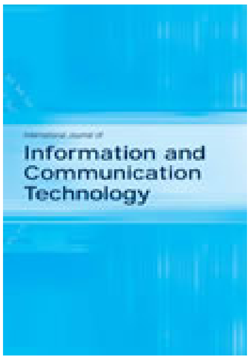
INDERSCIENCE PUBLISHERS
Linking academia, business and industry through research



International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

Textile pattern style classification based on popular mixture enhancement and attribute clustering

ZhaoJue Dai

Article History:

Received:	27 August 2024
Last revised:	13 September 2024
Accepted:	13 September 2024
Published online:	17 October 2024

Textile pattern style classification based on popular mixture enhancement and attribute clustering

ZhaoJue Dai

Wenzhou Polytechnic,
Wenzhou 325000, China
Email: daizhaojue@163.com

Abstract: Intending to the issue that traditional textile pattern classification methods have insufficient training samples and ignore the attributes possessed by the style objects, this article designs a textile pattern style classification method relied on popular mixture enhancement and attribute clustering. Firstly, the entropy discretisation technique is introduced to optimise the image attribute clustering method, and discrete values are used to represent the discretised data to eliminate the metric differences. Secondly, the original textile images are popularly mixed and enhanced according to the mixing parameter. And the visual feature intersection of the enhanced pattern is used as an object mask by using two-channel CNN output to map onto the original image to obtain an object-level image, and the features are enhanced by the channel attention mechanism. The simulation results show that the accuracy and average precision of the proposed method have a mean value of 83.59% and 91.36%, respectively.

Keywords: popular mixture enhancement; attribute clustering; textile style classification; CNN; entropy discretisation.

Reference to this paper should be made as follows: Dai, ZJ. (2024) 'Textile pattern style classification based on popular mixture enhancement and attribute clustering', *Int. J. Information and Communication Technology*, Vol. 25, No. 8, pp.49–63.

Biographical notes: ZhaoJue Dai is a Master Lecturer in Wenzhou Polytechnic. She mainly engaged in clothing and its design activation and application, textile innovative design, textile pattern design application research.

1 Introduction

In the era of big data, where patterns are gradually replacing text as the main content of the internet, the stylistic analysis of textile patterns has become an important research area in computer vision. Recently, as the field of computer vision has made great progress in textile modelling, recognition, and style analysis, this technology is crucial for realising textile applications from design to e-retail. At the beginning of the research, textile style classification methods relied too much on the background of professional knowledge (Shin et al., 2010), quantifying textile style characteristics based on information from expert interviews, identifying the connection between the cut shape of textile components and the overall style, and classifying textile styles based on the style characteristics (Sun et al., 2011). However, as the production standards of the textile industry continue to improve, and the patterns and colours of fabrics become more and more complex, the speed and accuracy of manual classification are gradually out of line with the requirements of the textile industry (Yang et al., 2019). Therefore, automated textile classification instead of manual classification is an inevitable trend in the development of the textile industry, and it is important to accurately, efficiently and automatically classify complex patterned printed fabrics (Khan et al., 2016).

Wen and Wong (2018) proposed that textile pattern styles can be recognised by computer, and defined style as an abstract description of objects with common characteristics. Xue et al. (2016) used eye tracking technology to obtain the most influential textile style features, and combined with fuzzy mathematical theories to achieve the establishment of a style classification model, but the categorisation is not satisfactory Kose et al. (2022) offered an autonomous classification algorithm for textile styles based on the autonomous developmental network (AND), but it is not suitable for textile pattern data. Ngo et al. (2021a) designed a textile style similarity matching algorithm based on gradient analysis method. In recent years, with the continuous maturity of deep learning technology, neural networks stand out in the field of textile pattern classification. Jeyaraj and Nadar (2019) proposed an improved retrieval algorithm for textile pattern classification based on deep learning, which has a low classification accuracy. Ngo et al. (2021b) investigated a textile pattern classification method based on hypergraphs, which achieves the capture of global information of the embedding layer and an approximate representation of class distribution. Koulali and Eskil (2021) suggested a method to automatically extract, identify and classify different textile style features using convolutional neural networks (CNN) to achieve the textile pattern classification task, but the classification labels are missing.

Attributes achieved knowledge migration between visible and invisible classes, providing an effective solution to the problem of missing category labels. Attribute clustering is the grouping of data objects based on similarities, through clustering we can understand the data better and discover hidden patterns and structures in the data. Xu et al. (2011) used k-means to cluster similar features and used CNN to build a textile pattern style classification model. Kim et al. (2021) identified rough shared attributes from a textile pattern database, matched long-term trends to shared attributes, and achieved the clustering of shared attributes, but the feature extraction is insufficient. Balan and Devi (2012) clustered labels to sample attributes for classification by exploring the constructive model of textile patterns. Celani et al. (2024) performed density peak clustering of internal and external attributes of textile patterns, which enhances the ability of predicting the future stylistic aspects. Lee et al. (2024) demonstrated experimentally that some of the popular attribute clustering techniques do not consistently improve the performance of pattern classification and are used for feature differences between samples, resulting in low classification accuracy.

Popular hybrid enhancement is to mix different samples together for training, and for each sample one or more data enhancement operations are randomly applied to get the enhanced samples. This technique solves the problem of different data labels and different distributions. Zhao et al. (2021) completed the textile pattern classification task by using two modules, self-channel interaction and contrast channel interaction, to enhance the discriminative features learnt by each channel. Zhang et al. (2023) processed the original textile patterns using Mixup enhancement technique, and the processed patterns were inputted into the generative adversarial network to classify them, to improve the classification accuracy of the textile patterns. Liu et al. (2024) used Mixup enhancement technique to train textile patterns, which are sequentially cropped with a crosshair at a random location, take the corresponding parts for splicing, and input them into a CNN for classification, but not highlighting key features.

Recent work by Hussain et al. (2020) has demonstrated the effectiveness of deep learning models, specifically the residual network (ResNet-50), for the classification and recognition of woven fabric textures. This study highlights the robustness of deep learning approaches in dealing with variations commonly encountered in textile pattern classification tasks. Moreover, Riba et al. (2020) have proposed an automatic sensing and sorting approach based on infrared spectroscopy (ATR-FTIR) for post-consumer textile waste. This method allows for the automatic classification of unknown fibre samples with 100% accuracy and high speed, without the need for any prior analytical treatment of the textile samples.

According to the analysis of the current research status, although the existing textile pattern style classification methods have achieved certain results, they still have the issues of insufficient accuracy and high classification error. In addition, there are very few publicly available datasets involving textile patterns, and there are no datasets that separately address pattern style and colour. To address the above issues, this article designs a textile pattern style classification method relied on popular hybrid enhancement and attribute clustering. Firstly, the image attribute clustering method is optimised to use discrete values to represent the discretised data. Then two convolutional blocks output the feature intersection set of the enhanced pattern as an object mask to generate an object-level image, which effectively reduces the interference caused by the complex background and is feature-enhanced by the channel attention mechanism. Next, the style attributes are clustered and mined using an optimised attribute clustering algorithm to obtain the corresponding pseudo-tagged features. Finally, the pseudo-features generated from the visual features and the style attributes are co-trained with softmax classifiers to achieve label prediction for textile patterns. Experimental results show that the proposed method has high accuracy and low classification error, which validates the effectiveness of the proposed method.

2 Theoretical analysis.

2.1 Popular hybrid enhancement techniques

The popular hybrid image data enhancement method generates new training samples by mixing two or more samples and their labels at a specific ratio, which is an effective strategy to improve the generalisation ability of the model (Ullah et al, 2020). Typical examples of this technique include Mixup and CutMix. Their counterparts are shown in Table 1.

Table 1 Comparison of mixup and CutMix

Features	*Mixup*	*CutMix*
Usage of full image region	Yes	Yes
Regional dropout	No	Yes
Regional dropout	Yes	Yes

1 The Mixup method (Liang et al., 2018) is a linearly interpolated image mixing method that generates new training samples by mixing two random samples and labels at a specific scale. Let x_1 and x_2 be the two input images, y_1 and y_2 be corresponding labels, and η be a randomly selected value from a beta distribution $Beta(\beta, \beta)$. Mixup generates a new image x' and label y'.

$$\begin{cases} x' = \eta x_1 + (1-\eta)x_2 \\ y' = \eta y_1 + (1-\eta)y_2 \end{cases} \tag{1}$$

2 The CutMix method (Jamshidi et al., 2023) generates a new sample by directly replacing a part of an image with the corresponding area of another image. Let A be the area randomly cropped from x_1, and μ be the area ratio of area A to x_1. The new image x' and label y' generated by CutMix.

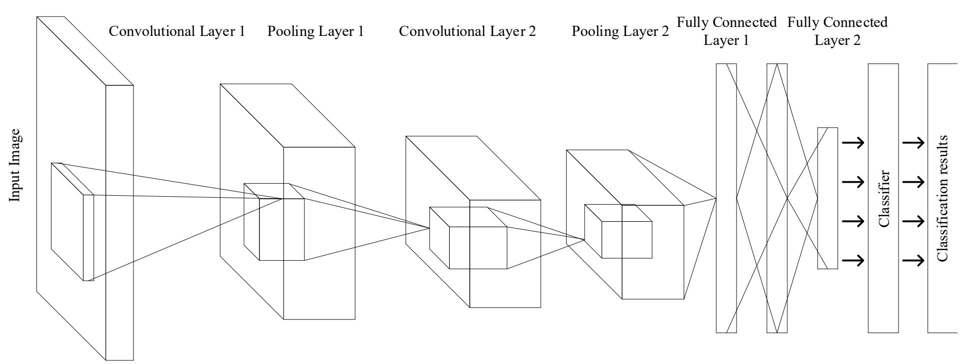
$$\begin{cases} x' = Ax_1 + (1-A)x_2 \\ y' = \mu y_1 + (1-\mu)y_2 \end{cases} \tag{2}$$

This approach not only preserves the original features of the mixed samples, but also introduces new feature variations that allow the model to better learn the feature distribution of the samples.

2.2 Convolutional neural network

The CNN performs convolutional operations on the input image several times to extract image features. As implied in Figure 1, a CNN consists of five parts: input layer, convolutional layer, pooling layer, fully connected layer and output layer. Except for the input layer and the output layer, the other three layers have the role of feature extraction (Mi et al., 2022). In the application area of textile pattern style classification, CNNs are often used for feature extraction of patterns to mine the deeper features within the pattern.

Figure 1 The architecture of CNN



In CNN, the convolutional and pooling layers are generally connected alternately, in the form of convolutional level, pooling level, convolutional level, and so on. Since each neuron in the output feature map of the convolutional layer is locally connected to its input, the input value of the neuron is weighted and summed by the corresponding connection weights and local inputs, and then added with the offset value in the network, which is equivalent to the convolution process. The fully connected layer is usually located after the last level of convolution and pooling, and the output of the k^{th} layer of the fully connected level is given by the following equation.

$$x^k = f\left(v^k x^{k-1} + a^k\right) \tag{3}$$

where x^k denotes the input to the k^{th} convolutional level, v^k denotes the weights of the convolutional kernel, and a^k denotes the bias coefficients

3 Image mixture attribute clustering based on entropy discretisation

For the goal of eliminating the difference between the similarity measures of numerical and categorical attributes in image mixture attributes, entropy discretisation technique (Norris et al., 2011) is introduced to represent the discretised data using discrete values, thus using a similarity measure (Li et al., 2004) to measure the similarity between the objects and eliminating the difference in the metrics.

Let the image mixed attribute dataset $D = \{x_1, x_2, \ldots, x_n\}$, n be the number of objects, and the object $x_i = \left(x_i^1, x_i^2, \ldots, x_i^q\right)$, where q is the number of attributes, and the number of numerical and categorical attributes are N_r and N_c, respectively, satisfies $q = N_r + N_c$. $d(x_i, x_j)$ is the distance between objects x_i and x_j, and $d_r(x_i, x_j)$ is the distance between x_i and x_j for categorical attributes.

1 Use entropy to divide the numerical attributes in D into discrete intervals, and select the maximum value of the interval as the discrete value, i.e., $f((a, b]) = b$, $(a < b)$, and $(a, b]$ are the intervals divided by the discretisation algorithm. If a continuous attribute with value range $[value_1, value_2]$ has z non-repeating attribute values $value_1 < value_2 < \ldots < value_z$, initially divide the intervals so that each interval contains one non-repeating attribute value, $(vlue_1 - \xi, value_1]$, $(vlue_1 - value_2]$, $(value_{z-1}, value_z]$, $(\forall \xi > 0)$.

   Remember the number of intervals as g, $1 \le g \le n$, n is the total number of samples, according to the definition of entropy (Samorodnitsky, 2016) calculated entropy is $G(g)$, as implied in equation (4), where num_i indicates the number of values corresponding to each interval. Then select two adjacent intervals to merge, so that $G(g)–G(g–1)$ is the minimum, if the interval before and after the merger makes $G(g)–G(g–1)$ the minimum more than one pair, then randomly merge a pair, and reset the division point, and then iterate on this step, the target function as implied in equation (5).

$$G(g) = -\sum_{i=1}^{g} \frac{num_i}{num} \log_2 \frac{num_i}{num} \tag{4}$$

$$F(g) = (g_0 - 1)G(g) - G(g_0)(g - 1) \tag{5}$$

   when $F(g–1) \le F(g)$ is satisfied the iteration is stopped, the interval division point is saved and the maximum value of the interval is selected as the discrete value. Equation (5) in g_0 is the number of intervals divided for the first time, $G(g_0)$ is the entropy of the interval divided for the first time.

2 Randomly select k objects from the discretised D as the initial cluster centres. Initially, the cluster centres are randomly selected, and when iterating, the attribute value of each attribute with the largest frequency in the cluster is selected as the new cluster centre, and the iteration is stopped when the objective function is satisfied, the objective function of the proposed attribute clustering algorithm is defined as follows.

$$F(W, C) = \sum_{l=1}^{k} \sum_{i=1}^{n} w_i d\left(x_i, c_l\right) \tag{6}$$

where $w_{ki} \in \{0,1\}, 1 \leqslant k \leqslant l, 1 \leqslant i \leqslant n, \sum_{k=1}^{l} w_{ki} = 1$, l denotes the number of clusters, W is the {0, 1}-subordinance matrix of a $n \times l$, $w_{ki} = 1$ denotes the i^{th} data object classified into the k^{th} class, and $C = (c^1, c^2, \ldots, c^k)$ is the centre of the k^{th} class. $d(x_i, c_i)$ is computed as follows, where σ denotes the Euclidean distance between two objects.

$$d\left(x_i, c_l\right) = \sum_{p=1}^{q} \sigma\left(x_i^p, c_l^p\right) \tag{7}$$

3 Measure the distance of each object from the cluster centre and classify each object into the cluster with the smallest distance.

4 Recalculate the cluster centre s and select the attribute value with the highest frequency among the data attributes in each cluster as the attribute value of the new cluster centre.

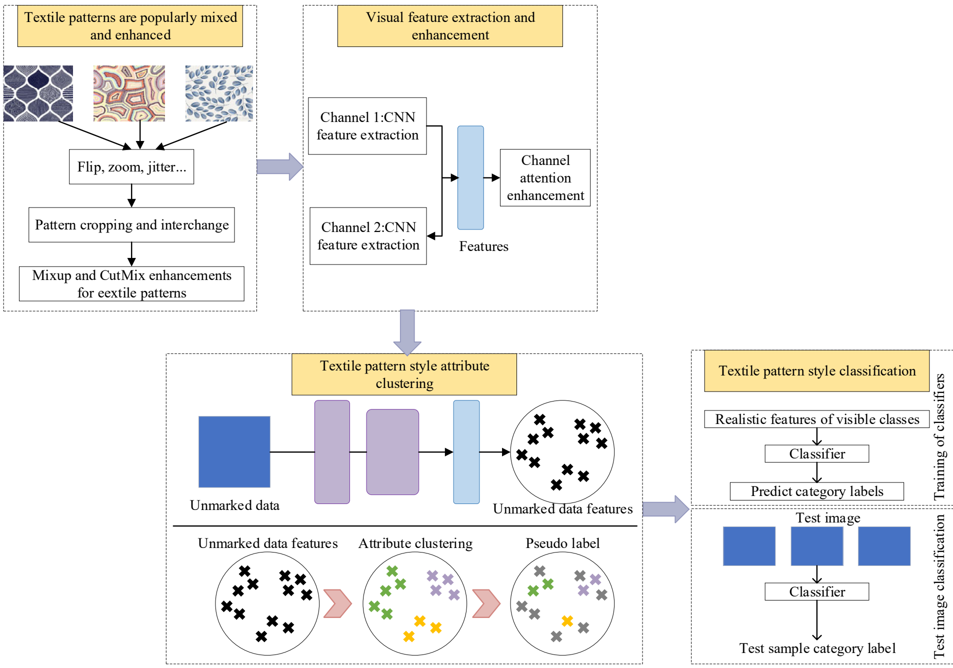
5 Repeat steps (3) and (4), and the algorithm ends when the objective function F does not change.

4 Textile pattern style classification based on popular hybrid enhancement and attribute clustering

4.1 Popular mix of textile patterns enhanced

Focusing on the issue that the samples of traditional classification methods are prone to uneven distribution and missing markers, firstly, the original textile images are popularly mixed and enhanced according to the mixing parameter, and secondly, the intersection set of visual features of the two convolutional blocks outputting the enhancement pattern is used as an object mask, which is mapped to the original image for cropping to obtain the object-level image, and its features are enhanced through the attention mechanism. Based on this, its style attributes are clustered and mined to generate style attributes. Finally, the pseudo-features generated by visual features and style attributes are used to jointly train softmax classifiers to achieve the prediction of labels for textile patterns. The designed model is shown in Figure 2.

Figure 2 The model of the suggested textile style classification method (see online version for colours)



In the popular hybrid enhancement technology, the original textile pattern is enhanced by a technology combining Mixup and CutMix, which randomly selects whether to cut and exchange local regions according to specific mixing parameters. If the clipping operation is not performed, the two samples are directly fused to generate a new mixed pattern; if clipping is performed, the local regions clipped from the two patterns will be replaced with each other to form a new feature combination, thus improving the generalisation ability of the model and reducing the over-fitting phenomenon. This enhancement method can effectively increase the diversity of training samples and improve the performance of classifier.

- Mixup and CutMix have some drawbacks in the classification of textile pattern styles: Mixup introduces unnatural pseudo-pixel information during the mixing process, and CutMix provides incorrect labels, which tends to confuse the network during the training of the network. Based on these two methods, this paper proposes an optimised popular mixup enhancement method to enhance the original textile pattern data, and control Mixup and CutMix by sampling probability, in order to help the model generalise to the unseen data better, reduce overfitting, and improve the classification effect of the model. The method is divided into two phases: the fusion of sample feature maps and the replacement of local regions with each other, and the adoption probability of Mixup and CutMix is controlled by the mixing parameter.
- The first stage: the original textile pattern is randomly flipped, scaled, dithered, colour gamut changed and other operations are performed. After the enhanced samples are inputted into the feature network, the two randomly selected samples are

not operated with the probability of μ, and some pattern blocks of the same position and size are cut out from the two randomly selected samples with the probability of $1-\mu$. The first stage: the original textile pattern is randomly flipped, scaled, dithered, colour gamut changed and other operations are performed.

- The second stage: If no clipping operation is performed on the two samples, they are fused to generate a fused pattern, and then continue to be sent to the next feature layer for training; if clipping operation is performed on the two samples, the local patterns cropped from the two patterns are replaced with each other to generate another hybrid feature map, and then continue to be sent to the next feature layer for training. The sample pattern fusion and local region replacement are shown in equation (8) and equation (9), respectively.

$$\lambda_{hybrid}\left(f_k\left(x_i\right), f_k\left(x_j\right)\right) = \beta f_k\left(x_i\right) + (1-\beta) f_k\left(x_j\right) \tag{8}$$

$$\lambda_{replace}\left(f_k\left(x_i\right), f_k\left(x_j\right)\right) = M \odot f_k\left(x_i\right) + (1-M) \odot f_k\left(x_j\right) \tag{9}$$

where $f_k(x)$ is the mapping from the input data to the k^{th} layer, β is a parameter that follows the χ-distribution with a value in the range of [0, 1], $M \in \{0, 1\}^{W \times H}$ is a binary mask that indicates the positions of deletions and fills in the pattern, W and H represent the width and height of the image, respectively, and $\odot$ is a pixel-by-pixel multiplication.

4.2 Visual feature extraction and enhancement of textile patterns.

The popular hybrid-enhanced textile pattern obtained above is fed into the feature extractor and visual features F_0 are obtained from the last convolutional layer, all the feature maps in F_0 are summed in the channel dimension to obtain the feature map A. After that, the average value of A is computed to obtain $\overline{A}$, and finally, a mask mapping B_1 is constructed to represent regions larger than the average activation value.

$$\overline{A} = \frac{\sum_{a=0}^{H-1} \sum_{b=0}^{W-1} A(a,b)}{H \times W} \tag{10}$$

$$B_1 = \begin{cases} 1, & if\ A(a,b) > \overline{A} \\ 0, & otherwise \end{cases} \tag{11}$$

According to the mask mapping the pattern samples are transformed into a multilayer object, which is located in the maximally connected component, so the mask mapping B_2 of the output of the penultimate convolutional block is obtained by equation (10) and equation (11). Finally, the intersection B of B_1 and B_2 is obtained.

$$B = B_1 \cap B_2 \tag{12}$$

By mapping the largest connected region in mask B, an object-centred object image is obtained, filtering out noisy background regions and reducing feature redundancy. The object feature map $F_{in} \in R^{W \times H \times C}$, where C represents the number of channels. Take the feature map F_{in} as the input to the CNN and perform global maximum pooling and global average pooling operations to obtain two $W \times H \times 1$ feature maps respectively.

$$F_{avg} = AvgPool\left(F_{in}\right) \tag{13}$$

$$F_{max} = MaxPool\left(F_{in}\right) \tag{14}$$

Then, these two object feature maps are concatenated according to the channels. After that, the number of channels is reduced to 1 by convolution operation, and finally, the spatial attention map S is generated by sigmoid activation function, which represents the most salient region in the feature map F. After obtaining the spatial attention map S, it is multiplied element-wise with F_{in} to get the final enhanced feature map X.

$$X_1 = M\left(F_{in}\right) = \delta\left(f^{7\times7}\left(concat\left[F_{avg}, F_{max}\right]\right)\right) \tag{15}$$

where δ is a sigmoid function and $f^{7\times7}$ denotes a convolution operation with a convolution kernel size of 7×7.

4.3 Stylistic attribute clustering and style classification of textile patterns

The augmented object feature graph obtained in the previous section contains feature representations of all unlabelled data, in this paper, an optimised attribute clustering algorithm is applied to cluster mine the mixed attributes in the object feature graph and group these unlabelled features to obtain the corresponding pseudo-labelled features. Samples close to the class centre of mass are labelled as reliable and are merged into the labelled data to update the base model for the next iteration. Finally, the pseudo-features generated from visual features and style attributes are used to jointly train softmax classifiers to predict the labels of textile patterns.

From the Section 3, it is clear that the style mixture attributes in the textile feature map contain numerical and categorical attributes, which need to be clustered separately.

1 Numerical attribute clustering. Firstly, find a core object p from the unidentified objects in D. Take p as the starting point to generate CoreRepSet, which forms a cluster with all its immediate neighbours until all the objects in D have been processed, and finally assign all the unprocessed data in the dataset to its class according to the density reachable.

2 Categorical attribute clustering. Assuming that $C = (C_1, C_2, \ldots, C_l)$ is a division of D and C_i is one of the classes, first calculate the entropy of each object in D as bellow.

$$E(C) = \sum\nolimits_{i=1}^{l}\left(\frac{n_i}{n_D}\left(-\sum\nolimits_{i=1}^{d}\sum\nolimits_{x\in X_i} p\left(x_i = x \mid C\right)\log_2\left(p\left(x_i = x \mid C\right)\right)\right)\right) \tag{16}$$

Then, from the unidentified data objects in D, select the value with the lowest entropy as the clustering centre p, mark the cluster ID, and with p as the clustering centre, use equation (17) to calculate the data in the unidentified objects whose similarity with p is greater than β to be added to this cluster, and mark all the processed data objects. Repeat the process until all attributes are processed.

$$S_{ij} = e^{-\beta d_{ij}} \tag{17}$$

where d_{ij} is the distance between x_i and x_j.

3 According to the numerical attribute cluster membership division $C_N = \{C_{n1}, C_{n2}, \ldots, C_{nl}\}$ and categorical attribute cluster membership division $C_C = \{C_{c1}, C_{c2}, \ldots, C_{ck}\}$ obtained in (1) and (2). Take any one cluster from C_N and C_C, its intersection set $\omega_t = C_{ni} \cap C_{ci}$, and concatenation set $\pi_t = C_{ni} \cup C_{ci}$. Set $\pi(i, j) = \pi_i \cap \pi_i$, as the threshold of merging clusters, the specific steps of clustering are as follows.

Step 1 Take any clusters C_n and C_c from C_N and C_C, respectively, and compute the intersection set w_i and the union set π_i.

Step 2 Iterate over all combinations of intersection sets ω_t containing more than two elements, and add the union set π_i of these two clusters to the empty set Φ.

Step 3 Calculate the ratio of the elements of the intersection between the two sets in Φ to θ, and arrange them in descending order.

Step 4 If $\theta > \xi$, then merge π_i and π_j, and update Φ, skip to step 3; otherwise if $\pi(i, j) \neq \varnothing$ exists, then if $|\pi_i| > |\pi_j|$, then $\pi_i = \pi_j - \pi(i, j)$, otherwise $\pi_j = \pi_i - \pi(i, j)$, update Φ, skip to step 3; otherwise if there is data that does not belong to any of the sets in Φ, create a new set for the data independently.

4 All labelled data in Φ is used as pseudo-feature F_e generated by the style mixing attribute, which is connected with visual feature F_0 in the textile feature map to obtain F as an input to a softmax classifier to classify the style of textile patterns, and the value with the highest probability of scoring the highest score is the value of category labels, as shown below.

$$y_i = \max_{x_j \in D}\{F \otimes x_j\} \tag{18}$$

where y_i denotes the predicted value. In the training phase, the aim of the classifier is to minimise the softmax loss. The loss function of the classifier is represented as follows.

$$L = -E\left[\log P\left(y_i \mid F^*; \varsigma\right)\right] \tag{19}$$

where ζ denotes the parameters of the classifier and $P(y_i|F; \zeta)$ denotes the probability that feature x is predicted to be correctly labelled.

5 Performance testing and analysis

5.1 Comparative analysis of classification performance

In this paper, the computer configuration is Intel i7 8700 K CPU and NVIDIA GeForce GTX1080TI GPU, the operating system is Ubuntu16.04, and the PyTorch deep learning framework is adopted, and the batch size is set to 2 in the experiment, and the number of training steps is 550,000, and the initial learning rate is 0.002, and the attenuation coefficient is 0.000 1. This article uses the textile patterns collected in the literature (Hussain et al., 2020) as the dataset, which contains 724 textile patterns, which are labelled and classified according to the pattern characteristics, with a total of 8 categories: plaid, stripe, print, polka dot, solid colour, zebra print, leopard print and embroidery. In this dataset, 65% is selected as the training set, and 20% and 15% are selected as the validation and test sets, respectively, to experiment and analyse the suggested method OURS and the comparison method.

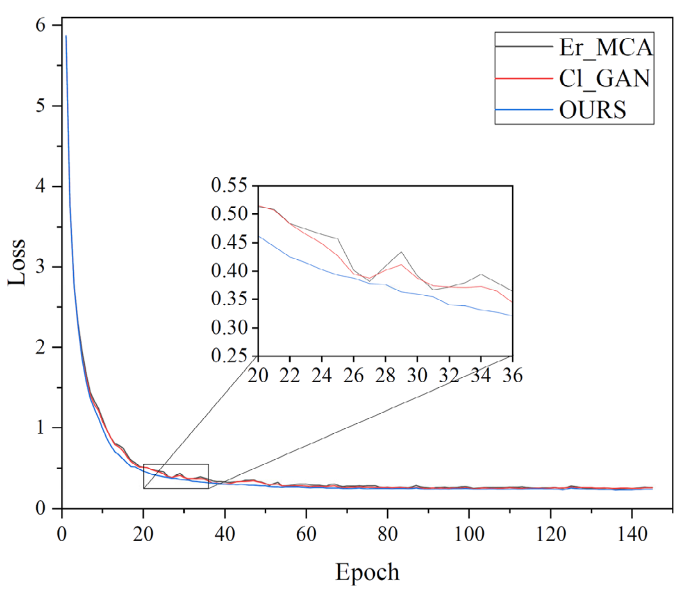
This article compares and analyses Er_MCA (Celani et al., 2024), Cl_GAN (Zhang et al., 2023) and OURS methods using Accuracy (Acc), mean accuracy mean (MAP) (Vujović, 2021), mean absolute percentage error (MAPE), and root mean square percentage error (RMSPE) (Guillera-Arroita et al., 2017). MAP is based on the combined consideration of precision and recall, which is obtained by weighted average of average percent correct (AP) for different categories of tests. MAPE measures the relative difference between the actual value and the predicted value. It is the average of all absolute errors, expressed as a percentage. RMSPE takes the absolute value of the percentage error for each sample, then averages it, and finally takes the square root. This metric is useful for assessing the accuracy of classification models on percentage or proportional data.

The experimental outcome are implied in Table 2. The MAP and Acc of OURS increased by 12.52% and 8.85% respectively compared to Er_MCA, and increased by 5.25% and 4.24% respectively compared to Cl_GAN. MAPE and RMSPE of OURS are 11.63% and 7.36% lower compared to Er_MCA, and 4.19% and 2.29% lower compared to Cl_GAN. Cl_GAN achieves pattern mixup enhancement by Mixup technique, but it does not carry out in-depth attribute clustering mining for textile patterns, which leads to a poorer classification efficiency than OURS, which can effectively improve the classification accuracy, and also improves the problem of large error, and has a stronger classification efficiency.

Table 2 Classification performance of different textile pattern classification methods

Method	*MAP/%*	*Acc/%*	*MAPE/%*	*RMSPE/%*
Er_MCA	71.07	82.51	14.98	8.92
Cl_GAN	78.34	87.12	7.54	3.85
OURS	83.59	91.36	3.35	1.56

Figure 3 Comparison of losses in different methods of classifying textile pattern styles (see online version for colours)

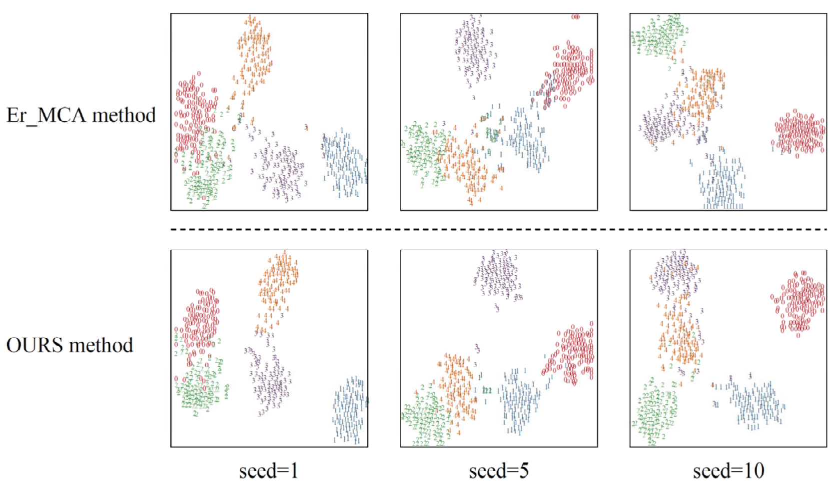


The loss pairs for different classification methods are implied in Figure 3, where the loss value decreases rapidly in the first 40 iterations, and the computational loss increases as the number of iterations increases. Then, the loss values of the three methods slowly oscillate downward and converge, and the final loss value stabilises at about 0.3, and the training result achieves the expected effect. The losses of Er_MCA, Cl_GAN and OURS are close to each other, with the difference that the loss of OURS is significantly lower than that of Er_MCA and Cl_GAN in the first 40 iterations. OURS combines the advantages of Er_MCA in balancing difficult and easy samples and Cl_GAN in strengthening the linkage between classes, in which the best classification results are achieved when $\zeta = 0.5$.

5.2 *Attribute clustering effect analysis*

For the purpose of better distinguishing the classification results, this article visualises the clustering effect of OURS and Er_MCA methods by randomly selecting 150 patterns of 5 categories in the dataset, as implied in Figure 4. In Er_MCA method, the boundary of each category is less precise and compact, especially when the seed is 5, the distributions of the features of the different categories overlap each other. The OURS method clusters the numerical and categorical attributes in the textile pattern mixture attributes separately by discretising the entropy, eliminating the metric differences, and the category features are contracted a bit more compactly.

Figure 4 Clustering visualisation results for methods ours and Er_MCA (see online version for colours)



The visualisation shows that attribute clustering can help the model to better focus on the parts of the model that are conducive to classification. However, the visualisation also shows that some categories are not well identified by the model, which may be related to the quality of the data, and therefore the quality of the data is also very important for the performance of the model. The higher the quality of the data, the better the clustering, and then the more efficient the classification. The compactness of the visualisation map and the experimental results demonstrate that there is a relationship between the compactness of the training set and the classification effect of the test set: the more compact the samples of the training set are in the mapping space, the better the classification effect is. Er_MCA clusters textile pattern attributes by density peak clustering with higher complexity without further analysing the features of the patterns, resulting in poor clustering results. Cl_GAN uses GAN to classify textile patterns without further considering the attributes of the individual categories, and thus the clustering results are also not as good as those of OURS. Therefore, the OURS method performs better under different seeds compared to the Er_MCA method. That is, the suggested method helps to form more compact clusters and classes with distinct boundaries.

To provide a comprehensive understanding of the proposed method, it is essential to highlight the advantages and limitations of both Mixup and CutMix data augmentation techniques in the context of textile pattern style classification. While Mixup generates interpolated images by linearly combining pairs of samples and their labels, it introduces unnatural pixel information that can confuse the network during training. On the other hand, CutMix replaces a random region of one image with a corresponding region from another image, which can lead to incorrect labels if not properly handled. These drawbacks are addressed in the proposed popular mixup method, which alleviates the overfitting situation and improves classification performance by controlling the mixing parameter and employing a two-stage process that combines sample feature maps and replaces local regions with each other. The optimised popular mixup method ensures a more natural representation of the data, thereby enhancing the robustness of the model. By leveraging the strengths of these techniques and mitigating their weaknesses, the proposed method achieves a classification accuracy of 91.36% and a MAPE of 3.35%, demonstrating its efficiency and effectiveness in textile pattern style classification.

6 Conclusions

Textile pattern style classification is the focus of computer vision field. There are many deficiencies in the current classification methods, so a textile pattern style classification method based on popular mixture enhancement and attribute clustering is proposed, which has the following advantages.

1 The entropy discretisation technique is used to optimise the image attribute clustering method, and the discrete values are used to represent the discretised data, to measure the similarity between the objects, and to eliminate the differences in the measurements.

2 The visual feature intersection of the augmented pattern is output using a two-channel CNN to generate an object-level image, which is augmented with features using an over-channel attention mechanism.

3 An optimised attribute clustering algorithm is applied to cluster mine the style attributes in the object feature graph to obtain the corresponding pseudo-label features. The pseudo-features generated from visual features and style attributes are co-trained with Softmax classifier to achieve the label prediction of textile patterns.

4 The proposed method has a classification accuracy of 91.36% and a MAPE of 3.35%, which is more efficient in classification and better in clustering.

The prerequisite for the textile pattern style classification method proposed in this paper is that the pattern has been processed with noise, and in the future, this paper will focus on investigating the impact of image quality on the classification effect of the designed model and comparing the method of this paper with other state-of-the-art methods in deep learning and computer vision on several large-scale datasets to fully validate the effectiveness of the proposed method.

Acknowledgements

This work is supported by the 'Clothing pattern design and application' in Zhejiang Teaching Letter of 2022 Provincial Curriculum Ideological and Political Demonstration Course (2022) No.51, 'clothing pattern design and application' in the first municipal 'Curriculum Ideological and Political Teaching Demonstration Course' (higher vocational colleges) Wen Jiao Gao (2022) No. 70 and Wenzhou Basic Scientific Research Project (No. G20210042).

References

Balan, S. and Devi, T. (2012) 'Design and development of an algorithm for image clustering in textile image retrieval using colour descriptors', *International Journal of Computer Science, Engineering and Applications*, Vol. 2, No. 3, pp.199–211.

Celani, C.P., Degano, I., Chen, C., Jaeger, O., Speed, A.M., Booksh, K.S. and Alcantara-Garcia, J. (2024) 'Exploring elucidation of red dye mixtures on woolen historical textiles via non-destructive spectroscopic analysis and multivariate cluster analysis', *Heritage Science*, Vol. 12, No. 1, p.48.

Guillera-Arroita, G., Lahoz-Monfort, J.J., van Rooyen, A.R., Weeks, A.R. and Tingley, R. (2017) 'Dealing with false-positive and false-negative errors about species occurrence at multiple levels', *Methods in Ecology and Evolution*, Vol. 8, No. 9, pp.1081–1091.

Hussain, I.M.A., Khan, B. Wang, Z. et al. (2020) 'Woven fabric pattern recognition and classification based on deep convolutional neural networks', *Electronics*, Vol. 9, No. 6, p.1048.

Jamshidi, M., El-Badry, M. and Nourian, N. (2023) 'Improving concrete crack segmentation networks through CutMix data synthesis and temporal data fusion', *Sensors*, Vol. 23, No. 1, p.504.

Jeyaraj, P.R. and Samuel Nadar, E.R. (2019) 'Computer vision for automatic detection and classification of fabric defect employing deep learning algorithm', *International Journal of Clothing Science and Technology*, Vol. 31, No. 4, pp.510–521.

Khan, B., Han, F., Wang, Z. and Masood, R.J. (2016) 'Bio-inspired approach to invariant recognition and classification of fabric weave patterns and yarn colour', *Assembly Automation*, Vol. 36, No. 2, pp.152–158.

Kim, H.J., Youn, S., Choi, J., Kim, H., Shim, M. and Yun, C. (2021) 'Indexing surface smoothness and fibre softness by sound frequency analysis for textile clustering and classification', *Textile Research Journal*, Vol. 91, Nos. 1–2, pp.200–218.

Kose, Y., Muftuoglu, S., Cevikcan, E. and Durmusoglu, M.B. (2022) 'Axiomatic design for lean autonomous maintenance system: an application from textile industry', *International Journal of Lean Six Sigma*, Vol. 14, No. 3, pp.555–587.

Koulali, I. and Eskil, M.T. (2021) 'Unsupervised textile defect detection using convolutional neural networks', *Applied Soft Computing*, Vol. 113, p.107913.

Lee, S., Han, Y. and Yun, C. (2024) 'Development of a fabric classification system using drapability and tactile characteristics', *Fashion and Textiles*, Vol. 11, No. 1, p.2.

Li, M., Chen, X., Li, X., Ma, B. and Vitányi, P.M. (2004) 'The similarity metric', *IEEE Transactions on Information Theory*, Vol. 50, No. 12, pp.3250–3264.

Liang, D., Yang, F., Zhang, T. and Yang, P. (2018) 'Understanding mixup training methods', *IEEE Access*, Vol. 6, pp.58774–58783.

Liu, R., Yu, Z., Fan, Q., Sun, Q. and Jiang, Z. (2024) 'The improved method in fabric image classification using convolutional neural network', *Multimedia Tools and Applications*, Vol. 83, No. 3, pp.6909–6924.

Mi, J-X., Feng, J. and Huang, K-Y. (2022) 'Designing efficient convolutional neural network structure: a survey', *Neurocomputing*, Vol. 489, pp.139–156.

Ngo, V.M., Duong, T-V.T., Nguyen, T-B-T., Nguyen, P.T. and Conlan, O. (2021a) 'An efficient classification algorithm for traditional textile patterns from different cultures based on structures', *Journal on Computing and Cultural Heritage* (JOCCH), Vol. 14, No. 4, pp.1–22.

Ngo, V.M., Helmer, S., Le-Khac, N-A. and Kechadi, M-T. (2021b) 'Structural textile pattern recognition and processing based on hypergraphs', *Information Retrieval Journal*, Vol. 24, No. 2, pp.137–173.

Norris, S., Richards, P. and Mallinson, G. (2011) 'Improved finite volume discretisations of entropy generation and turbulence production', *Computers and Fluids*, Vol. 49, No. 1, pp.302–311.

Riba, J-R., Cantero, R., Canals, T. et al. (2020) 'Circular economy of post-consumer textile waste: classification through infrared spectroscopy', *Journal of Cleaner Production*, Vol. 272, p.123011.

Samorodnitsky, A. (2016) 'On the entropy of a noisy function', *IEEE Transactions on Information Theory*, Vol. 62, No. 10, pp.5446–5464.

Shin, Y., Kim, Y. and Kim, E.Y. (2010) 'Automatic textile image annotation by predicting emotional concepts from visual features', *Image and Vision Computing*, Vol. 28, No. 3, pp.526–537.

Sun, J., Yao, M., Xu, B. and Bel, P. (2011) 'Fabric wrinkle characterization and classification using modified wavelet coefficients and support-vector-machine classifiers', *Textile Research Journal*, Vol. 81, No. 9, pp.902–913.

Ullah, Z., Farooq, M.U., Lee, S-H. and An, D. (2020) 'A hybrid image enhancement based brain MRI images classification technique', *Medical Hypotheses*, Vol. 143, p.109922.

Vujović, Ž. (202) 'Classification model evaluation metrics', *International Journal of Advanced Computer Science and Applications*, Vol. 12, No. 6, pp.599–606.

Wen, J. and Wong, W. (2018) 'Fundamentals of common computer vision techniques for fashion textile modeling, recognition, and retrieval', *Applications of Computer Vision in Fashion and Textiles*, Vol. 8, pp.17–44.

Xu, H.J., Zou, F.Y., Wei, J. and Zhang, Y. (2011) 'Research on clothing styles classification model based on the MDS and K-Means method', *Advanced Materials Research*, Vol. 331, pp.616–619.

Xue, Z., Zeng, X., Koehl, L. and Shen, L. (2016) 'Interpretation of fabric tactile perceptions through visual features for textile products', *Journal of Sensory Studies*, Vol. 31, No. 2, pp.143–162.

Yang, C-S., Lin, C-J. and Chen, W-J. (2019) 'Using deep principal components analysis-based neural networks for fabric pilling classification', *Electronics*, Vol. 8, No. 5, p.474.

Zhang, H., Chen, X., Lu, S., Yao, L. and Chen, X. (2023) 'A contrastive learning-based attention generative adversarial network for defect detection in colour-patterned fabric', *Colouration Technology*, Vol. 139, No. 3, pp.248–264.

Zhao, X., Zhang, M. and Zhang, J. (2021) 'Ensemble learning-based CNN for textile fabric defects classification', *International Journal of Clothing Science and Technology*, Vol. 33, No. 4, pp.664–678.