Neural network method for patch-oriented microtextures analysis to detecting textile structural heterogeneity for automated sorting

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Abstract

The paper proposes a neural network method for patch-oriented analysis of microtextures of textile materials to detect structural heterogeneity and support guided automated sorting in industrial conditions. In contrast to the global classification of a microimage as a whole object, the approach interprets the sample as a set of local fragments, for which neural network estimates are independently calculated, after which the dominant material type and structural heterogeneity index are formed based on the consistency of local responses. Experimental verification was performed on an open dataset of microimages of natural and synthetic fabrics with a volume of 3107 images with a division into training, validation and test samples in the ratio of 70/15/15 without leakage of local fragments between subsamples. Local analysis was implemented on square patches of 64×64 pixels with an overlap of 50% using a single neural network model for all fragments. It is shown that the heterogeneity indicator, built on the lower quantile of local fragment confidence, provides a better compromise between the risk of error and the proportion of samples admitted to direct sorting, compared to the patch prediction consistency indicator and the patch voting entropy indicator (area under the «risk–coverage» curve 0.1023 versus 0.1224). During stress testing with local microstructure disturbances, the performance of the ranking of samples for selective selection for re-inspection was preserved. The results obtained confirm that the patch-oriented analysis is sensitive to local microtexture conflicts and is suitable for integration into industrial sorting circuits within the circular economy.

Keywords

patch-oriented analysis, textile microtexture; automated sorting; selective prediction; convolutional neural network; textile structural heterogeneity; circular economy

1. Introduction

The modern development of intelligent industry and the concept of Industry 4.0 determines the growing need for automated inspection and sorting systems of materials, capable of operating in conditions of high variability of raw materials and unstable production factors [1]. This problem is especially relevant for textile industry, where efficient sorting of materials by type of raw material is key stage in the processes of reuse and recycling within framework of the circular economy [2].

In practical scenarios of automated textile sorting, decisions are often made based on spectral analysis tools, but such solutions are expensive and require application conditions that are often incompatible with efficient high-speed sorting on the production line [3]. As a result, there is a noticeable shift in research and engineering focus towards visual and sensor approaches that can be integrated into inline inspection and provide the necessary processing speed and be relatively affordable [4].

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One such promising direction is the analysis of microtextures obtained using optical sensors or digital microscopes. Such images are characterized by significant local heterogeneity, the presence of impurities, surface defects, wear or partial damage, which complicates the correct interpretation of the material as a whole object [5]. In this context, standard approaches focused on global image classification can generate confident but structurally unstable solutions that are unacceptable for industrial sorting systems [6].

Recent advances in deep learning have significantly improved the accuracy of textile classification, particularly in the task of distinguishing between natural and synthetic fibers. However, most existing solutions consider the microimage as a single entity and focus exclusively on improving classification accuracy [7]. This approach does not take into account the internal structural heterogeneity of microtextures and does not provide mechanisms for selecting samples that require additional verification or re-inspection.

Given the requirements of industrial applications, especially in the context of automated sorting for textile reuse, a more appropriate approach is to consider the microimage as a collection of local fragments, each of which may contain different textural information. [8] Analysis of the consistency of neural network predictions at the patch level allows the detection of samples with internal structural conflicts, which potentially indicate mixed materials, surface degradation, or unstable imaging conditions.

The paper proposes a neural network method for patch-oriented analysis of microtextures to detect structural heterogeneity of textile materials with an orientation to automated sorting tasks. The method is based on the aggregation of neural network predictions for local patches of microimages and on the assessment of the consistency of these predictions as an indicator of the structural stability of the material. This approach allows not only to perform material identification, but also to selectively select samples that require additional verification, without the need to retrain the model. The proposed method was experimentally verified on the author's dataset [9] of microimages of textile materials with stress testing under conditions of local image degradation. The obtained results prove the hypothesis that patch-oriented analysis is more sensitive to structural microtexture disturbances compared to global approaches, which confirms its feasibility for industrial automated sorting systems within the circular economy.

2. Related works

Automated textile material recognition and sorting has emerged as an active research area due to its direct impact on supporting sorting processes within the circular economy, as well as applied control tasks in production. In practice, a significant part of textile waste sorting is still performed manually, which requires significant human resources and results in unstable quality of solutions under conditions of high material variability, wear and tear, and mixed composition. In industrial and laboratory scenarios, physicochemical methods, in particular near-infrared spectroscopy and hyperspectral imaging, are widely used for objective material identification. For example, in [10] shows the potential of a hyperspectral approach for quantitative prediction and visualization of physicochemical indicators (although the object of the study is different), which illustrates the general power of spectral technologies in the tasks of «material-oriented» analysis. At the same time, for textile sorting, such solutions are often expensive, require complex maintenance, specialized calibration and energy costs, which limits their scalability and integration into high-speed industrial sorting lines.

Due to these limitations, interest is growing in approaches based on the analysis of images in the visible spectrum, which are potentially more economically feasible and easier to implement in inline inspection. The development of computer vision and deep learning, in particular convolutional neural networks and transformer architectures, has created the prerequisites for automating the recognition of fabrics by structure, microtexture and color characteristics. A separate direction is represented by systems that combine sensory and mechanical parameters of tissues with algorithms for intelligent analysis. The paper [11] considers the classification of sensory properties of tissues taking into account deformation and tactile characteristics (in particular, softness): first, classes are formed using fuzzy c-means cluster analysis with subsequent confirmation by expert assessment, and class prediction is carried out by a neural network based on mechanical characteristics on a sample of 534 samples. The obtained accuracy of 83.5% on validation data confirms the practical feasibility of combining formalized material features with neural network prediction, however, the approach is focused on sensory/mechanical properties and does not directly address the problem of local heterogeneity of microtextures in images.

A significant body of research has been devoted to recognizing fiber types from fabric surface images using neural network models and transfer learning. In [12], an ensemble approach is proposed that combines several pre-trained CNNs (Inception, ResNet, VGG, MobileNet, DenseNet, Xception) to increase generalization ability and reduce the impact of errors of individual models. The results (about 84% accuracy and high F_1) demonstrate the effectiveness of the ensemble as a means of strengthening classification from surface images. A similar logic of strengthening classification decisions is supported by the approach with spatial fusion of deep features: in [13] integrates features obtained from different neural networks, which allows for a more complete consideration of spatial texture characteristics for distinguishing cotton and flax fibers. In the mentioned works, the key goal is to increase the accuracy of classification, but to a lesser extent the issue of internal structural heterogeneity of the sample as a separate control object, critical for automated sorting of waste and mixed materials, is considered.

A separate segment is laboratory methods for fiber identification aimed at ensuring quality and combating commercial fraud. In the study [14], ATR FT-IR in combination with scanning electron microscopy, as well as chemometric methods, in particular PLS-DA, were used to distinguish animal fibers (cashmere, mohair, yak, camel, alpaca, vicuña, llama, sheep wool), which provided a classification accuracy of 87% and an explained variance of 94.88%. Such results confirm the high informativeness of spectral-microscopic approaches for reliable fiber identification, but at the same time emphasize their resource and hardware complexity, which complicates integration into high-speed industrial sorting flows.

In parallel, visual approaches to fabric defect control and detection tasks are being developed, where, unlike fiber type classification, the object is local damage or structural defects. The paper [15] considers the application of YOLOv10 to determine fabric types and detect damage, including tears, on a specialized annotated dataset; the authors report an accuracy of 85.6% and speed advantages. The paper [16] describes a prototype of a defect control system based on Google Teachable Machine with Raspberry Pi 3B integration for image processing and fabric rewinding control; the system performs two-class defect classification and demonstrates an accuracy of 98.4% at an average speed of 4.85 frames/s. These examples demonstrate the pragmatic engineering focus of modern solutions and their orientation towards integration with «hardware», however, in the context of waste sorting, not only the presence of a defect becomes important, but also the structural consistency of the microtexture as an indicator of material mixing or degradation. It is also worth noting the trend towards using pre-trained networks as feature extractors with subsequent feature fusion and classifier construction. In the paper [17] mentioned VGG16, ResNet50 and SE-ResNet50 networks in the context of deep feature extraction, and in the work [18] InceptionV3 and hierarchical feature fusion were used to increase the generalization ability. Although the examples given are not specifically textile, they reflect a general methodological line relevant to microtexture analysis tasks: combining transfer learning and spatial-structural feature fusion to work with highly variable visual domains. At the same time, in textile sorting tasks, there is a growing need to go beyond a single global prediction and consider local heterogeneity as a separate factor in decision management.

Thus, a review of current research suggests the dominance of two approaches: high-precision laboratory methods (spectroscopy, electron microscopy, chemometrics), which provide strong identification but do not scale well for inline sorting, and visual methods based on computer vision and deep learning, which have a higher potential for integration into industrial processes due to their lower cost and non-invasiveness. At the same time, in many visual solutions, the microimage is considered as a holistic object, and the main goal remains to increase the accuracy of classification, which is not always adequate for automated sorting tasks within the circular economy, where mixing, wear and local structural conflicts are critical. This motivates patch-oriented approaches, in which the consistency of local predictions is considered as an indicator of structural homogeneity or heterogeneity of the material and is used for a guided decision to directly sort or redirect the sample for additional inspection.

3. Method design

3.1. Idea of the approach

In the context of the restoration and development of industry in post-war Ukraine, there is an increasing need for technologies that simultaneously support resource efficiency, reduce production costs, and scale engineering solutions. Textile sorting within the framework of the circular economy is a prime example where automation allows for reduced raw material losses, improved secondary stream quality, and reduced dependence on expensive laboratory procedures. That is why practical interest is shifting toward visual approaches in the visible spectrum that can be integrated into inline circuits on production lines and implemented on more affordable hardware. In such conditions, patch-oriented microtexture analysis is appropriate, as it allows for taking into account the structural heterogeneity of samples and making controlled decisions about sorting or re-inspection, which is critical for working with heterogeneous and worn raw materials.

The idea of the method is based on representing a microimage of a textile material not as a single object, but as a collection of local microtexture fragments (patches). Each patch is analyzed by the neural network independently, after which the aggregation of local predictions and assessment of their consistency are performed [19]. The degree of consistency of patch predictions is interpreted as an indicator of the structural homogeneity or heterogeneity of the material, which is used for automated sorting and selective selection of samples that require additional inspection. The scheme of the approach is shown in Figure 1. The textile material is interpreted as a set of local microstructural fragments, whose consistency determines structural homogeneity and guides automated sorting decisions.

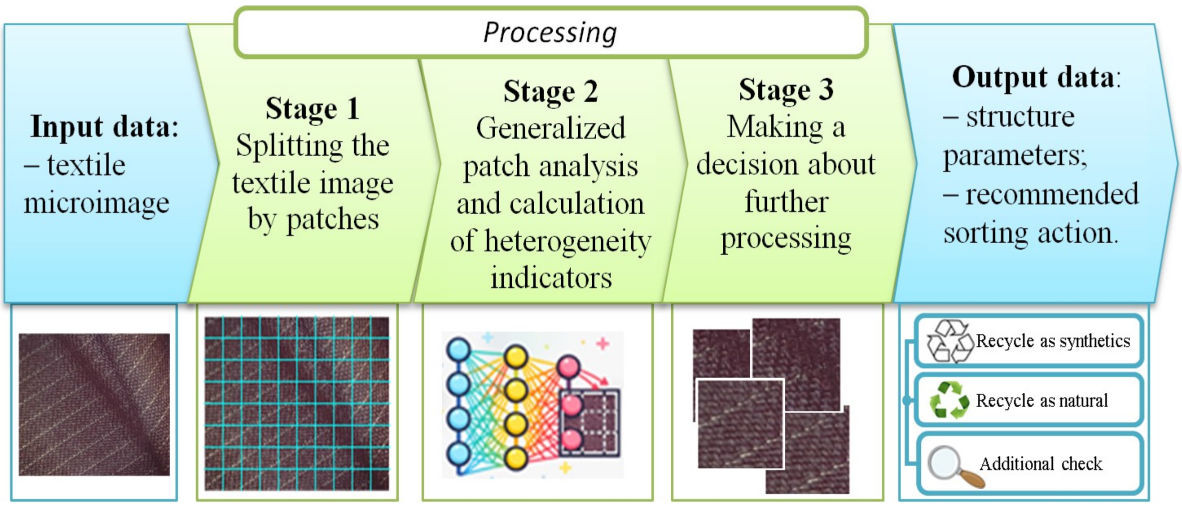


Figure 1: Approach for patch-oriented microtextures analysis for automated sorting.

The output consists of two complementary components: an aggregated material decision and a structural heterogeneity measure, formed on the basis of the scatter of local predictions [20]. Heterogeneity manifests itself as the presence of conflicting patches for which the prediction differs from the dominant solution. In the automated sorting circuit, this is used as a control rule:

samples with high heterogeneity are redirected for additional inspection, while structurally consistent samples are allowed to be sorted directly for further processing as natural or synthetic raw materials.

3.2. Proposed method

The proposed method is aimed at analyzing the microtextures of textile materials in the context of automated sorting and is based on a patch-oriented image representation. Unlike traditional methods, in which the microimage is considered as a single whole, in this method each image is interpreted as a set of local fragments, which allows taking into account the internal structural heterogeneity of the material. The method consists of a sequence of steps (Figure 2), which include the formation of local representations, independent analysis of fragments, construction of the distribution of local reactions, assessment of the dominant material and calculation of the structural heterogeneity index, which is used for decision-making in the automated sorting system.

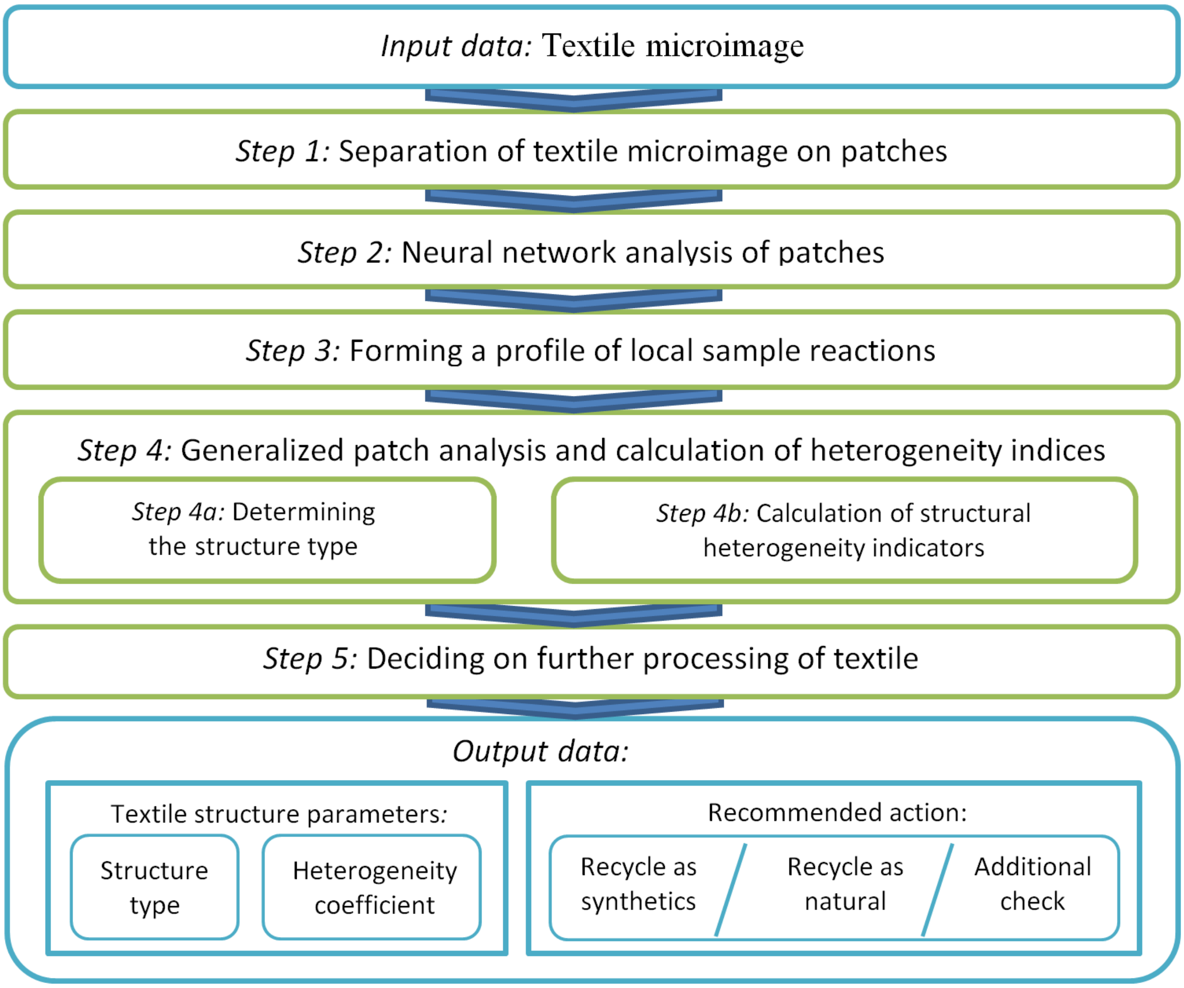


Figure 2: Scheme of method for patch-oriented microtextures analysis for automated sorting.

Step 1 is to provide a transition from a single image to a set of local observations so that the model can see the microstructure not in an averaged manner but in detail. Let the input microimage be:

$$I \in R^{H \times W \times C}, \tag{1}$$

A set of local fragments is formed:

$$P=\{p_1,p_2,\ldots,p_N\},\, p_i\in R^{h\times w\times C}. \quad (2)$$

In practice, this is done by a regular sliding window with a given fragment size and offset step; overlapping is allowed if necessary to reduce sensitivity to fragment boundaries.

Step 2. Calculation of local neural network responses. For each local fragment p_i, a standardized response of the neural network model is obtained – a local estimate that reflects the type of microstructure in this fragment. Each fragment is fed into the same neural network:

$$f_\theta : p_i \to z_i, \quad (3)$$

where z_i is the local response vector (logit) or local probability distribution

$$q_i = softmax(z_i), \quad (4)$$

In the work, it is advisable to use a single model for all fragments (common parameters θ), which ensures comparability of local reactions among themselves.

Step 3. Construction of the distribution of local reactions [21]. At this step, local reactions are collected into the sample profile: the area of interest here is not a single prediction, but how the model behaves over the entire microtexture.

A set of local reactions is formed:

$$R=\{q_1,q_2,\ldots,q_N\}. \quad (5)$$

For further steps, it is convenient to consider it as a distribution (empirical sample) by fragments. Additionally, a set of local confidences is formed:

$$c_i = \max_k q_{i,k}, \quad (6)$$

which allows to evaluate weak and conflicting areas of the image.

Step 4a. Evaluation of the dominant material type. The goal of the step is to obtain a single generalized material label based on a set of local assessments, i.e. the dominant interpretation of the sample. The dominant class is determined by the aggregation of local responses:

$$\bar{q}=\frac{1}{N}\sum_{i=1}^{N} q_i \qquad \hat{y}=arg\max_k \bar{q}_k. \quad (7)$$

Alternatively, aggregation by voting on local *arg max* or robust aggregation is allowed if it is necessary to reduce the influence of single noisy fragments.

Step 4b. Calculate the structural heterogeneity index. The purpose of this step is to measure how well the local estimates are consistent with each other; conflicts between fragments are interpreted as structural heterogeneity of the microtexture.

The heterogeneity index is given by the function:

$$H=\Phi(R). \quad (8)$$

Within the framework of a patch-oriented approach, two types of assessments are practically convenient:

1. inconsistency of predictions (the proportion of fragments supporting the dominant class):

$$patc\, h_{agreement}=1-\frac{1}{N}\sum_{i=1}^{N}\delta\left(arg\max q_i,\hat{y}\right), \quad (9)$$

where $\delta(\cdot,\cdot)$ is the Kronecker symbol. It is an indicator of structural heterogeneity (the fraction of fragments that do not support the dominant class, i.e., 1 – agreement), with larger values corresponding to greater conflict between local predictions.

2. evaluation of the worst fragments through the lower quantile of local confidence:

$$H_q = 1 - Q_\alpha(\{c_i\}_{i=1}^N), \tag{10}$$

where Q_α is the α-quantile capturing weak areas of the image. In the following, this heterogeneity indicator, calculated from the lower quantile of local confidence (for $\alpha = 0.10$), will be denoted as *patch_q10.*

Additionally, the basic indicator *vote_entropy_conf* is used for comparison, which estimates the heterogeneity of the microtexture through the distribution of patch votes by class. Higher values of this indicator correspond to greater uncertainty and conflict of local predictions within one sample.

Step 5. Automated sorting rule – conversion of analysis results into a controlled action of the production loop: direct sorting or redirection to additional inspection.

The decision rule is defined:

$$a = g(\hat{y}, H), \tag{11}$$

where α is the system action.

The decision in the automated sorting system is formed on the basis of a joint analysis of the dominant type of material and the structural heterogeneity index of the microtexture [22]. If the value of the heterogeneity index does not exceed a given threshold level, the sample is considered structurally homogeneous and is directly sent to the appropriate sorting flow according to the specified type of material. In the case when the structural heterogeneity index exceeds the threshold value, the sample is redirected for additional inspection, regardless of the specified dominant class. This approach minimizes the risk of erroneous sorting of materials with mixed or degraded microstructure and increases the reliability of the automated sorting line in conditions of high variability of raw materials.

The result of the proposed method is a set of output characteristics that reflect both the material interpretation of the sample and its structural state. The input data includes a defined dominant material type, formed on the basis of aggregated local predictions, as well as an indicator of structural homogeneity or heterogeneity of the microtexture, which characterizes the consistency of local fragments. In addition, the method generates a controlled action for an automated sorting system that determines the further route of the sample in the technological process, in particular, direct sorting, redirection for additional inspection or reprocessing. Such an input data structure ensures the integration of the method into industrial control loops and supports decision-making in circular economy scenarios.

3.3. Method assumptions and parameters

The proposed method is not tied to a specific neural network architecture and can be implemented using any model capable of generating local estimates for microtexture fragments. The main parameters of the method include the size of local fragments, the step of their formation, the method of aggregation of local predictions, and the threshold value of the structural heterogeneity indicator used in the sorting rule. The values of these parameters are determined empirically, taking into account the characteristics of the dataset and the requirements of a specific production scenario. At the same time, the logic of the method itself remains unchanged and does not depend on the specific implementation of neural network analysis.

Within the framework of the study, the parameters of the proposed method were fixed, taking into account the characteristics of microimages of textile materials and the requirements for the reproducibility of experiments. The input images were analyzed in the original resolution without prior segmentation of the material. The formation of local fragments was carried out by regularly dividing the microimage into square patches of a fixed size of 64×64 pixels with an overlap of 50%, which allowed to reduce the influence of boundary effects between fragments and increase the stability of local estimates.

A single neural network model ResNet-18 with common parameters for all fragments was used to analyze each patch, which ensures comparability of local reactions within one sample. The local reaction was used as a vector of class probabilities obtained after applying softmax to the model output. The local confidence of the patch was defined as the maximum probability value among all classes.

Aggregation of local reactions to determine the dominant type of material was carried out by averaging local probability distributions across all patches with subsequent selection of the class with the maximum average value. The structural heterogeneity was assessed based on two complementary indicators: the consistency of local predictions with the dominant class and the assessment of weak areas of microtexture through the lower quantile of local confidence. In the experiments, the quantile value was fixed at $\alpha = 0.10$, which allowed us to focus on the most problematic image fragments.

The threshold value of the structural heterogeneity indicator was determined empirically on the validation sample and was used exclusively to make a decision on redirecting the sample for additional inspection, without affecting the training process of the neural network model. Such fixation of parameters ensures the reproducibility of experiments and emphasizes the universality of the proposed approach, which does not require retraining the model when changing the sorting logic.

4. Experimental setup

4.1. Applied research plan

The experimental study plan is designed to consistently test two key properties of the Neural network method for patch-oriented microtextures analysis to detect textile structural heterogeneity for automated sorting: the ability to form a correct dominant material label and the ability to detect structural heterogeneity of the microtexture due to conflicts and weak local areas.

First, data quality control and elimination of potential leaks (duplicates and near-duplicates) are performed, after which the sample division protocol into train/validation/test is fixed and the basic neural network model of local analysis is trained. Next, the patch-oriented procedure is implemented and two complementary indicators of heterogeneity (patch prediction agreement and local confidence quantile) are evaluated together with the dominant classification.

The final block of experiments is devoted to a comparison with the global approach and an analysis of the behavior of heterogeneity indicators under conditions of local microstructural disturbances that simulate industrial sorting factors, as well as to verify the practical applicability of the «direct sorting vs re-inspection» rule based on the heterogeneity threshold.

4.2. Dataset for experiment

For experimental verification, the author's dataset of microimages of textile materials «Natural and Synthetic Fabrics Dataset» was used, which the authors published on the Kaggle platform [9]. The dataset contains 3107 microimages obtained using a digital optical microscope and covers two classes of materials: natural fabrics (1547 images) and synthetic fabrics (1560 images). Such a distribution provides a close to balanced class structure, which is important for the correct evaluation of classification models [23].

Microimages are characterized by significant internal texture variability, the presence of local defects, impurities, fiber heterogeneity and variations in shooting conditions, which makes the dataset representative for scenarios of industrial sorting of textile materials, in particular in the context of a circular economy [24]. At the same time, such properties complicate the application of global approaches to image analysis and create prerequisites for the use of patch-oriented methods.

Before conducting experiments, the dataset was subjected to preliminary quality analysis and checking for potential data leaks. An automatic check of images for the presence of damaged or incorrectly read files was performed, as well as the detection of images with excessively low information content (almost uniform or empty frames). In addition, a check for the presence of exact duplicates using cryptographic hash functions and an analysis of near-duplicates based on perceptual hashing were performed. The identified duplicates were removed from further analysis, which reduced the risk of information leakage between the training and test samples.

4.3. Experiment description

The experiments were conducted with a fixed protocol of dividing the dataset into training, validation and test samples in the ratio of 70% / 15% / 15%, maintaining the balance of classes. The division was carried out at the image level before patch formation, which prevents leakage of local fragments of one sample between different samples. The neural network model was trained only on the training sample, using the validation sample to select hyperparameters and determine the threshold values of structural heterogeneity indicators [25]. The test sample was used exclusively for the final quality assessment and comparative analysis.

The method was evaluated in the selective prediction setting, where the goal is not only to obtain a dominant class, but also to reliably separate samples with potentially conflicting microstructures for re-inspection. For each sample, the structural heterogeneity indicator was calculated, the samples were ranked by its value, and the coverage level c (accepted fraction) was set, which determines the proportion of samples that are allowed for automated sorting. The quality on the accepted subset was assessed by the selective accuracy and selective F_1 metrics, and the risk was defined as 1 − selective accuracy (or 1 − selective F_1). The dependence of risk on coverage was analyzed by risk-coverage curves, and to compare the heterogeneity indicators, the integral AURC indicator was used as the area under the risk–coverage curve (a smaller value means a better ability to maintain high quality with greater coverage). Additionally, the stability of the indicators was checked in stress test scenarios of local distortions and additive noise by changing the risk-coverage and AURC relative to the clean mode. The emphasis on these metrics is due to the applied formulation of the sorting problem: in an industrial process, it is critically important to manage the trade-off between productivity (coverage, proportion of automatically accepted samples) and quality (risk of error on accepted samples), leaving complex cases for operator control.

4.4. Software implementation

The software implementation of the experiments was performed in the Google Colab environment [26], which ensures the reproducibility and accessibility of the computing environment. The training of the neural network model and the processing of microimages were carried out using the NVIDIA Tesla T4 graphics processor [27], which allowed to efficiently perform calculations for patch-oriented analysis and aggregation of local predictions. The implementation of the Neural network method for patch-oriented microtextures analysis to detect textile structural heterogeneity for automated sorting was performed using standard deep learning libraries [28] and image processing, without hardware-specific optimizations, which simplifies the transfer of the approach to other computing platforms and industrial environments.

5. Results and discussion

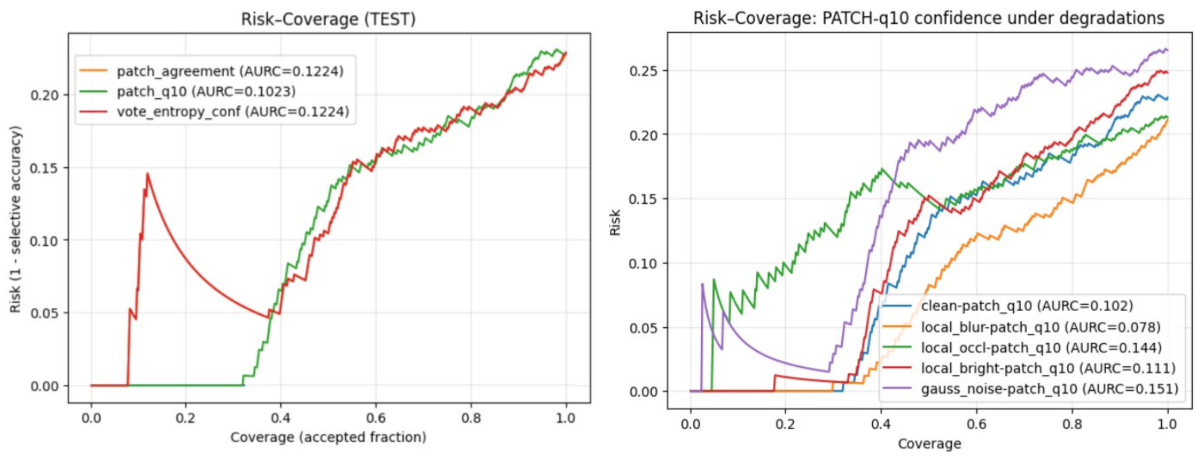
Before training the model, the dataset was checked for potential data leakage. SHA256 was used for exact duplicates, and perceptual hashing (pHash) was used for near-duplicates [29]. No near-duplicate clusters with mixed class labels were detected, which excludes inter-class leakage due to repeated or visually close images. The distribution of near-duplicate cluster sizes for pHash is given in Table 1: the vast majority of samples form single clusters, and a small number of clusters are small in size, without class intersections. After data quality control and screening of incorrect or duplicate images in the implementation, the size of the test subsample was 460 images.

The basic neural network model of local analysis was trained for three epochs; already in the 2nd epoch, metrics saturation was observed. After training, *train acc* = 0.998 and *val acc* = 1.000 were obtained with *train loss* = 0.0087 and *val loss* = 0.0008. At the same time, such rapid saturation should be interpreted cautiously, since it may reflect the relatively high separability of the current two-class benchmark under the given acquisition protocol rather than guaranteed robustness under production domain shift. For the correct interpretation of the local confidence of patch forecasts, temperature scaling was applied on the validation sample, which ensured a low calibration error (ECE = 8.1×10^{-4}). Further experiments were aimed at testing the key property of the developed method – the detection of structural heterogeneity by conflicts and weak local areas.

Figure 3 shows the results of assessing the suitability of structural heterogeneity indicators for guided sorting using the *selective prediction* scheme in *risk-coverage* coordinates on the test sample.

Table 1
Data leakage check: exact duplicates (SHA256) and near duplicates (pHash)

Verification block	Indicator	Value
General data	Total number of images	3107
SHA256 (exact duplicates)	Number of groups of exact duplicates	4
SHA256 (exact duplicates)	Number of duplicate files (excluding one reference file in the group)	4
SHA256 (exact duplicates)	Interclass conflicts among exact duplicates	0
pHash (Hamming ≤ 4)	Number of images checked for close duplicates (pHash available)	3107
pHash (Hamming ≤ 4)	Number of groups of similar images (clusters of size > 1)	70
pHash (Hamming ≤ 4)	Number of images included in groups of similar ones (sum of cluster sizes > 1)	157
pHash (Hamming ≤ 4)	Interclass conflicts among groups of similar images	0



a) *b)*

Figure 3: Risk-coverage analysis of structural heterogeneity indicators and patch-q10 stability under degradations: (a) comparison of indicators; (b) patch-q10 in stress test scenarios.

Figure 3(a) presents the risk-coverage curves for the structural heterogeneity indicators calculated on the test sample. The comparison is made for the *patch_agreement*, *patch_q10* and *vote_entropy_conf* indicators. The smallest value of the area under the risk-coverage curve is obtained for the *patch_q10* indicator (AURC = 0.1023), while *patch_agreement* and *vote_entropy_conf* have larger AURC values (0.1224). At the same level of coverage, *patch_q10* provides a lower risk, which corresponds to a more stringent selection of samples with local structural violations and is suitable for guided automated sorting scenarios.

For ease of comparison, the key numerical results for the structural heterogeneity indicators are summarized in Table 2. The table contains the AURC values on the test sample and a qualitative assessment of the indicators' resilience to local degradations considered in the stress tests.

As can be seen from Table 2, the *patch_q10* indicator demonstrates the lowest AURC, i.e. it provides the best compromise between risk and coverage in the selective prediction scenario. This confirms the feasibility of using *patch_q10* as the main criterion for redirecting samples for re-inspection in the industrial sorting circuit.

Table 2
Performance of structural heterogeneity indicators (test set)

Indicator	AURC ↓	Robust under degradations
patch_agreement	0.1224	medium
vote_entropy_conf	0.1224	medium
patch_q10 (proposed)	**0.1023**	**high**

Figure 3 (b) shows the risk-coverage for *patch_q10* in degradation scenarios. For *local_blur*, AURC = 0.078 was obtained, for *local_bright* – 0.111, for *local_occl* – 0.144, for *gauss_noise* – 0.151 (clean: 0.102). Ranking by *patch_q10* retains its performance under local microstructure disturbances, with occlusions and additive noise being the most unfavorable.

For practical interpretation of the obtained curves, operating modes with a fixed coverage level accepted fraction were considered, which meets the requirements of the production circuit, where a part of the samples is redirected for re-inspection. For a target coverage of about 0.85, the *patch_q10* indicator sets a threshold τ of about 9.0×10^{-4} and rejects 69 out of 460 samples of the test sample (accepted = 391, rejected = 69). In this mode, the selective accuracy for accepted samples is 0.808, selective F_1 is 0.792. For a target coverage of about 0.90, the threshold shifts towards less stringent selection (rejected = 46, accepted = 414), while the selective accuracy and selective F_1 decrease to 0.787 and 0.773, respectively. This behavior is consistent with the selective prediction formulation: increased coverage is achieved by allowing a larger proportion of samples with locally unstable regions, which increases the risk.

Unlike indicators based on vote agreement (*patch_agreement)* or vote entropy (*vote_entropy_conf*), the *patch_q10* indicator uses information about the weakest local image fragments and thereby implements a conservative strategy for detecting structural violations. In the context of the proposed mathematical model, this corresponds to the definition of $H_q=1-Q_\alpha(\{c_i\})$, α=0.10, i.e. an estimate that captures the lower tail of local confidence and responds to the presence of even a small number of problematic patches, regardless of the dominant class.

For visual analysis [30] of the reasons for the deviation, examples from the test sample were generated for which *patch_q10* exceeded the operating mode threshold (Figure 4).

In the above visualizations, the patch vote dominance (syn/nat) and |dominance| maps localize areas where patches support different classes or have weak dominance, which forms a conflict structure within a single sample.

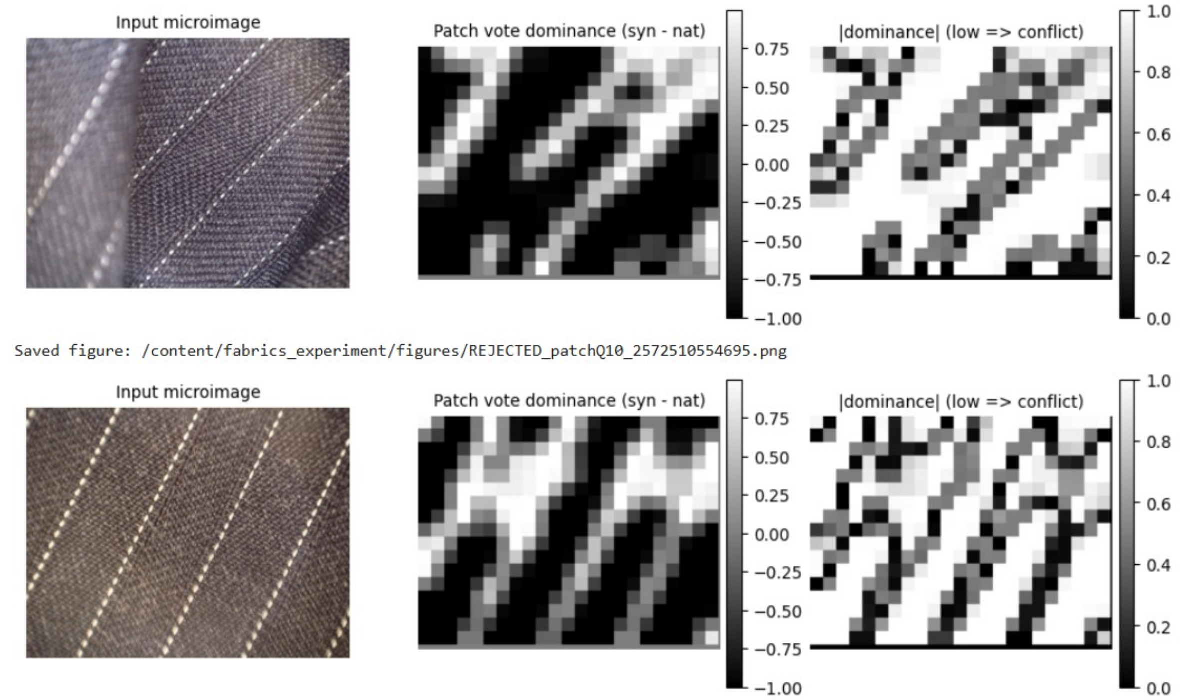


Figure 4: Examples of rejected samples with patches maps.

Rejected samples are characterized by the presence of areas with different fiber density and regularity, local artifacts or uneven illumination, which do not violate the global visual integrity of the image, but create structural heterogeneity at the microtexture level [31]. In a production scenario, such cases correspond to a class of samples for which direct sorting based on the dominant label is undesirable, and redirection for re-inspection or additional control reduces the risk of an erroneous routing decision.

6. Conclusions

The neural network method for patch-oriented microtexture analysis has been developed and experimentally tested, which simultaneously generates a generalized label of the type of textile material and an indicator of structural heterogeneity for a guided decision on direct sorting or redirecting the sample for additional inspection without changing basic model training procedure.

Key results confirm the superiority of the indicator based on the lower quantile of local patch confidence: the area under the "risk-coverage" curve on the test sample is 0.1023, while the patch prediction consistency indicator and the patch voting entropy indicator are 0.1224. In the presence of local image degradations (local blur, local brightness change, local occlusion, additive Gaussian noise), the performance of sample ranking was preserved, and in operating modes with a fixed coverage of about 0.85, an accuracy of 0.808 for accepted samples and a balanced classification quality measure of 0.792 were achieved.

The limitations of the study are related to the verification on a two-class task of distinguishing natural and synthetic tissues, the use of one basic neural network architecture for local analysis, and the modeling of microstructure violations mainly by synthetic degradation scenarios that may not fully reproduce the conditions of real production lines. Additionally, the threshold value of the structural heterogeneity indicator was determined empirically and may require re-adjustment when changing the sensor, lighting conditions, or domain shift of data. The present study should be interpreted as a proof-of-concept for patch-oriented heterogeneity-aware sorting rather than as a complete material-science characterization model. In this work, the heterogeneity index is used in an operational sense, i.e. as an indicator of inconsistency of local microtexture responses and a control signal for re-inspection, rather than as a direct physical descriptor of fiber morphology. The current experimental setup is limited to a two-class task, one baseline architecture for local analysis (ResNet-18), and mainly synthetic degradation scenarios, which may not fully reproduce real production-line conditions. In addition, the settings $\alpha = 0.10$, patch size 64×64, and 50% overlap were fixed empirically to provide a reproducible baseline and were not optimized within a dedicated sensitivity study. The rapid saturation of training and validation metrics indicates that the current benchmark is relatively well separable under the given acquisition protocol; however, additional validation under stronger domain shift is required to confirm generalization.

Further research should therefore focus on expanding the framework to multi-class fiber identification and explicit analysis of mixed materials; studying the sensitivity of the method to α, patch size, and overlap in order to better capture heterogeneity at different spatial scales; validating the approach on data from different microscopes, sensors, illumination regimes, and real production-line conditions; comparing CNN and transformer backbones under the same patch protocol to verify whether the observed heterogeneity effect is architecture-invariant; improving the interpretability and stability of structural heterogeneity indicators; and optimizing the computational procedure for real-time operation and integration into a closed-loop automated sorting system.

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Declaration on Generative AI

The authors have not employed any Generative AI tools. All experimental procedures, calculations, results, interpretations, and conclusions were produced by the authors, who take full responsibility for the content of this publication.

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