this context, the challenge is to evaluate the possibilities of using macro-level detailed images of fabrics to accurately determine the percentage of synthetic fibers using deep learning models, which allows bringing these methods closer to practical application in industry and research.

3. Materials and method

3.1. Approach of classification of textile macrostructures by synthetic-to-natural fiber ratio

The proposed approach is based on the use of deep neural networks to classify textile macrostructures by the percentage of synthetic component, which allows for a non-invasive, highly accurate and scalable alternative to spectral and chemical studies. The diagram of the approach is shown in figure 1.

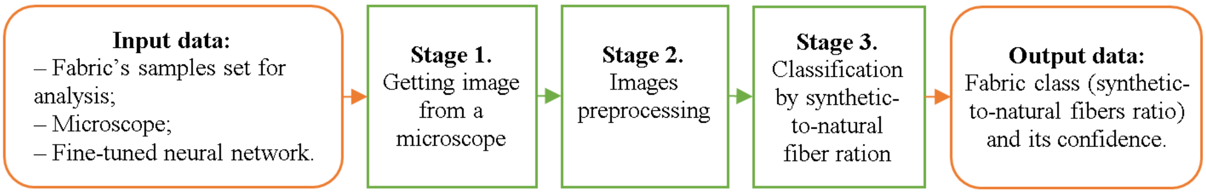

Figure 1: Approach of classification of textile macrostructures by synthetic-to-natural fiber ratio.

In the first stage, fabric samples are obtained using a microscope, which allows capturing high-quality images of the fabric surface with a resolution of 1280x960 pixels to identify structural features of the fibers. The next stage includes image preprocessing, which includes normalization, scaling and conversion into a format suitable for the deep neural network model. In the third stage, the prepared images are submitted for classification using a customized deep neural network, which determines the fabric class according to the synthetic fiber content: 30-50%, 50-70% or 70-100%.

The output data are the predicted class of the percentage ratio of synthetic and natural fibers and the assessment of the neural network's confidence in the adopted classification decision. The proposed approach provides the possibility of implementing non-invasive, highly accurate and scalable analysis as an alternative to spectral and chemical methods.

3.2. Justification of interval parameterization of the synthetic component in the neural network tissue analysis system

The choice of intervals of synthetic component 30-50%, 50-70% and more than 70% is due not only to the statistical distribution of typical textile materials on the market, but also to practical aspects of their secondary processing. In the context of fabric recycling, it is the ratio of natural and synthetic fibers that determines the technological feasibility of choosing a specific processing method and the quality of the resulting secondary product [15].

Fabrics with a low content of synthetic impurities (up to 50%) retain most of the physicochemical properties of natural fibers, which allows them to be used mainly by mechanical methods of grinding and re-spinning. Such materials demonstrate acceptable fiber stability during reprocessing and can be reintegrated into production cycles without significant loss of quality. In the range of 50-70% of synthetic components, a boundary state of the material occurs, when the properties of the natural and polymer parts are balanced. These fabrics are the most technologically complex to process, as they require combined physicochemical approaches, such as thermomechanical or solvent separation of fibers. In this range, even minor variations in composition can radically change the melting parameters, density, hygroscopicity, and behavior of the material during heat treatment, making accurate identification critically important [16].

Materials with a predominance of a synthetic component (over 70%) are most often directed to chemical recycling or energy recovery, where a high content of polymer structures is a technological advantage. For such fabrics, determining the composition with high accuracy allows optimizing the processes of decomposition and repeated polymer synthesis, minimizing energy costs.

Thus, the proposed three-level categorization is not arbitrary – it reflects the significant limits of technological compatibility of fabrics in secondary processing processes. Automated determination of belonging to these intervals not only ensures efficient classification of materials, but also creates the basis for building adaptive sorting systems focused on an environmentally balanced textile industry.

3.3. Dataset creation

The dataset used in this study was independently created based on previous studies [17]. It consists of three classes according to the percentage of synthetic component in the fabric:

- 30-50% (1240 samples);
- 50-70% (1275 samples);
- 70-100% (1265 samples).

The samples included in the dataset were obtained directly from manufacturers as test tailoring samples. For each sample, there are labels with the name of the fabric, its type and composition (figure 2). The fabrics include both natural fibers (cotton, linen, wool) and synthetic fibers (polyester, polyamide, elastane). Such detailed labeling allows both the classification of fabrics into natural and synthetic, and the assessment of the proportion of synthetic fibers in mixed materials. All samples were photographed under controlled conditions to ensure consistent image quality for further analysis using deep learning.

Figure 2: Fabric marking samples (photos obtained by the authors from real products).

The image was obtained using a Delta Smart MP5 Pro USB microscope [18] with a working distance of 6.5 cm from the sample to the objective. A system of five built-in LEDs was used for illumination, which provided uniform and stable illumination of the fabric surface. The illumination intensity was 400–420 lux, which provides sufficient brightness to recognize fine textural details of the material. The microscope camera captured images at a resolution of 1024×1024 pixels in JPEG/PNG formats, with manual adjustment of white balance and exposure to ensure color stability and contrast between samples. Figure 3 shows examples of fabric samples with different synthetic fiber contents (30-50%, 50-70%, 70-100%). As the synthetic fiber content increases, the texture and visual appearance of the fabrics change, which is captured under standardized photographic conditions. These images were used to train and validate the deep learning model for fabric classification based on synthetic fiber proportion.

Figure 3: Fabric samples with different percentages of synthetics (samples according to Figure 2).

For further processing, the dataset was organized into 3 directories depending on the percentage of synthetic fiber content, each of which contained the corresponding images. All files were previously renamed and standardized to ensure compatibility with deep learning algorithms. The data were also divided into training and validation subsets in a ratio of 80/20, which allows us to adequately assess the generalization ability of the models. During the formation of the dataset, artificial variations in the state of the fabrics were additionally introduced: the samples were subjected to light twisting, stretching and deformation. This approach allows the model to recognize the textural and structural features of the fabrics even under non-standard or deformed conditions, bringing the training data closer to real-world usage scenarios. This makes the dataset more representative and resistant to changes in the shape and tension of the fibers [19].

3.4. Information technology for neural network textiles classification

Information technology is a means of combining the components of the design and implementation approach into an intelligent software system based on a non-invasive and scalable approach, which creates the basis for its integration into application software [20].

Figure 4 shows the information technology for classification of textile macrostructures by synthetic-to-natural fiber ratio.

Stage 1 is responsible for the transformation of the dataset: based on the available fabric samples, classes were created with the level of synthetic fiber content, as indicated in the fabric composition from the manufacturer (the basic dataset was supplemented with samples by hand). In this study, all fabric images previously underwent standardization and normalization stages aimed at improving data quality and reducing the risk of overtraining.

Within the framework of the study (within Stage 2), three modern deep learning architectures were selected – ViT-B/16 [21], ConvNeXt-Tiny [22] and EfficientNet-B0 [23, 24]. These models combine different approaches to image processing and proven effectiveness in classification tasks, which allows us to compare their ability to recognize textural and structural features of fabrics.

First, the images were read in RGB format and scaled to a fixed size that meets the requirements of the ViT-B/16, ConvNeXt-Tiny and EfficientNet-B0 architectures. Next, the pixel values were normalized to the range [0,1] with subsequent centering according to the statistics of the ImageNet set [25], which ensures the correct use of pre-trained weights.

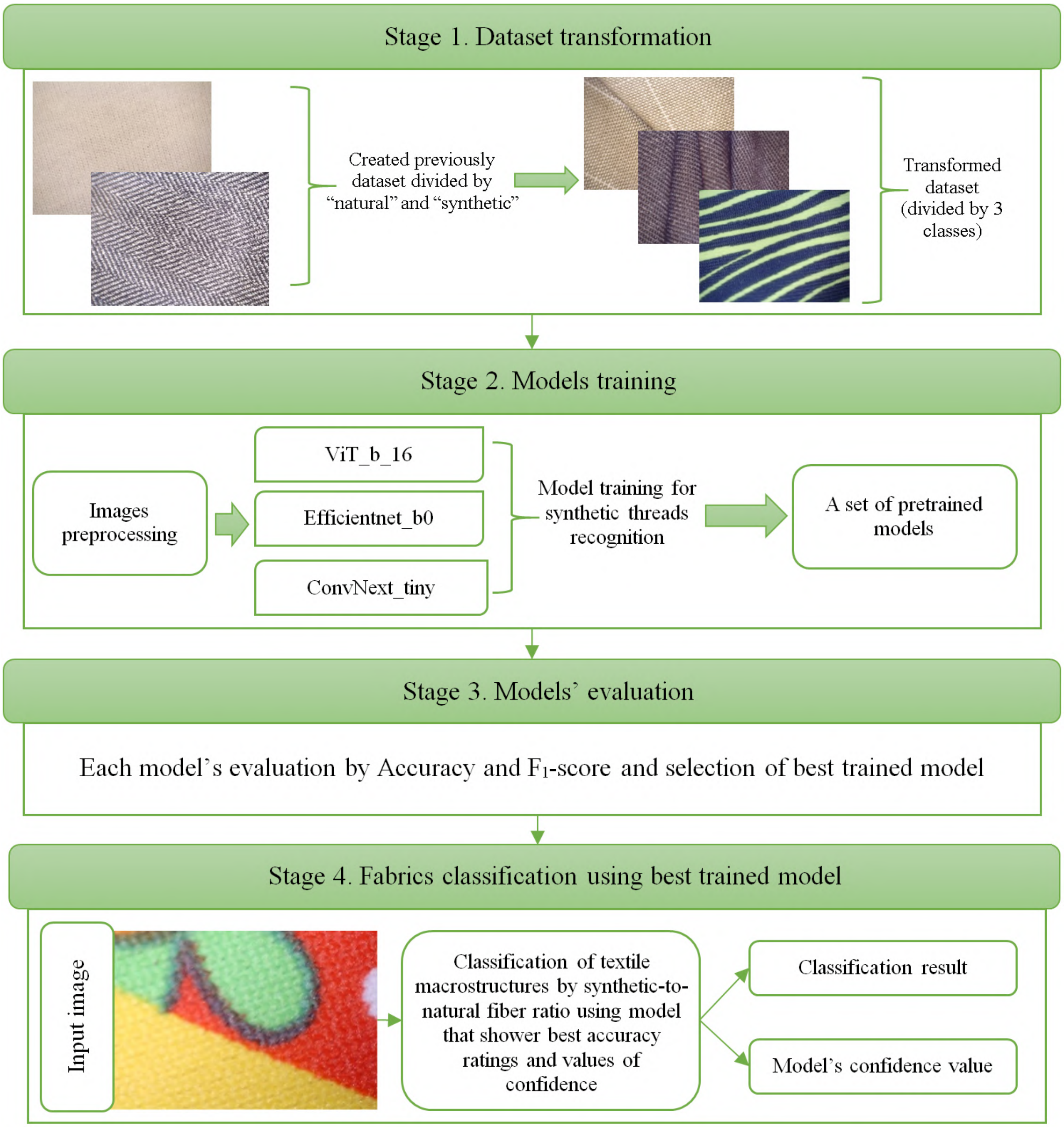

Figure 4: Information technology for neural network classification of textiles by percentage of synthetic component.

At Stage 3, the trained neural network models are evaluated. It is advisable to determine the best model by the Accuracy and F_1-score indicators, since they most fully reflect the quality of classification. Accuracy shows what proportion of samples the model classifies correctly, and F_1-score takes into account the ratio between Precision and Recall [26]. Using both indicators allows for a more objective assessment of the model's effectiveness.

At the final stage, the most effective model (according to the results of Stage 3) was applied for automated classification of textile macrostructures by the ratio of synthetic and natural fibers. The input image after preliminary transformation is fed to the input of the selected neural network architecture, the parameters of which were optimized at the previous stages. The model recognizes the structural features of the fabric and interprets them in the context of the formed classes, which correspond to different proportions of the fiber composition. The result is the formation of a forecast with an indication of the corresponding class and the calculation of the level of confidence, which allows assessing the reliability of the decision made and provides the possibility of further integration of the model into production or control systems.

The presented information technology will allow implementing an intelligent system based on a non-invasive and scalable approach to the quantitative identification of the fiber composition of fabrics through the analysis of their macrostructure and creates the basis for its integration into applied systems for control, sorting and recycling of textiles.

4. Experiment

Experimental studies were conducted to evaluate the possibility of determining the ratio of synthetic and natural fibers in textile fabrics based on image analysis with macro-level detailing of fabrics.

Pre-processing of images involved resizing to 224×224 pixels, normalizing intensity, and improving contrast using the histogram equalization method. This image size is optimal for the selected neural network architectures, which operate on 16×16 pixel patches and allows for compatibility with previously trained models. The features of the architectures selected for the study are presented below.

The ViT-B/16 architecture is a representative of transformer models [27] adapted for image analysis, which, due to its structure, is able to detect spatial dependencies between remote areas of the image, which is important for recognizing small structural differences in fabrics, in particular those caused by synthetic impurities [28].

EfficientNet-B0 provides high performance due to the optimal ratio of depth, width and resolution of the network. Its compactness and ability to focus on local texture patterns make the model effective for analyzing fiber interweaving and minor variations in the structure of the material [29].

In turn, ConvNeXt-Tiny, as a modern interpretation of convolutional networks, combines the advantages of CNN and transformer approaches. Thanks to extended filter kernels and LayerNorm normalization, it is able to capture both local and global image context, which contributes to more accurate recognition of complex fabrics texture structures [30].

The model was trained on an NVIDIA RTX 3050 Laptop GPU graphics processor (4 GB of video memory) [31]. Metrics such as Accuracy and F_1-score were used to evaluate the effectiveness of the model.

To demonstrate the applied value of the study, a graphical user application was created that provides interactive interaction with the classification model (figure 5).

The experimental software allows the user to upload a fabric image or obtain it directly from a USB microscope, after which the system automatically determines the probability of the sample belonging to each of three classes: 30-50%, 50-70% or 70-100% according to the ratio of synthetic and natural fibers in textile fabrics based on image analysis with macro-level detail of fabrics.

The graphical interface was implemented using the Tkinter library [32], which is included in the standard Python set [33] and provides rapid development of desktop applications. The application was created taking into account the principles of intuitiveness [34] and ease of user interaction with the classification model.

5. Results and discussion

Within the framework of the experiment, all models were trained on the same data set and tested under the same conditions, which ensured the objectivity of the comparison.

During the evaluation, the following metrics were taken into account: Accuracy, F_1-score and Loss on the training and validation samples. Additionally, the Confusion matrix was analyzed, which allowed to identify typical cases of misclassification between neighboring classes of synthetic fiber content. Analysis of training on the training sample showed the result for Accuracy, F_1-score close to unity, and the indicators obtained as a result of training on the validation data are given in table 1.

The results of training on the training sample confirmed the correctness of the model settings and the balance of the data, since the accuracy and F_1-measures were close to unity and were not accompanied

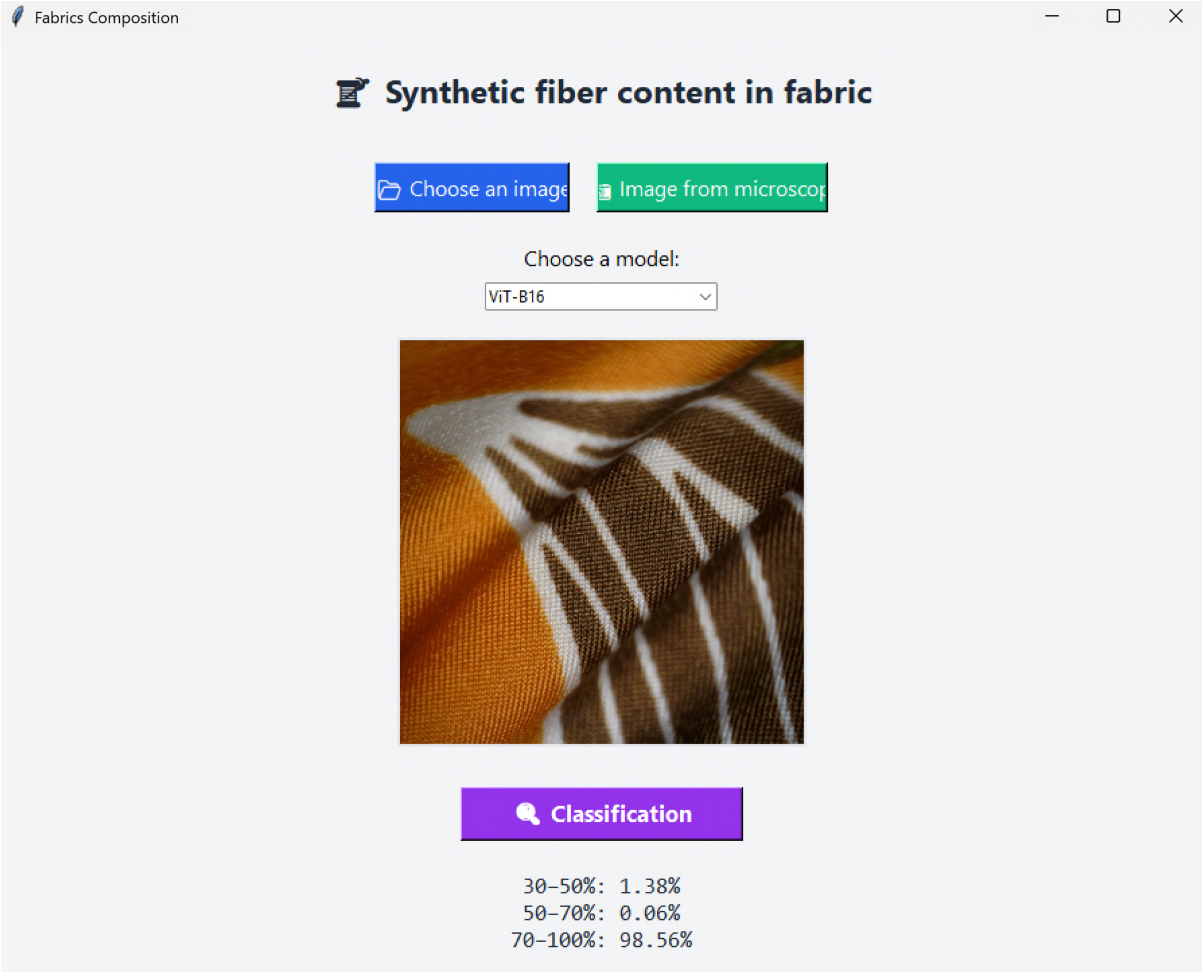

Figure 5: Developed experimental software for neural network textiles classification.

Table 1
Results of training models on validation data.

Model's name	Validation loss	Accuracy	F_1-score
ViT-B/16	0.0602	0.9820	0.9851
EfficientNet-B0	0.3943	0.9272	0.9316
ConvNeXt-Tiny	0.1761	0.9211	0.9182

by signs of overtraining. Testing on validation data made it possible to assess the real generalizability of each architecture and identify differences in the ability of the models to work with textures that differ in the degree of synthetic component. The highest results were demonstrated by the ViT-B/16 model, which achieved Accuracy 0.9820 and F_1-score 0.9851 at the minimum value of the loss function. The advantage of the transformer architecture in this task is explained by a fundamental difference in the method of image analysis. Unlike convolutional networks, where processing is performed locally at the fragment level, ViT operates with patches and uses a self-attention mechanism to detect spatial dependencies between remote areas of the textile sample. This is especially important for fabric macrostructures, where synthetic impurities are manifested not through isolated texture fragments, but through changes in the general nature of the weave, density, reflectivity and contrast of fibers.

EfficientNet-B0 and ConvNeXt-Tiny showed a lower ability to recognize such patterns. Both architectures capture local texture patterns well, but are less sensitive to global structural changes that are formed by a combination of fibers of different nature. For EfficientNet-B0, this was manifested in a higher loss value (0.3943), which indicates uneven classification confidence within classes. ConvNeXt-Tiny demonstrated lower loss, but loses accuracy due to limitations in modeling the relationships between image fragments that do not have clear spatial continuity. Therefore, the advantage of ViT-B/16 in this study is not accidental and is due to the nature of the characteristic structure of fabrics: determining the synthetic component requires the analysis of not only microtextures, but also macro-level correlations that are formed across the entire image plane.

Given the results obtained, only ViT-B/16 indicators will be considered in the future. Figure 6 shows the confusion matrix of the ViT-B/16 model. The final efficiency of the model was assessed on a validation dataset that included 756 samples evenly distributed between three classes of synthetic fiber content: 30-50%, 50-70% and 70-100%.

Confusion matrix analysis confirms both the general robustness of the ViT-B/16 model and the specificity of the distinction between neighboring classes of the synthetic component. Classes with minimum and maximum values (30-50% and 70-100%) turned out to be the least problematic: the model correctly classified 243 out of 248 samples of the first class and 253 out of 253 samples of the third class, which corresponds to a clear recognition of edge groups, where textural and structural patterns have a pronounced difference. The presence of five cases of false assignment to the class with the maximum synthetic content is explained by the similarity of reflective properties and weave density for individual fabrics with a low content of polymer impurities. The largest number of errors is observed in the intermediate class of 50-70%, where 231 out of 255 samples were correctly identified. The errors are symmetrical: 12 cases are assigned to the classes 30-50% and 70-100%. This distribution indicates a gradual transition of features between classes, where macrostructural characteristics do not always form discrete boundaries. This confirms that the intermediate values of the synthetic component form multimodal patterns, which are partially superimposed on the edge groups, which naturally complicates recognition. The absence of cases of cross-classification between 30-50% and 70-100% additionally confirms the correctness of the choice of intervals and the ability of the model to avoid gross classification shifts.

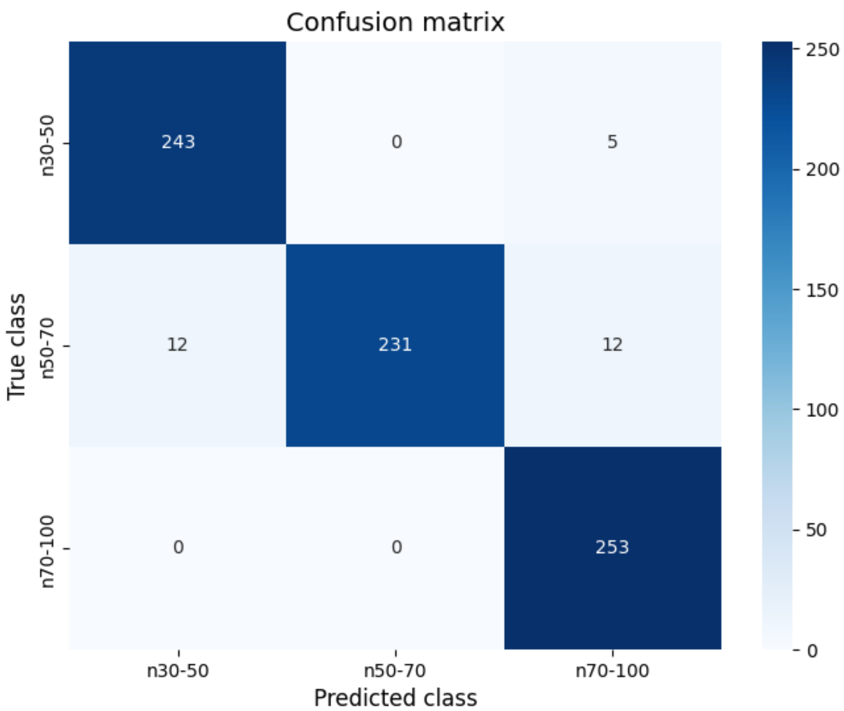

Figure 6: ViT model confusion matrix for determining the percentage of synthetic and natural fibers.

Table 2 shows the obtained results comparison with existing analogues considered in the research.

Comparative analysis showed that the proposed method based on the ViT-B/16 architecture outperforms existing approaches in terms of Accuracy and F_1-score and practical applicability. The proposed

Table 2
Comparison of the obtained results with analogues.

Research	Used models	Accuracy	F_1-score	Classes	Notes
Proposed method	ViT-B/16	98.2%	98.5%	Divided by content of synthetic fibers	Requires a regular digital microscope
Ohi et al. [14]	Inception, ResNet, VGG, MobileNet, DenseNet, and Xception	84%	90%	Fiber type classification (silk, artificial leather, polyester, etc.)	–
Zhou et al. [8]	VGG16, InceptionV3	97.8%	-	Linen and cotton	-
Tsai and Yuan [11]	PCA, KNN, SVM, RF, ANN, and CNN	>95%	-	Cotton (CO), Polyester (PES), PES/CO with PES $\geq$ 70%, PES/CO with PES $<$ 70%, PES/Elastane, Others	Requires expensive equipment and specific research conditions

method has indicators that are 14.2% higher in accuracy and 8.5% higher in F_1-score than in the study [14]. Compared with the results of the study [8], where the accuracy of 97.8% was achieved, the method proposed in this work demonstrates higher efficiency – 98.2%, which is 0.4% higher than the previous indicator. In addition, a significant advantage of the developed approach is the ability to determine the percentage of synthetic and natural fibers, which provides higher applied value and expands the possibilities of practical use of the method.

Although Tsai and Yuan [11] achieved classification accuracy rates of over 95%, their approach is based on the use of expensive and technologically complex equipment, in particular infrared spectroscopy. In contrast, the method proposed in the study demonstrated an even higher accuracy – 3.2% higher, and was implemented using a conventional digital microscope, which significantly simplifies the process and expands the possibilities of practical use of the technology in industrial and laboratory conditions.

The set of results confirms the ability of the ViT-B/16 model to non-invasively identify the fibrous composition by macro-level visual features, which creates a basis for practical integration of the approach into automated sorting and quality control systems. However, the study has a number of limitations. All samples were collected under controlled lighting and focal length conditions, which may affect the generalizability of the results in industrial environments. Fabrics with complex heterogeneous impurities were not considered, and the discretization of synthetic component intervals does not take into account cases with boundary values. In addition, the classification was carried out on the basis of flat fragments, without the analysis of multilayer or worn materials.

6. Conclusions

The study confirmed the possibility of highly accurate determination of the ratio of synthetic and natural fibers in textile materials based on the analysis of images of their macrostructure. The developed information technology covers the full cycle – from the formation of a dataset and image preparation to training, evaluation and application of a neural network model. The best results were obtained using the ViT-B/16 architecture, which achieved an accuracy of 98.2% and an F_1-score of 98.5%, exceeding the efficiency of EfficientNet-B0 and ConvNeXt-Tiny, as well as the indicators of existing analogues using CNN or spectral methods. The model is able to recognize fabrics in three intervals of the synthetic component (30-50%, 50-70%, 70-100%), which gives the approach applied value for the tasks of secondary processing, control of labeling and sorting of materials. Also beyond the scope of this study was explicit external validation on an independent dataset obtained under different lighting settings, optical devices, and fabric wear conditions.

Despite the proven effectiveness of the proposed approach, the results should be interpreted taking into account the context of data acquisition and experimental setup. Training and testing of the models was carried out on images formed under standardized visual conditions, which reduces the influence of noise inherent in real production flows. The studied samples represented homogeneous macrostructures with clearly defined intervals of the synthetic component, therefore, the behavior of the model in the case of combined or borderline fabric compositions requires additional verification. In addition, the analysis was carried out on planar images, while multilayering, wear defects or surface deformations can change the expressiveness of the features. These factors do not reduce the significance of the obtained results, but outline the framework for their practical generalization and form the basis for further adaptation of the methodology.

Prospects for further research include expanding the dataset due to different shooting conditions, refining interval boundaries and integrating methods for assessing the uncertainty of predictions. Another future research prospect is to conduct external validation on independent test sets. An important direction is the application of the model in sorting production lines taking into account the variability of textures, defects and physical deformations of fabrics. The results form the basis for developing industrial solutions in the field of textile recycling and support the transition to circular economy models.

Author contributions

Conceptualization, Olexander V. Mazurets; methodology, Maryna O. Molchanova and Olha O. Zalutska; formulation of tasks analysis, Oksana V. Zakharkevich and Valeriia I. Klimenko; software, Maryna O. Molchanova and Olha O. Zalutska; writing–original draft, Maryna O. Molchanova and Liudmyla V. Bukhantsova; analysis of results, Olha O. Zalutska and Olexander V. Mazurets; visualization, Valeriia I. Klimenko and Olha O. Zalutska; reviewing and editing, Olexander V. Mazurets and Oksana V. Zakharkevich. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Data availability statement

In the course of this study, the authors independently created a new dataset that is hosted on the Kaggle platform [17].

Conflicts of interest

The authors declare no conflict of interest.

Acknowledgments

The authors are grateful Program Committee members for organizing and conducting the 8th Workshop for Young Scientists in Computer Science & Software Engineering (CS&SE@SW 2025).

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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