Deep Learning-Driven Fabric Classification: Distinguishing Natural and Synthetic Materials

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Abstract

This paper addresses automated discrimination of textile materials into natural and synthetic fiber types from visible-spectrum microscope images using deep learning. We curate and release an open dataset of 3,107 images (1,547 natural; 1,560 synthetic) captured from face and reverse fabric sides and under mild deformations, and benchmark Vision Transformer (ViT-B/16), ConvNeXt-Tiny, and EfficientNet-B0 within a unified training and evaluation protocol, with interpretability provided via Grad-CAM and occlusion sensitivity. On the validation split, ViT and ConvNeXt achieve accuracy 0.9984 with F_1-score 0.9984 and recall 1.0000, while EfficientNet-B0 attains accuracy 0.9968, indicating consistent, near-perfect performance across architectures. Error analysis reveals residual confusions on ribbed and striped patterns where cross-class visual similarities persist, motivating further dataset diversification and multi-scale modeling. Compared with reported results on related tasks, the proposed approach yields accuracy improvements of at least 0.0054 and up to 0.0384 while preserving transparency and reproducibility through open data access; these outcomes support scalable textile sorting pipelines aligned with circular-economy practices.

Keywords

fabric classification, deep learning, Vision Transformer, ConvNeXt, EfficientNet, XAI, circular economy

1. Introduction

The increase in textile waste is one of our time's most serious environmental threats [1]. According to the European Environment Agency, more than 5 million tons of textile waste are generated annually in the European Union alone, much of which cannot be reused or recycled due to the lack of effective sorting mechanisms [2].

Existing systems are mainly based on manual labour, which is not only resource-intensive but also an insufficiently accurate method of classifying materials by fibre type [3]. Inefficient sorting leads to the mixing of natural and synthetic fabrics, which makes high-quality processing impossible and significantly reduces the environmental value of the textile raw material flow [4].

In this context, the development of automated, technologically efficient methods for recognising tissue types is an extremely urgent task. The application of such approaches contributes to the implementation of circular economy principles [5], reducing the burden on solid waste landfills, and achieving the UN Sustainable Development Goals, in particular Goal 12 – "Responsible Consumption and Production," which directly relates to supporting the processes of sorting and reusing materials [6].

This study proposes an automated method for classifying fabrics as natural or synthetic using deep learning technologies. The approach aims to improve accuracy, a key factor in effectively processing textile waste and minimising its environmental impact. The contributions of the paper are:

- Creation of an open dataset for classifying textile materials by fibre type (natural/synthetic), taking into account images of fabrics from the front and back sides, as well as artefacts (creases,

ProfIT AI'25: 5th International Workshop of IT-professionals on Artificial Intelligence, October 15–17, 2025, Liverpool, UK
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twists, overlaps).

- Improving classification accuracy by using a modified dataset and applying transfer learning to the Vision Transformer model.
- Visual explainability of the obtained solutions through the use of heat maps.

2. Related works

Traditional methods of textile waste sorting are mostly based on manual identification, which is resource-intensive and does not ensure high accuracy of material classification. In industrial conditions, physicochemical methods are used, in particular near-infrared spectroscopic probing and hyperspectral imaging [7] and thermogram analysis [8].

Although these methods demonstrate high accuracy in laboratory conditions [9], they have a number of limitations [10]: they require expensive and complex equipment, significant energy consumption, and specialised calibration. This significantly limits their scalability and use in industrial sorting conditions [11].

In this regard, methods based on the analysis of images in the visible spectrum, which are potentially less costly and easier to implement, are attracting increasing attention [12]. Recent advances in computer vision and deep learning, particularly the use of convolutional neural networks and transformer architectures, are paving the way for the automation of textile classification based on structure, texture, and colour [8].

The paper [13] is devoted to the development of a classification system for the sensory properties of fabrics based on drapeability and tactile characteristics, in particular softness. The c-means fuzzy cluster analysis method was used for classification, and the results were confirmed by expert evaluation. Further prediction of the belonging of fabrics to classification groups was carried out according to mechanical properties using an artificial neural network trained on 534 samples. The system achieved a prediction accuracy of 83.5% on validation data, which indicates its effectiveness for the objective assessment of subjective characteristics of fabrics.

The research [14] and [15] are focused on automating the detection and classification of fabric defects in textile manufacturing using machine learning and image processing technologies. The first paper applies the YOLOv10 model to determine fabric types and detect tears using a specialised annotated dataset with various fabric samples, achieving 85.6% accuracy and surpassing previous versions of YOLO in speed and accuracy. The second paper describes the creation of a prototype defect inspection system based on Google Teachable Machine, integrated with Raspberry Pi 3B for image processing and fabric rewinding control. The system classifies defects into two categories – slap and sparse – and demonstrated 98.4% accuracy with an average speed of 4.85 frames/s. Both approaches demonstrate the effectiveness of deep learning and hardware solutions for improving the automation of fabric quality control in manufacturing processes.

The paper [16]is devoted to the analysis of the composition of animal fibres in textile products to ensure quality control and detect possible commercial counterfeiting. To identify cashmere, mohair, yak, camel, alpaca, vicuna, llama, and sheep wool fibres, the Fourier transform infrared spectroscopy (ATR FT-IR) method was used in combination with scanning electron microscopy. For alpaca, vicuna, llama, and sheep wool, Fourier transform infrared spectroscopy (ATR FT-IR) was used in combination with scanning electron microscopy and chemometric tools, in particular partial least squares discriminant analysis (PLS-DA). The models built allowed us to effectively distinguish between the fibres of eight animal species and determine the origin of cashmere from different regions, achieving a classification accuracy of 87% and an explained variance of 94.88%, confirming the effectiveness of the approach for fibre identification in the textile industry.

Research [17] proposes an approach to automatic fabric classification using ResNet50, optimized by the particle swarm method. The authors demonstrate an accuracy of 98.32%, but the dataset used is closed, making it impossible to verify and reproduce the results.

A similar approach is presented in [18], which uses transfer learning based on ResNet-50. An accuracy of 99.3% was achieved, but the authors work on their own dataset, which is also not available for independent testing. In addition, the research focuses exclusively on tissue structures and does not address the issue of fibre type classification, a key factor for environmentally friendly recycling.

An analysis of current research shows that, despite significant achievements in the application of deep neural networks and transfer learning for tissue classification, several problems remain unresolved:

- lack of open datasets for model verification;
- insufficient attention to classification by fibre type, rather than just weave structure;
- limited reproducibility and explainability of existing research.

These factors justify the need to develop new approaches to automated tissue classification that combine high accuracy, low hardware requirements, and openness of methodology.

3. Problem statement

Despite significant progress in the application of deep learning methods for automated tissue classification, there is a scientific contradiction between the high accuracy demonstrated in a number of studies [17] and the limited reproducibility of results due to the closed datasets used.

Most research primarily targets the recognition of fabric weave structures, while the identification of the type of fibre – whether synthetic or natural – remains underexplored. This distinction is critically important for the ecological sorting and subsequent processing of textile waste.

The complexity of the problem is also exacerbated by the variability of the visual characteristics of fabrics (creases, overlaps, and different sides of the material), which complicates the formation of noise-resistant models.

Therefore, the current task is to develop an open dataset and create a deep learning model capable of ensuring high accuracy of fibre type classification based on image analysis in the visible spectrum. The results must be reproducible and transparent.

4. Method design

Textile materials are characterised by a variety of structures, components, and surface properties that directly affect their visual characteristics. Natural fibres (cotton, linen, wool, silk) are formed by natural biopolymers such as cellulose or keratin, which causes irregularity in the shape of the fibres, the presence of microdefects, and surface heterogeneity. This creates characteristic textural features: a fibrous structure, chaotic arrangement of elements, natural variation in colour and fibre thickness [19].

On the other hand, synthetic fabrics like polyester, nylon, or acrylic are man-made and produced in controlled conditions. They're more consistent, have a smooth surface, and have a regular thread shape. Synthetic materials often have a glossy surface, clear fibre boundaries, and a repetitive microstructure, which significantly distinguishes them from their natural counterparts [20].

Such morphological differences can be captured using optical and digital imaging methods, including microscopy. Analysis of high-resolution images allows the detection of characteristic texture patterns, orientation, and fibre thickness, which creates the conditions for automated recognition using computer vision and deep learning algorithms [21]. The diagram of the deep learning-driven fabric classification method is shown in Figure 1.

The input data for the method consists of a fabric sample for analysis, a microscope that allows visualisation of the material's structure, and a trained neural network capable of performing binary classification. In stage 1, an image of the fabric is obtained using a microscope, which provides a detailed picture of its microstructural characteristics. In stage 2, the obtained image is prepared for further analysis, which includes pre-processing procedures aimed at adapting it to the requirements of the input image for neural network analysis. At stage 3, the prepared image is sent to the input of the neural network, which classifies the fabric sample into the categories "natural" or "synthetic" and also generates an explanation of the decision made, providing additional interpretation of the results.

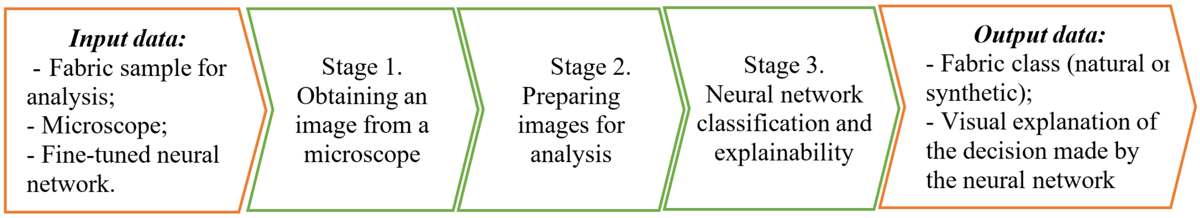


Figure 1: Deep learning-based fabric classification method.

The input data for the method is a defined fabric class (natural or synthetic) and a visualised explanation of the decision made by the neural network. This not only automates the classification process but also increases confidence in the analysis results thanks to the transparency of the decision-making mechanism.

4.1. Dataset creation

Within the scope of the research, a proprietary dataset of fabric images [22] was created, comprising two classes: natural fibres and synthetic fibres. The total number of examples is 3,107 images, of which 1,547 belong to the natural class and 1,560 to the synthetic class. The dataset formation scheme is shown in Figure 2.

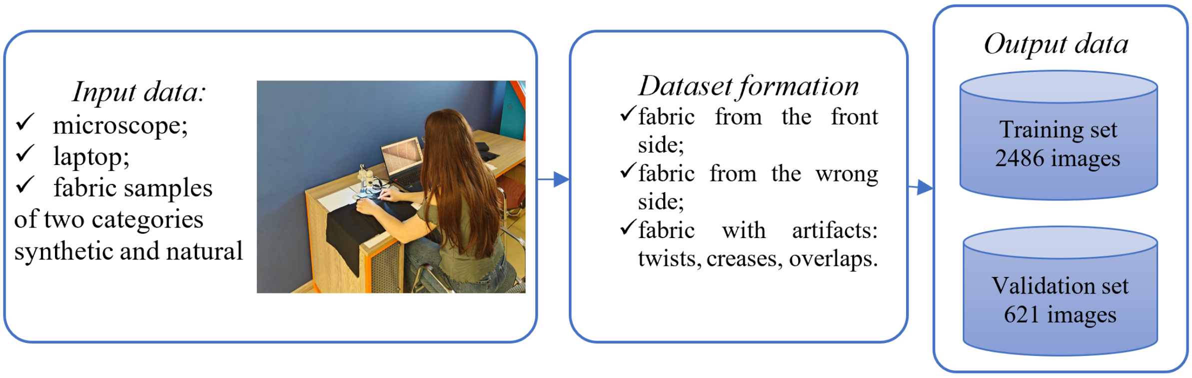


Figure 2: Dataset formation diagram.

The purpose of data collection was to ensure representativeness [23], sufficient diversity of fabric samples, and to record the characteristic textural and morphological features of fibres that distinguish natural and synthetic fabrics.

The image was obtained using a Delta Smart MP5 Pro USB microscope [24] with a working distance of 6.5 cm from the sample to the lens. A system of five built-in LEDs was used for illumination, providing uniform and stable illumination of the fabric sample surface. The light intensity was 400–420 lux, which ensured sufficient brightness for the visibility of fine textural details of the fabrics. The microscope camera took pictures with a resolution of 1024×1024 pixels in JPEG/PNG format, with manually adjusted white balance and exposure to ensure colour stability and contrast between samples. 3107 images were collected, including 1547 images of natural and 1560 images of synthetic fabrics. Examples of fabric samples and their microscope-enlarged photos are shown in Figure 3.

This approach provides sufficient detail for further automated classification and can be scaled in industrial applications for sorting textile waste.

For further processing, the dataset was structured in two directories (synthetic and natural), each containing the corresponding images. All files were pre-renamed and standardised to ensure compatibility with deep learning algorithms. Additionally, the data was divided into train and validation subsets in an 80/20 ratio to test the generalisation ability of the models adequately.

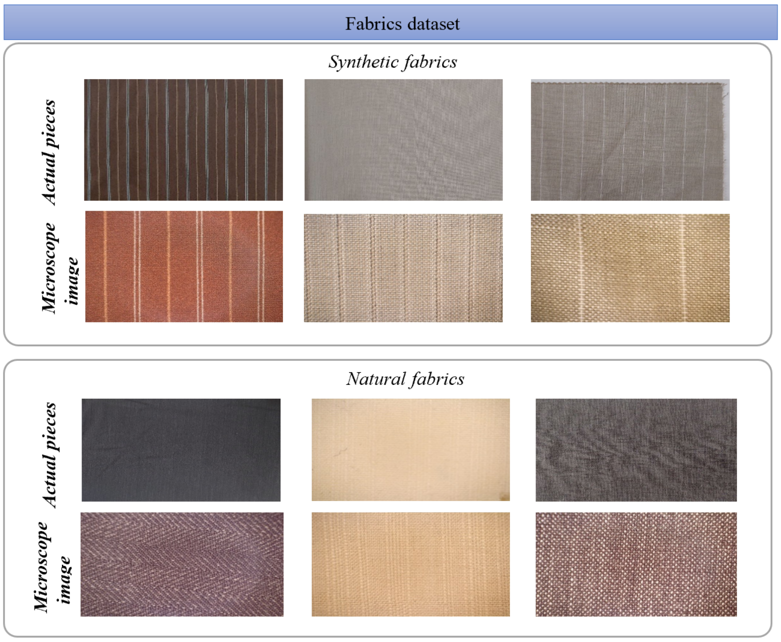


Figure 3: Images of fabric samples obtained using a microscope and under normal conditions.

During the formation of the dataset, artificial variation in the state of the fabrics was additionally introduced: the fabric samples were subjected to slight twisting, stretching, and deformation. This approach allows the model to recognise a fabric's textural and structural features 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 fibres.

4.2. Pipeline distinguishing natural and synthetic materials

Figure 4. shows a pipeline for distinguishing natural and synthetic materials.

After forming the dataset, all images were resized to a single size of 224×224 pixels and normalised by mean and standard deviation:

$$I' = \frac{I - \mu}{\sigma}, \tag{1}$$

where I is the input image, μ and σ are the mean and standard deviation of the channels, respectively. To improve the generalisation ability of the models, augmentations were applied: random horizontal reflection, image rotation by a random angle $[-10°, 10°]$, and random scaling. This avoids overfitting and improves the stability of the algorithm.

The proposed automated fabric classification pipeline consists of several key stages. The first stage involves the formation and structuring of the dataset, which includes the collection of images, their preliminary processing, and distribution into training and test samples. To improve the quality of training, augmentation methods are used to account for possible variations in the fabric's appearance, simulating real-world conditions.

The second stage involves training deep learning models that receive images as input data and generate a class prediction ("natural" or "synthetic" fabrics). Training is based on optimising the loss function and updating the model's weight coefficients.

The third stage involves evaluating the quality of the classification. Performance metrics are used to do this: accuracy, recall, precision, and F_1-score. This allows for a comprehensive assessment of the effectiveness of the approach.

A separate critical stage is the implementation of artificial intelligence explainability methods. They ensure transparency of decision-making by the model and allow us to investigate which visual features [25] most significantly influence the classification result. In particular, heat maps of attention and occlusion sensitivity analysis provide additional insight into which areas of the image the algorithm focuses on.

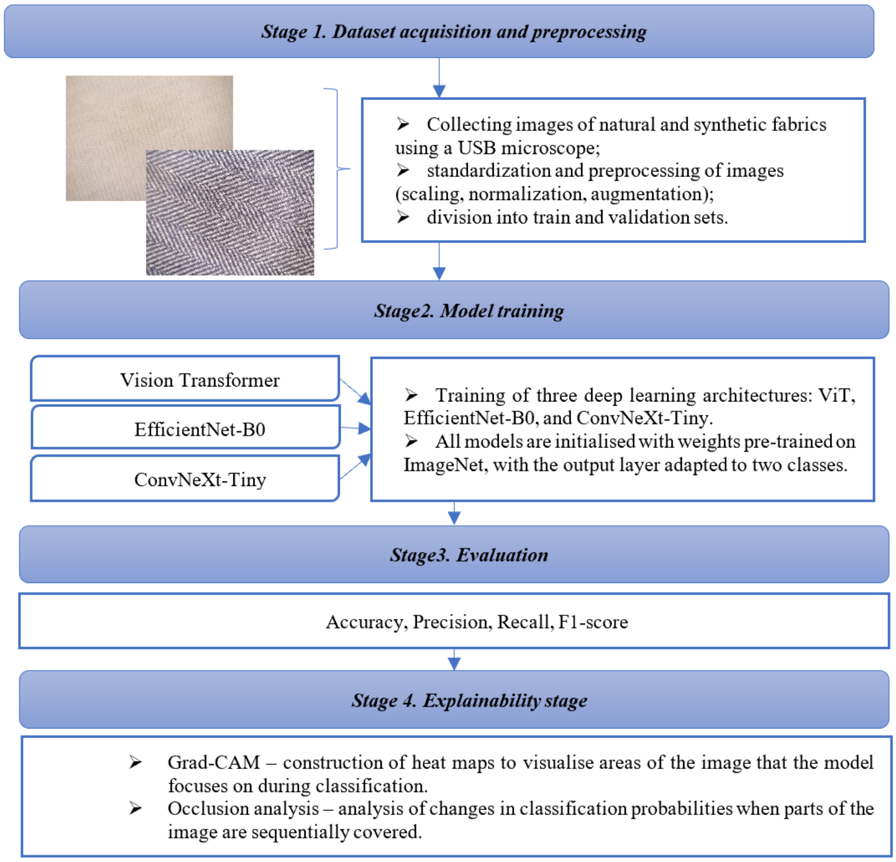


Figure 4: Pipeline distinguishing natural and synthetic materials.

Thus, the research methodology combines the formation of a representative dataset, training of classification models, evaluation of results, and explainability tools, which allows for creating a comprehensive system for analysing and sorting textile materials.

5. Experiment

Unified parameters were used to train the models, ensuring the correct comparison of results from different architectures. The input images were pre-scaled to 224×224 pixels, which corresponds to the standard parameters of most modern deep neural network models. Training was performed using batch size = 32, with AdamW [26], which is a modification of the classic Adam algorithm and allows effective control of the weight norm through the weight decay parameter (1×10^{-2}). Cross-entropy, the standard for two-class classification tasks, was used as the loss function. Regularisation was additionally supported by applying dropout=0.1. Training lasted 10 epochs, with the dataset divided 80/20 into training and validation samples.

An NVIDIA [27] GeForce RTX 3050 Laptop GPU (CUDA 12.1, 4GB VRAM) graphics card was used for the experiments, providing sufficient performance for training medium-scale models.

Three architectures representing different computer vision paradigms were used in the research. Vision Transformer (ViT-B/16) [28] implements a transformer-based approach [29] with a self-attention mechanism that allows the model to detect global dependencies between image fragments effectively. EfficientNet-B0 [30], as a representative of convolutional neural networks, is based on the concept of compound scaling, which optimally balances the network's depth, width, and resolution while maintaining high accuracy. ConvNeXt-Tiny [31] combines the properties of classic CNNs and modern transformer-based architectures, using large convolution kernels (7×7), layer normalisation, and a simplified structure, which makes it competitive in image classification tasks.

An explainable artificial intelligence approach was used in this work to increase the transparency of the classification and validation process. It aims to identify the visual features that most significantly influence the model's decisions. This allows the evaluation of the quality of the neural network using standard metrics and understanding whether the fabric classification is actually based on relevant textile characteristics. The research used several complementary methods: Grad-CAM and Occlusion Sensitivity Analysis.

Gradient-weighted Class Activation Mapping uses gradients from the model's output layer to calculate the weight coefficients of neurons in the last convolutional or transformer blocks [32]. The resulting coefficients allow us to build heatmaps that visualise the spatial areas of the image that the model focuses on when making decisions. In the context of fabric classification, Grad-CAM allows us to confirm that the model analyses the textural and structural features of the material rather than background factors.

Occlusion Sensitivity Analysis is based on sequentially covering certain parts of an image and observing changes in classification probability [33]. If excluding a specific region significantly reduces the model's confidence, this indicates the high importance of this area for decision-making. Thus, Occlusion Sensitivity Analysis allows you to experimentally confirm the correctness of the model's visual attention and exclude the possibility of "false correlations".

The application of XAI methods [34] demonstrates that the models are indeed focused on the characteristic properties of textiles – fibre density, weave structure, and surface defects. This provides additional validation of the architectures and forms the basis for the practical implementation of the proposed approach in automated textile waste sorting systems [35].

To evaluate the results of the proposed methodology, a software application based on the Tkinter library was created (Figure 5).

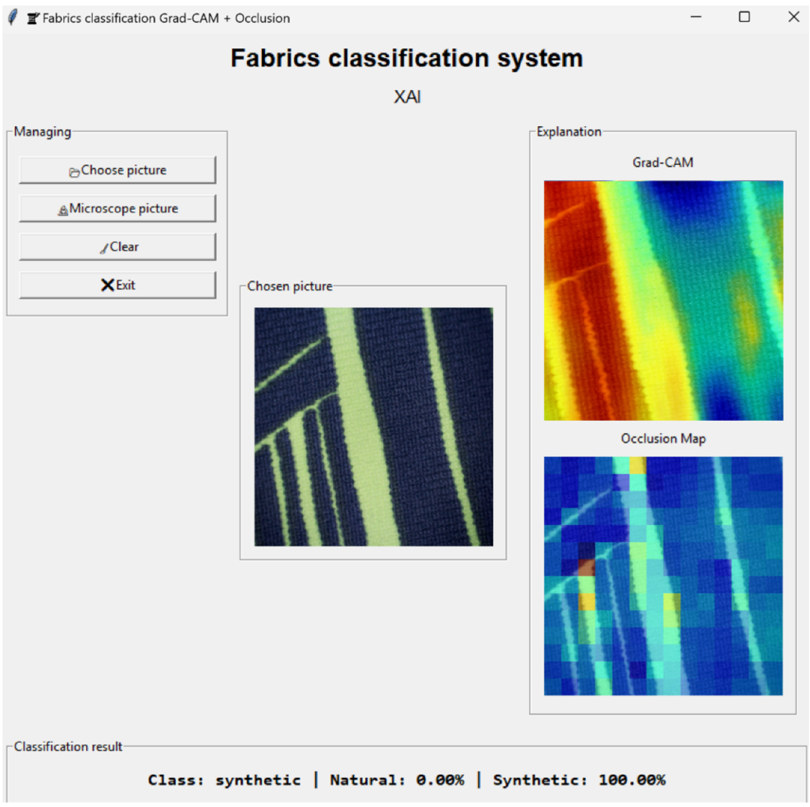


Figure 5: Interface of the implemented software application.

The implemented software application allows viewing the original image, Grad-CAM analysis results, and occlusion map.

6. Result and discussion

The research found that the best results were achieved for natural and synthetic materials with a similar structure, with apparent visual differences between classes. This result is reasonably expected, since convolutional and transformer-based models used for image classification are good at identifying global patterns without significant variations. A comparison of the training results of the Vit, efficientnet_b0, and ConvNeXt neural network models is shown in Table 1.

Table 1
Results of fabric classification using trained models

	ViT	EfficientNet_b0	ConvNeXt
Accuracy	0.9984	0.9968	0.9984
Precision	0.9968	0.9936	0.9968
Recall	1.0000	1.0000	1.0000
F_1-score	0.9984	0.9968	0.9984

All three models demonstrated results exceeding 99% across all key metrics in the experiments conducted. The most effective were the Vision Transformer and ConvNeXt architectures, which showed identical accuracy values of 0.9984, recall of 1.0000, precision of 0.9968, and F_1-score of 0.9984. This demonstrates their ability to generalise features effectively even when there is a high similarity between classes. In contrast, the EfficientNet-b0 model showed only slightly lower results, with an accuracy of 0.9968, precision of 0.9936, and F_1-score of 0.9968, which confirms its effectiveness, albeit with less clarity than the other two architectures.

The results of the Vision Transformer model training process are shown in Figure 6 and Figure 7. In particular, the graphs of the loss function and accuracy values (Figure 6) on the training and validation samples during the training epochs show a rapid decrease in losses and an increase in accuracy to almost maximum values already at the initial stages of training. The insignificant difference between the training and validation curves indicates minimal manifestations of overfitting, which do not affect the overall generalization ability of the model. The ROC curve and error matrix are also presented (Figure 7).

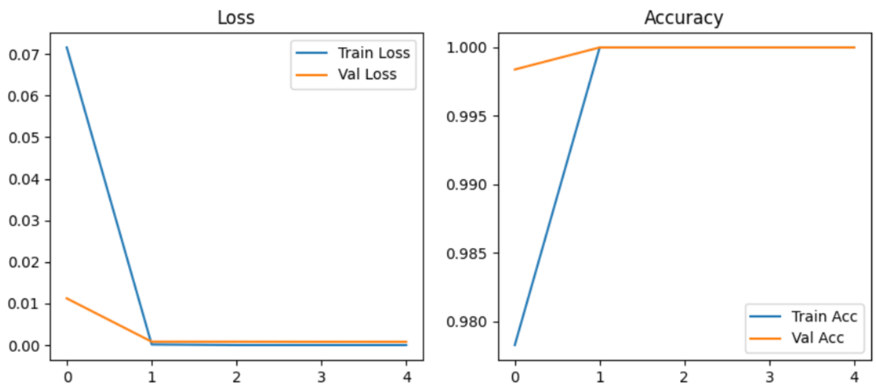
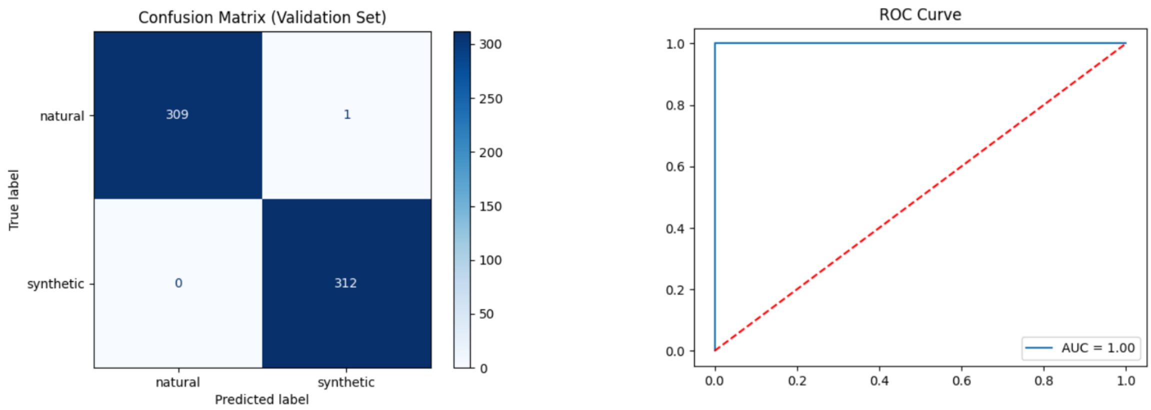


Figure 6: Accuracy and loss function change graph for ViT model.

The error matrix shows almost perfect agreement between the predicted and true classes, confirming the high accuracy of the model. The ROC curve is characterized by an area under the curve (AUC) of 1.0, indicating the excellent ability of the model to discriminate between classes.

Compared to other works in textile material classification, the proposed approach demonstrates higher efficiency. Thus, in the work [17] results were obtained with an accuracy metric ranging from 0.58 for CNN to 0.9567 for VGG16 and 0.96 for ResNet50. Accordingly, the proposed approach outperforms the considered one by at least 0.0384.



(a) **(b)**

Figure 7: Additional graphs of the ViT model training: (a) confusion matrix; (b) ROC curve

In the paper [18] where deep convolutional neural networks were used to recognise fabric patterns, significant classification results were also achieved – 0.993 according to the Accuracy metric. However, the developed approach showed even higher results, exceeding these values by 0.0054. A comparison of the results obtained with existing analogues is shown in Table 2.

Table 2
Comparison of the results obtained with existing analogues

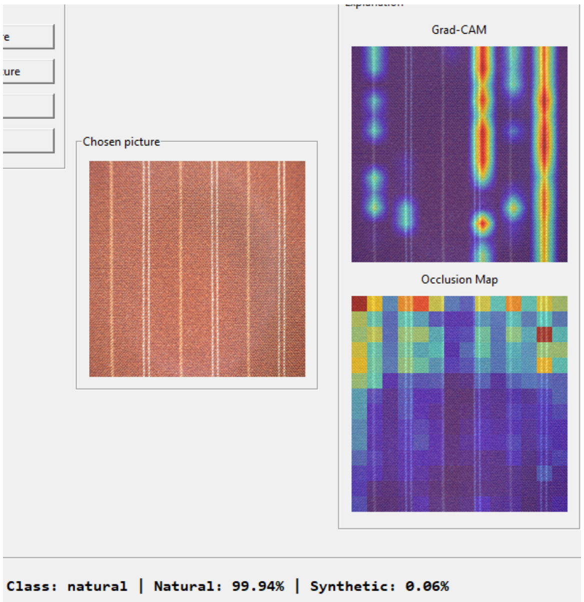
Study	Model	Dataset	Accuracy
Conducted study	ViT	Implemented dataset	0.9984
	ConvNeXt	Implemented dataset	0.9984
Akram et al. [17]	CNN	Dataset A	0.58
	CNN	Dataset B	0.65
	DenseNet121	Dataset A	0.86
	DenseNet121	Dataset B	0.92
	VGG16	Dataset B	0.9567
	ResNet50	Dataset B	0.96
Iqbal Hussain et al. [18]	ResNet-50		0.993

Thus, the experiments' results confirm that modern transformer-type architectures not only increase accuracy but also improve the system's generalisation ability. This is especially important for practical use in the automatic sorting of textile waste, where even a slight reduction in the number of misclassifications can significantly impact the efficiency of the recycling process.

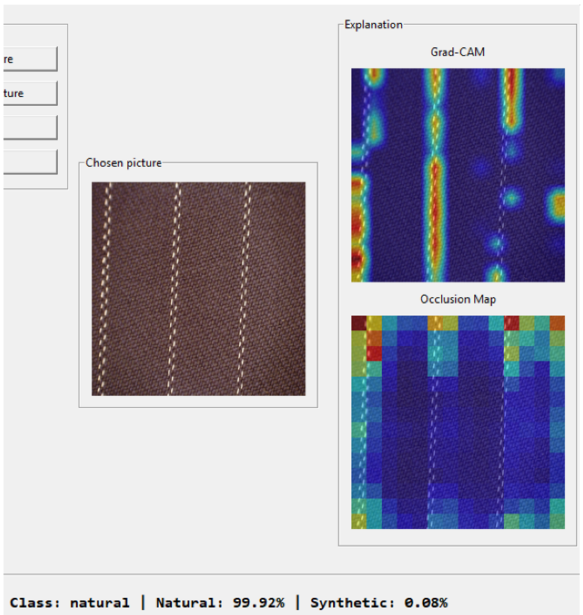
Therefore, ViT and ConvNeXt are optimal architectures for automated textile classification, as they provide the best possible performance on the formed dataset. At the same time, it is essential to note that practical implementation requires further testing of models on more diverse datasets, particularly those with complex textures and lighting variations, to confirm their superiority over other approaches definitively.

Analysis of explainability visualisations revealed difficulties in classifying samples with expressed ribbed or striped patterns. When classifying natural fabric with a striped pattern, the model incorrectly assigns the image to the class of natural fabrics. This is because during the dataset formation and training, the sample contained a large proportion of natural fabrics with a striped pattern and ribbed texture (Figure 8). In other words, the model focuses primarily on local repetitive texture elements rather than on more complex features that could distinguish between artificial and natural fibres.

This effect reveals one of the key problems of automated fabric classification – overlapping visual characteristics between classes, leading to errors in assigning samples to categories. For the model, such fabrics are "borderline cases" where basic texture features do not provide sufficient distinguishability.



(a)



(b)

Figure 8: Fabrics classification with ribbed pattern: (a) incorrect classification; (b) correct classification

This is confirmed by Grad-CAM visualisations, which show that the model's attention is focused primarily on linear structures. At the same time, other material properties, such as gloss, weave density, or surface microdefects, remain outside the analysis.

Thus, the strength of the proposed approach is the recognition of fabrics with a clearly defined homogeneous texture. On the other hand, its weakness is its sensitivity to complex structural patterns repeated in different classes, particularly striped patterns. This limitation can be overcome by expanding the training sample to include more fabric samples with similar characteristics, using multi-scale analysis mechanisms, or integrating additional descriptors that consider the material's colour, gloss, and other physical properties. In addition, combining visual features extracted by a neural network with traditional texture analysis methods is promising, as it can improve the system's ability to distinguish between fabrics that are similar in pattern but different in origin.

Overall, the obtained results demonstrate the model's potential in practical application and outline areas for its improvement. Striped and ribbed fabrics can be considered as "critical cases" for further research, which will allow the formation of a more universal and robust system for fabric classification in automated recognition of textile materials.

7. Conclusion

The study aimed to develop and validate an approach for automated fabric classification into natural and synthetic using deep learning technologies. The developed approach made it possible to increase accuracy by at least 0.0054 (compared to known analogues), which is a key factor in ensuring the effective processing of textile waste and minimising its negative impact on the environment.

Accordingly, within the scope of the study, an open dataset was created for fabric classification by fibre type (natural/synthetic), taking into account images of fabrics from the front and back sides, as well as with artefacts (creases, twists, overlaps), available for download from the Kaggle platform. The total number of samples is 3,107 images, of which 1,547 belong to the "natural" class and 1,560 to the "synthetic" class.

The proposed neural network solution, which allows classification with an accuracy of 0.9984 through the use of a modified dataset and transfer learning for the Vision Transformer model, has the added benefit of visual explainability of the obtained solutions, which also contributes to understanding the strengths and weaknesses of the proposed neural network classification.

Additional analysis of the results revealed that the most significant difficulties arise in cases of fabric classification with a strong striped or ribbed structure. Synthetic samples with similar patterns are often confused by the model with natural fabrics that have similar patterns. This indicates a limitation of the current approach, as the model focuses primarily on repetitive textural elements, ignoring other material, visual and physical characteristics.

To overcome these limitations, it is necessary to expand further and balance the dataset, particularly by including a larger number of fabric samples with different textures and structural variations, which will be done in future studies.

Thus, the study's results are significant in the context of computer vision development and the broader perspective of sustainable development. Automated classification and further processing of textile waste reduce the burden on the environment, optimise resources, and implement the principles of the circular economy. This, in turn, opens up opportunities for forming more environmentally responsible and technologically oriented production that meets global sustainable development goals.

Acknowledgments

The authors are grateful to Dmytro Chumachenko, Igor Potapov, Sergiy Yakovlev and other Program Committee members for organizing and conducting the 5th International Workshop of IT-professionals on Artificial Intelligence (ProfIT AI 2025).

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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