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Colour Difference Classification for Dyed Fabrics Based on Differential Evolution with Dynamic Parameter Selection to Optimise the Output Regularisation Extreme Learning Machine

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Abstract
A novel optimisation technique based on the differential evolution (DE) algorithm with dynamic parameter selection (DPS-DE) is proposed to develop a colour difference classification model for dyed fabrics, improve the classification accuracy, and optimise the output regularisation extreme learning machine (RELM). The technique proposed is known as DPS-DE-RELM and has three major differences compared with DE-ELM: (1) Considering that the traditional ELM provides an illness solution based on the output weights, DE is proposed to optimise the output of the RELM. (2) Considering the simple parameter setting of the traditional algorithm, the DE algorithm with DPS is adopted. (3) For DPS, an optimal range of parameters is chosen, and the efficiency of the algorithm is significantly improved. This study analyses the colour difference classification of fabric images captured under standard lighting based on the DPS-DE-RELM algorithm. First, the colour difference of the fabric images is calculated and six color-difference-related features extracted, and second the features are classified into five different levels based on the perception of humans. Finally, a colour difference classification model is built based on the DPS-DE-RELM algorithm, and then the optimal classification model suitable for this study is selected. The experimental results show that the output method with regularisation parameters can achieve a maximum classification accuracy of 98.87%, which is higher compared with the aforementioned optimised original ELM algorithm, which can achieve a maximum accuracy of 84.67%. Therefore, the method proposed has the advantages of greater convergence speed, high classification accuracy, and robustness.

Key words: *colour difference classification, differential evolution, extreme learning machine, output regularisation extreme learning machine, parameter selection.*

Introduction

In the textile printing and dyeing industry, colour difference is considered to be an important index for the quality evaluation of textiles. The traditional colour difference detection method is manual, has strong subjectivity, is significantly affected by work environments, and the detection efficiency is low [1]. Colour difference detection based on the RGB colour space is the most common method. The RGB colour space is used for image preprocessing and then converted to the CIELAB colour space, considering the colour difference formula, to calculate the colour difference [2]. This method represents the colour difference numerically and thus reflects the difference value between the two images, with no classification of the colour difference. Wu [3] proposed the Naive Bayesian method based on the genetic algorithm (GA) as the method uses prior knowledge of training samples; however, if the training samples have micro changes, the classification accuracy is significantly reduced. Moreover, if the GA optimisation process lasts long, the classification accuracy is not considered ideal. Zhang [4] proposed a model to evaluate colour difference for dyed fabrics based on the support vector machine (SVM); but there is a risk of falling into the local optimum. Therefore, the least square SVM (LS-SVM) [5] was built based on the SVM, which solved the shortcomings of the original SVM.

The traditional back propagation (BP) neural network method performs optimisation based on the gradient descent and helps adjust network parameters based on the error feedback mechanism; however, it has a slow convergence and a risk of falling into the local optimum [6]. Considering the problem of the BP neural network, Huang [7] proposed a single-hidden-layer feedforward neural network (SLFN), known as the extreme learning machine (ELM). Compared with the BP network, ELM has the following advantages: simple structure, less adjustable parameters, random initiation of input weights and bias of hidden layers, and fast learning speed [8, 9]. In recent years, a textile defect detection method was proposed [10] based on multiscale dictionary learning and improved ELM. To improve the generalisation ability and robustness of the illumination correction model for printing and dyeing products, the rotating forest algorithm is used as the integration framework, and the improved online sequential ELM is used as the basis of the learning device instead of the regression tree in the rotation forest algorithm [11]. This helps the illumination correction algorithm model to obtain higher prediction accuracy. Zhang [12] proposed the outlier-robust ELM for regression problems and introduced the regularisation ELM for the illness solution. Recently, the colour difference classification of dyed fabrics via a kernel ELM based on an improved grasshopper optimisation algorithm was proposed [13].

The differential evolution (DE) algorithm has played an important role in optics [14-15], pattern recognition [16], and image processing [17] owing to its easy operation. Qu [18] proposed the optimisation of a local coupled ELM based on DE. Yakoub [19] proposed the classification of hyperspectral images based on the DE algorithm, which optimises the ELM. The algorithm is very sensitive to the parameter setting, and a precise parameter combination can obtain optimal results. Therefore, for different optimisation problems, the parameter setting is the most difficult part of the DE algorithm. Millipeddi [20] proposed a DE algorithm with an ensemble of parameters and mutation strategies which were used for 10 different data sets to obtain the best ensemble parameters of each data set. Ruhul [21] proposed a DE algorithm with dynamic parameter selection (DE-DPS) used for different optimisation problems. However, the parameter range of the algorithm is extremely wide, thus making the algorithm complicated and yielding redundant experimental results along with the desired ones.

In recent years, deep neural networks [22-24] have been rapidly developed and applied to classification learning. Deep neural networks improve classification performance, which can help to better deal with specific problems, reflecting the strong ability of the neural networks; however, the training time of the deep neural network model is large.

In this study, an optimised ELM for the colour difference classification of textile images is proposed. The main contributions of this study are as follows:

(1) A colour difference classification model for textiles is established. Six colour difference features are proposed; a colour difference classification standard is established; a colour difference classification model is constructed, and the optimal classification model is selected.

(2) To obtain the optimal classification model, this study proposes a DE algorithm to optimise the RELM and then uses the DPS strategy to select the optimal model.

(3) The DPS strategy is adopted. Over the parameter selection process, the optimal parameter range is set, which helps reduce the complexity of the algorithm and solves the problem of ill-conditioned solutions when the DE algorithm optimises the traditional ELM in the output stage. Moreover, the strategy improves classification accuracy.

DE algorithm for optimising output RELM

In this study, we propose a DE algorithm to optimise the output RELM for the randomly generated input weights and hidden bias of the original ELM, and thus we derive the illness solution in the process of calculating output weights. First, we introduce the output RELM and add the regularisation parameter that represents the structural risk while analysing the output weights to obtain the illness solution pertaining to the output weights. Then, the DE algorithm is used to iteratively search for optimal input weights and hidden bias. A set of input weights and hidden bias is generated randomly, defined as the initial population, using the mutation, crossover, and selection operations to obtain the optimal population, thus acquiring the optimal input weights and hidden bias. Finally, a DE algorithm with DPS is proposed to optimise the output RELM. In the optimisation process of the DE algorithm, the DPS strategy is used to select the optimal parameter combination. Owing to a broad range of parameters, the algorithm becomes complicated, and the result is not satisfactory. Therefore, in this study, we set a pool of mutation strategies and the optimal range of F and CR, which can help avoid the complexity of the algorithm, and the best classification model can be easily derived. Then, the algorithm flows according to specific instructions: Given a training dataset: $N=\{(x_i,t_i)\mid x_i\in \mathrm{R}^n,\ t_i\in \mathrm{R}^m, i=1,2,...,N\}$ the activation function is $g(x)=\dfrac{1}{1-exp(-x)}$, and the number of hidden neurons is L.

(1) Initialise the number of network-hidden neurons (L) and population size (NP); select a group of mutation strategies; set an optimal range of crossover probability (CR) and a scaling factor F, and set the maximum number of iterations (G_{max}).

(2) Randomly initialise the population $G_{NP\times D}$; D denotes the dimension of population G. Choose the input weights and the hidden bias as the population members that constitute each population ψ.

$$\psi=[\mathrm{w}_{11},\mathrm{w}_{12},...,\mathrm{w}_{1L},\mathrm{w}_{21},\mathrm{w}_{22},...,\mathrm{w}_{2L},...,\mathrm{w}_{N1},\mathrm{w}_{N2},...,\mathrm{w}_{NL},\mathrm{b}_1,\mathrm{b}_2,...,\mathrm{b}_L] \quad (1)$$

(3) For each population ψ, calculate the hidden-layer output matrix H:

$$H=\begin{bmatrix} g(\mathrm{w}_{11}\cdot \mathrm{x}_1+\mathrm{b}_1) & \dots & g(\mathrm{w}_{1L}\cdot \mathrm{x}_1+\mathrm{b}_L) \\ . & & . \\ . & & . \\ . & & . \\ g(\mathrm{w}_{N1}\cdot \mathrm{x}_N+\mathrm{b}_1) & \dots & g(\mathrm{w}_{NL}\cdot \mathrm{x}_N+\mathrm{b}_L) \end{bmatrix}_{N\times L} \quad (2)$$

(4) After the mutation, crossover, and selection operations, generate the offspring population. In the process of selection, use the error classification rate as a fitness function to control the premature convergence of the population.

(5) Repeat (3) and (4) until the maximum number of iterations is reached, complete the searching process, and obtain the optimal input weights and hidden bias.

(6) Obtain the hidden-layer output matrix H and calculate the output weights (β):

$$\beta=\left(\frac{I}{C}+HH^{\mathrm{T}}\right)^{-1}H^{\mathrm{T}}T. \quad (3)$$

(7) Dynamically adjust the parameters of the DE algorithm, compare the DE algorithm with different parameter combinations, and select the optimal colour difference classification model for dyeing fabric.

Colour difference classification

The purpose of colour difference classification is to determine the colour similarity degree between dyeing fabric and standard fabric. The light source and lighting system must avoid the high reflection area of the detection object to improve detection accuracy or avoid detection failure. The research objects of this study are cotton and polyester fabric surfaces; therefore, we choose D65, D50, and a light source, which is most common in the textile industry.

Colour space

CIEDE2000 uses the latest colour difference formula. Compared with CIE94, CIEDE2000 is more complex and exhibits a significantly improved accuracy. CIEDE2000 has the following advantages over CIE94: (1) improved prediction performance of neutral colour; (2) an enhanced lightness weight function (an approximate V-shape function); (3) hue angle consideration in the hue

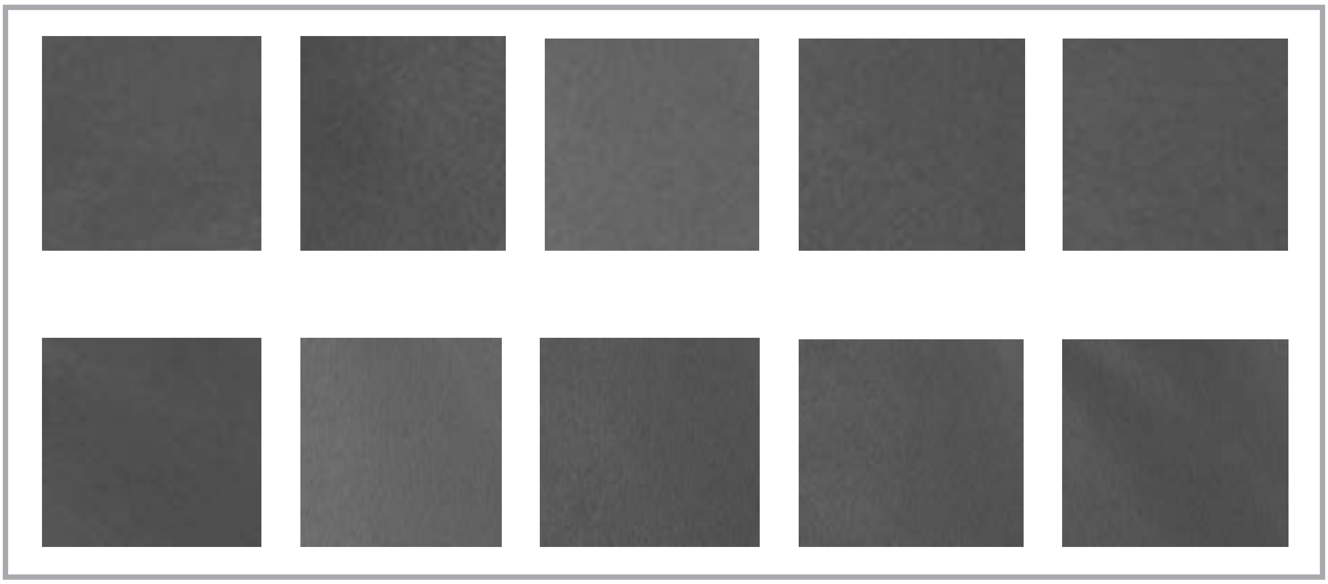

Figure 1. *Textile images.*

weight function to reflect the changes in tolerance with the hue of the colour, and (4) an ellipse selection option to reflect the blue region. The colour difference tolerance ellipse does not point to the centre point.

Algorithm flow

We propose a colour difference classification model for textile images based on the DE algorithm with DPS to optimizes the output RELM; the model is in accordance with the national colour difference evaluation standard [4] to classify the colour difference of textile images. The main steps are as follows:

(1) Under standard lighting, we capture the same textile image (***Figure 1***) for experimental analysis.

(2) One of the textile images is used as a template image and the others as test images. Considering two of them, we specifically elaborate on the process of colour difference calculation.

(3) The captured images are improved by a median filter, which uses 3*3 templates, removing the noise in the images.

(4) After the filtration process, the image is changed from the RGB color space to the HSV color space. Then, we calculate ΔH, ΔS, and ΔV characteristic values.

(5) Next, the image is changed from the RGB colour space to the tri-stimulus colour space, and then we calculate the tri-stimulus values, X, Y, and Z, respectively.

$$\begin{cases} X = 0.4124*r + 0.3575*g + 0.1804*b \\ Y = 0.2128*r + 0.7152*g + 0.0722*b \\ Z = 0.0193*r + 0.1192*g + 0.9502*b \end{cases} \tag{4}$$

where X_n, Y_n, and Z_n denote the tri-stimulus values under ideal illumination; the three attribute values are set up in the reverse Hamming coordinate theory. Then, ΔL, Δa, and Δb of the two images are calculated.

(6) Using CIEDE2000, the colour difference value of the two images is calculated.

I: L', a', b', and h calculations.

In this study, $L' = L$, $b' = b$, and $a' = (1 + G)*a$.

Here

$$G = 0.5*\left\{1-[(\frac{c+c_s}{2})^7 / \sqrt{(\frac{c+c_s}{2})^7 + 25^7}\,]\right\} \tag{5}$$

Where, $c=\sqrt{a^2+b^2}$ denotes the template image, $c_s=\sqrt{a_s^{\,2}+b_s^{\,2}}$ denotes the test image, $h = \tan^{-1}(b'/a')$, and h represents the hue.

II: ΔL, ΔC, and ΔH calculations.

$\Delta L = L' - L_s'$, $\Delta C = c - c_s$, and $\Delta H = h - h_s$, where ΔL the luminance difference, ΔC the chrome difference, and ΔH the hue difference.

III: Colour difference calculation.

$$\Delta E = [(\Delta L/K_L \cdot S_L) + (\Delta C/K_C \cdot S_C)^2 + (\Delta H/K_H \cdot S_H)^2 + rt(\Delta C/K_C \cdot S_C)(\Delta H/K_H \cdot S_H)]^{1/2} \tag{6}$$

(7) Steps (3), (4), (5), and (6) are repeated, as a result of which, the colour difference data set comprises the colour difference ΔE and represents colour difference values of ΔH, ΔS, ΔV, ΔL, Δa, and Δb. The color difference data set is a group of 500*6; then, the DPS-DE-RELM algorithm is used to classify the colour difference.

Experimental results and discussions

For different optimisation problems, different mutation strategies and parameter combinations are required to determine the global optimal value and the least optimal time. We randomly selected 470 groups of trained data from the total data set and selected the remainder as test data. In the optimisation process of the DE algorithm, we adopted the DPS strategy and selected the optimal parameter combination. Five mutation strategies were selected: DE/best/1, DE/rand/1, DE/rand-to-best/1, DE/best/2, and DE/rand/2. A large number of experiments showed that when $NP \in [5D, 10D]$, $CR \in [0.8, 1]$, and $F \in [0.5, 0.9]$, the DE algorithm easily converges to the global optimal value. Then, in this study, the population size (NP) was 8D, and the number of hidden neurons (L) was 40. The crossover probability (CR), scaling factor (F), and mutation strategies were dynamically selected. Various parameter combinations of the DE algorithm are listed in ***Table 1***.

As listed in ***Table 1***, we define the DE algorithm with different combinations of

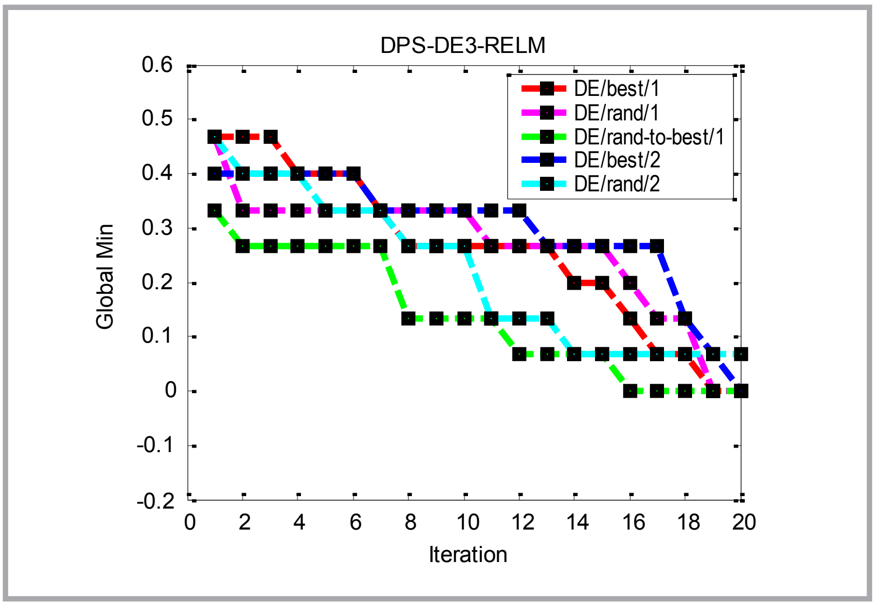

Figure 2. *Convergence condition of DPS-DE3-RELM with different mutation strategies.*

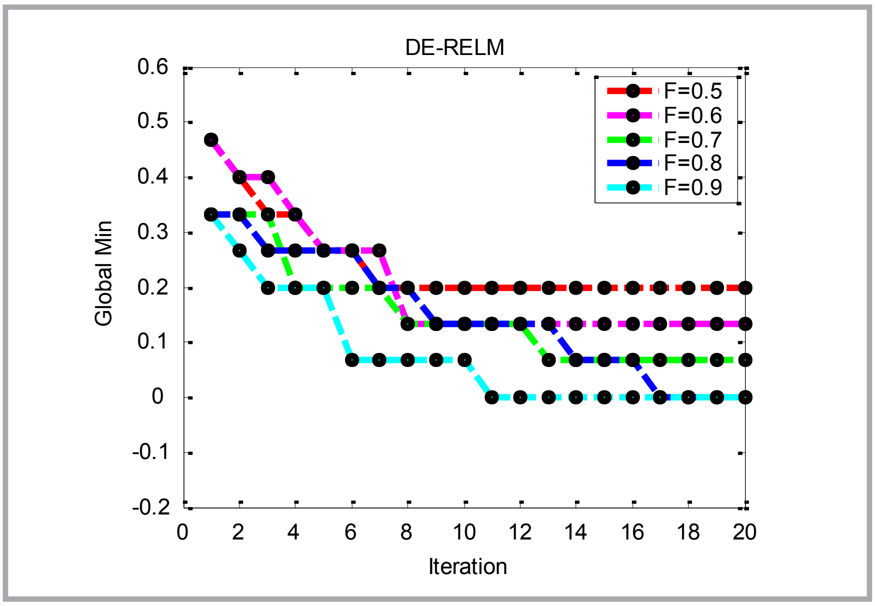

Figure 3. *Convergence condition of DE-RELM with different F values.*

CR and F: DPS-DE1, DPS-DE2, DPS-DE3, DPS-DE4, DPS-DE5, DPS-DE6, and DPS-DE7. First, DPS-DE1, DPS-DE2, and DPS-DE3 are used to optimise the original ELM and output RELM; the results under different mutation strategies are compared, and then the best mutation strategy for the optimisation problem is selected. Second, DPS-DE4, DPS-DE5, DPS-DE6, and DPS-DE7 are used to optimise the original ELM and output RELM and select the best scaling factor (F). Finally, the optimal parameter combinations for the problem in this study are selected. The results are 10 times the average. The DE algorithm is used to optimizes the original ELM because there is no regularisation parameter in the process of calculating output weights. It requires considerable time for optimisation and falls into the local best problem; the testing accuracy is low. Even if the output weights are part of the illness solution, there is a large gap between the results obtained under the different conditions, and the output weights are large. Under this condition, the generalisation performance of the algorithm is poor. In the training phase, the training accuracy is high, but the testing accuracy is very low. When the DE algorithm optimises the output RELM, the searching time is short and the testing accuracy high. In this situation, the output weights are relatively stable and close to the optimal solution. Aiming at optimisation problems in this study, we can obtain better classification accuracy under the DE/rand-to-best/1 strategy; the best classification accuracy is obtained when the combination includes CR = 1 and F = 0.9, and the mutation strategy is DE/rand-to-best/1. Then, CR = 1 remains unchanged, while the scaling factor (F) changes. The results of DPS-DE4, DPS-DE5, DPS-DE6, and DPS-DE7 are used to optimizes the original ELM and compared with those of DPS-DE4, DPS-DE5, DPS-DE6, and DPS-DE7, which are used to optimise the output RELM. Considering the best scaling factor (F) of this study, we can determine the optimal parameter combination for the optimisation problem.

The original DE-algorithm-optimised ELM still has the problem of long searching time; the testing accuracy is low, and yields an illness solution with respect to β. It is clear that the generalisation performance of the algorithm is poor with high training accuracy, while the testing accuracy is low. Moreover, there is a problem of overfitting; the classification accuracy is 100%. The DE algorithm optimises the output regularisation ELM; the training accuracy and test accuracy are consistent and high. In the case of CR invariant, by changing the values of F, we can still obtain high testing accuracy under the DE/rand-to-best/1 strategy. The highest classification accuracy is obtained at F = 0.9. Therefore, the larger the F value, the higher the classification accuracy. Aiming at the problem of this study, the algorithm of the best parameter combination is DPS-DE3+DE/rand-to-best/1. Using DPS, the optimal algorithm is selected.

When NP = 8D, the global convergence condition of the DPS-DE3 algorithm optimises the output regularisation ELM under different strategies (***Figure 2***). When NP = 8D, CR = 1 and the mutation strategy is DE/rand-to-best/1, the global convergence condition of the DE algo-

Table 1. *DE algorithm with different parameter combinations.*

DPS-DE1	DPS-DE2	DPS-DE3	DPS-DE4	DPS-DE5	DPS-DE6	DPS-DE7
CR = 0.8	CR = 0.9	CR = 1	CR = 1	CR = 1	CR = 1	CR = 1
F = 0.9	F = 0.9	F = 0.9	F = 0.5	F = 0.6	F = 0.7	F = 0.8

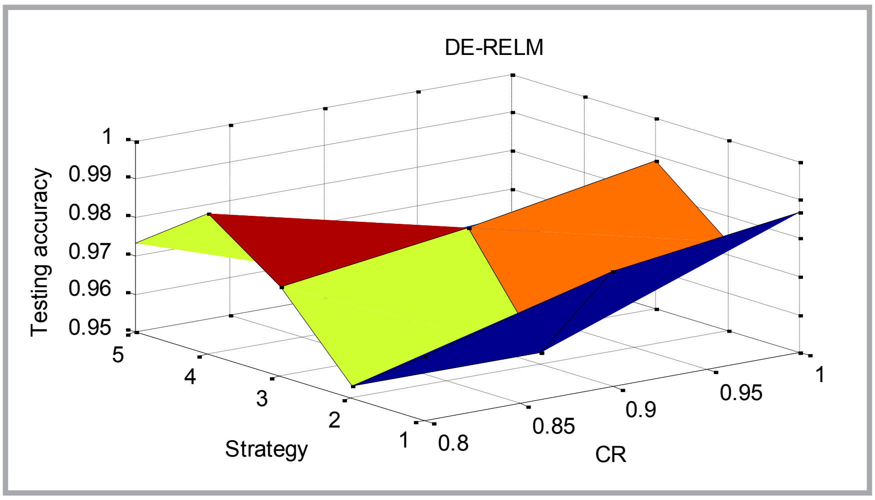

Figure 4. *Testing accuracy of DE-RELM.*

rithm optimises the output RELM under different strategies (***Figure 3***). When NP = 8D, F = 0.9, and *CR* ∈ [0.8, 1], the three-dimensional graph regarding testing accuracy for the DE algorithm optimises the output RELM (***Figure 4***).

The DE algorithm does not easily converge during the optimisation of the original ELM, while the DE algorithm optimises the output RELM and converges to the global optimum. In the case of DE/rand-to-best/1, the optimisation problem in this study has a robust convergence characteristic. The optimal parameter combination algorithm is verified as DPS-DE3+DE/rand-to-best/1.

Under the same control condition, the convergence of two conditions is generally consistent. The smaller the scaling factor F, the more it becomes difficult to converge, and it is easier to fall into the local optimum. The curves for F = 0.8 and F = 0.9 are the same and both converge to the global optimisation. However, in the initial phase of convergence, there is a problem of instability and volatility. Meanwhile, it is proven that F = 0.9 satisfies the best parameter combination.

Based on the optimisation problems, the population size (NP), crossover probability (CR), scaling factor (F), and mutation strategies are dynamically selected. In this study, we set a group of mutation strategies: DE/best/1, DE/rand/1, DE/rand-to-best/1, DE/best/2, and DE/rand/2, considering the optimal range of parameters defined as CR ∈ [0.8, 1], and F ∈ [0.5, 0.9]. The parameter setting influences the accuracy of the colour difference classification model. Therefore, the optimal parameter combination can obtain the best classification model. As shown in ***Figure 4***, the testing accuracy of the DE algorithm better optimises the output regularisation ELM compared with the original ELM. The former can achieve the highest classification accuracy of 98.87% and the latter 84.67%. Furthermore, we can see that the optimal parameter combination is NP = 8D and DPS-DE3+DE/rand-to-best/1; both problems yield the highest classification accuracy.

In this study, the DE algorithm based on the DPS strategy of the optimal RELM method performs better than the traditional ELM. First, the input weight and hidden layer bias of the limit learning machine are obtained using iterative optimisation with the global searching ability of the DE algorithm. Meanwhile, as the traditional ELM considers empirical risk when calculating the output weight, regularisation parameters representing structural risk are introduced to prevent the generation of the illness solution matrix. Finally, the DPS method is adopted to select the optimal parameter combination model of the DE algorithm and construct the optimal colour difference classification model.

Conclusions

The DE algorithm model is proposed to optimise the output regularised ELM for the colour difference classification of textiles, which is based on the DPS strategy, and a complete colour difference classification model is established. In this study, in the DE iterative optimisation process, the DPS strategy is adopted to select the optimal parameter combination. The experimental results show that the RELM optimised by the DE algorithm can converge to the global optimal value; the optimisation process consumes less time, and the accuracy is high. In the case of DPS-DE3+DE/rand-to-best/1, the classification accuracy is the highest.

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