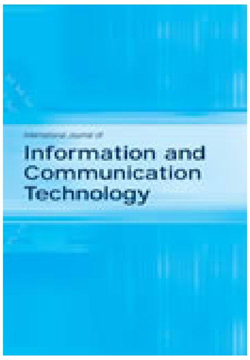


International Journal of Information and Communication Technology

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

Intelligent classification of oil painting style based on dynamic fuzzy neural network

Tianyi Xiao

DOI: 10.1504/IJICT.2025.10073282

Article History:

Received:	20 May 2025
Last revised:	07 June 2025
Accepted:	08 June 2025
Published online:	26 September 2025

Intelligent classification of oil painting style based on dynamic fuzzy neural network

Tianyi Xiao

Art School,
Wuhan University of Bioengineering,
Wuhan, 430000, China
Email: wsy20250225@163.com

Abstract: This article presents a dynamic fuzzy neural network (DFNN)-based intelligent classification approach for oil painting styles. When it comes to images like oil painting styles, which are high-dimensional, sophisticated and feature a lot of fuzzy elements, traditional oil painting style classification techniques still provide difficulties. DFNN teaches the deep features of oil painting images from data automatically by combining fuzzy logic and neural networks. Moreover, the dynamic learning mechanism of DFNN helps it to dynamically modify its structure and parameters in response to changes in the training data, hence preserving excellent classification accuracy in the face of new oil painting styles or style evolution. The testing results reveal that the technique greatly surpasses the conventional one in many respects, thereby offering fresh technical assistance for the automatic identification of oil paintings and other sectors.

Keywords: oil painting style classification; dynamic fuzzy neural network; DFNN; intelligent classification; feature extraction; dynamic learning.

Reference to this paper should be made as follows: Xiao, T. (2025) 'Intelligent classification of oil painting style based on dynamic fuzzy neural network', *Int. J. Information and Communication Technology*, Vol. 26, No. 34, pp.82–99.

Biographical notes: Tianyi Xiao received her Master's degree at Hubei Institute of Fine Arts in June 2013. She is currently a Lecturer in the College of Art at Wuhan University of Bioengineering. Her research interests include oil painting, contemporary art, machine learning and dynamic learning.

1 Introduction

1.1 Research background and significance

Particularly in image processing and analysis, the application of computer vision and artificial intelligence technology in many spheres has gotten more and more broad as information technology advances constantly. In the realm of computer vision, artwork analysis, especially the style recognition of oil paintings, has always been a vital and demanding study direction (Castellano and Vessio, 2021). Oil painting is a very artistic and expressive kind of visual art with a range of genres including but not limited to Realism, Impressionism, Abstraction, etc. These styles have not only different expressions but also special qualities in terms of colour, composition, brushwork, and so on. Thus, the question of how best to categorise the styles of oil paintings is both a matter of intellectual worth and a significant concern in pragmatic use. Strong support for artwork identification, cultural heritage preservation, art production analysis and other sectors can come from accurate classification of oil painting genres.

Although manual feature extraction and rule-based classification algorithms form the foundation of most traditional oil painting style classification systems, their inherent shortcomings are clear. Manual feature extraction cannot adequately handle the diversity and complexity of oil painting techniques and sometimes misses completely the underlying information of the image (Zhao et al., 2022). While current deep learning-based image classification techniques show considerable success on large-scale datasets, they still have difficulties with high-dimensional, complicated images including a lot of fuzzy features including painting styles. These difficulties are mostly shown in the model's low generalisation capacity and lack of robustness as well as in the difficulty of catching minute variations between styles.

In this context, fuzzy neural networks (FNN), as a hybrid intelligent algorithm combining fuzzy logic with neural networks, have attracted a lot of interest recently (Pezeshki and Mazinani, 2019). By means of a dynamic adjustment mechanism, dynamic fuzzy neural network (DFNN) which is an extension of FNN is able to have more adaptability in handling uncertainty and ambiguity. By dynamically adjusting the network structure and parameters, DFNN can continuously change environment to learn the artistic aspects of oil paintings and considerably increase the classification accuracy (Kim et al., 2019). Especially in the face of higher stylistic diversity and uncertainty, DFNN demonstrates more outstanding classification results and has more nonlinear modeling power than conventional approaches, which helps to effectively capture complicated artistic style elements in oil paintings.

This work is intended to create a fresh intelligent classification system based on DFNN for oil painting styles. An effective and strong oil painting style classification model is developed by extensively investigating the visual and stylistic aspects of oil painting images and merging the adaptive ability and fuzzy processing mechanism of DFNN. Apart from increasing the accuracy and efficiency of oil painting style classification, the approach offers fresh concepts and technical support for the application in the domains of automatic identification of oil painting artworks, art style analysis, digital art preservation and so on. As this method is constantly improving and developed, it should have significant effects on the management of cultural legacy and preservation of art.

1.2 Research questions and innovations

This work is focused on the intelligent classification problem of oil painting styles and aims to solve numerous technological challenges typical in artistic categorisation. First of all, the variety of techniques in oil painting as a medium makes it challenging for conventional image categorisation systems to handle its complexity and unpredictability. Oil paintings represent not just the artist's creative notion, emotional expression, and other abstract level aspects but also their stylistic qualities in visual features including shape, colour and texture. Thus, one of the main concerns of this work is how best to extract the multi-level stylistic elements of oil paintings, particularly about handling the identification of minute variations between several styles.

Second, the uncertainty of image features is another crucial problem in oil painting technique categorisation. While oil paintings generally include complicated textures, colour transitions, and hazy local details, which makes it challenging for previous approaches to precisely capture these blurred elements, standard computer vision algorithms usually depend on obvious and unambiguous features for categorisation. Conversely, DFNN has a special advantage in handling data with uncertainty and ambiguity and can better adapt to these complex visual features by means of fuzzy rules and neural networks, therefore enhancing the accuracy and resilience of classification.

Furthermore, current oil painting style classification systems sometimes only consider static analysis, therefore neglecting the artistic progress and dynamic elements that artworks could show across time. DFNN's dynamic learning capacity helps it to adapt to such changes; by always changing and optimising the network topology, the model can keep good classification performance when using fresh or unexplored oil painting techniques. Consequently, one of the developments of this work is how to connect the dynamic adjustment mechanism of DFNN with the issue of oil painting style classification.

The originality of this work is:

1. An oil painting style classification method based on DFNN is proposed: By combining fuzzy logic and neural networks, DFNN is able to automatically learn the deep aspects of oil painting images from data. It particularly shows a special advantage in fuzzy and challenging-to-quantify artistic features including texture, colour transitions, and brush strokes. Consequently, a more intelligent and effective solution for the oil painting picture classification problem is given by the DFNN-based oil painting style classification approach suggested in this work.

2. Introduction of dynamic learning mechanism: In this work, a dynamic learning mechanism of DFNN is proposed. This mechanism helps the network to dynamically modify its structure and parameters in response to changes in training data, so enabling the model to be continuously optimised during the training process and preserve high classification accuracy in face of new oil painting styles or style evolution, so greatly improving the accuracy and dependability of oil painting style classification.

3. Combining oil painting art features with computer vision technology: This work allows the model to pay more attention to the fuzzy features and uncertainties in oil paintings, so improving its sensitivity to artistic features and offers a more complete and artistically valuable perspective for oil painting style classification by introducing the fuzzy logic mechanism of DFNN. This invention not only raises the model's classification accuracy but also offers fresh methodological assistance for digital analysis, conservation, and artwork identification.

By means of the foregoing developments, this work intends to offer a fresh solution in the field of intelligent classification of oil painting styles and thereby advance the field towards greater accuracy and wider application.

2 Related technology and theoretical basis

2.1 Intelligent classification of oil painting styles

Aiming to automatically recognise the artistic styles of oil paintings by computer algorithms, intelligent categorisation of oil painting styles is a hot issue in the field of computer vision. Traditional image classification techniques find several difficulties in oil painting style recognition given the variety and intricacy of oil painting techniques. Researchers have tried several sophisticated algorithms in the oil painting style classification issue to overcome these challenges. Each of these algorithms offers unique ideas and methods for the classification of oil painting styles, together with different advantages and drawbacks.

Conventional approaches of classifying traditional oil painting styles mostly depend on hand extraction of image elements including morphological, colour, and texture aspects (Kumar et al., 2019). Classical machine learning algorithms include support vector machine (SVM), K-nearest neighbour algorithm (KNN), etc., identify the images using these hand-operated characteristics. Appropriate for high-dimensional data, SVM uses construction of a hyperplane in a high-dimensional space to classify data. SVM has been used, for instance, to differentiate impressionist from realist style paintings by extracting their local textural characteristics and colour distribution, therefore obtaining effective style differentiation (Gultepe et al., 2018). Using colour and texture data, KNN has been used to classify painting styles, therefore separating modern artworks from impressionist paintings. KNN has simple implementation and does not call for a training process, which are benefits; the drawbacks include Particularly in cases of a big dataset, high computational complexity will greatly lower the classification efficiency. Furthermore, sensitive to noise and outliers, KNN may influence the classification result accuracy should aberrant samples exist in the dataset.

Deep learning, especially convolutional neural network (CNN), has been extensively applied in oil painting style classification to overcome the limits of conventional approaches. By automatically extracting features from images, CNNs eliminate the restrictions of hand feature selection. By means of multi-layer convolutional layers (Du et al., 2020). CNNs automatically learn low-level to high-level features of an image, e.g., in identifying Impressionist and Post-Impressionist oil paintings, they can efficiently extract the features such as brush strokes, colour distribution, structural layout, etc. in oil paintings, thus helping the classifier to distinguish between different oil painting styles. Deep learning techniques often demand a lot of labelled data for training; hence the oil painting style dataset is rather under-labelled, and the model is less competent of generalisation in some circumstances.

Generative adversarial networks (GANs) have been progressively implemented as a generative model to improve oil painting style classification models even more. Two networks in adversarial training constantly optimise GANs; this helps the generator to produce oil painting images with certain styles while the discriminator improves the classification effect by separating the produced images from the real images. In another research, for instance, GAN has been used to create oil painting images with various styles, such Impressionist and Cubist style oil paintings, which is utilised to increase the training dataset and improve the style recognition capacity of the classifier (Bengamra et al., 2024). Image style migration has also been done using GAN; for instance, an oil painting in the realism style can be converted into an impressionist style oil painting, therefore offering a range of styles of data for the training of oil painting classifiers. Image style migration has also made advantage of GANs. Nevertheless, especially in oil paintings with minor artistic variations, the training process of GAN is more complicated and prone to instability; so, the produced samples may suffer from stylistic distortion or inconsistency, which could influence the classification outcomes. GAN also frequently takes a lot of processing resources and a protracted training period.

Given the great uncertainty of oil paintings itself, conventional deep learning techniques and generative models could not be able to sufficiently capture these ambiguous transition signals. FNNs have surfaced to solve this issue. Combining fuzzy logic with neural networks, FNNs handle uncertainty and ambiguity in images during the classification process. FNN has been used, for instance, to classify changes in oil painting techniques, that is, to address minute variations between Impressionist and Expressionist approaches. FNN learns by employing neural networks to adjust to intricate art style traits and explains ambiguity through fuzzy rules (Zheng et al., 2021). Conversely, DFNN is a development of FNN that can dynamically change the fuzzy rules based on input image attributes to enhance the oil painting style transition recognition capacity. For instance, dynamically changing the network parameters helps DFNN to more precisely capture these small stylistic variations while identifying oil paintings in Baroque and classical forms. Although FNNs and DFNNs can efficiently handle uncertainty, their performance is still restricted by the design of fuzzy rules, which takes a lot of a priori knowledge to ascertain the rules and may still suffer from overfitting when confronted with complex styles.

At last, integrated learning approaches have also showed good success in oil painting style classification. Combining the prediction findings of several classifiers helps integrated learning to increase the accuracy and robustness of categorisation. Effective in lowering the bias potentially induced by a single classifier, common integrated learning techniques include random forest (RF) and gradient boosting decision tree (GBDT). RF has been used, for instance, to categorise several oil painting genres where researchers have enhanced the accuracy and stability of categorisation by combining the outputs of several decision trees. Furthermore, extensively used in oil painting style classification is GBDT, which weightedly averages the outputs of several base classifiers so improving classification accuracy (Fakayode et al., 2024). When dealing with the issue of dataset imbalance where varied base classifiers balance the distribution between categories, the integrated learning strategy is especially suited. But especially in large-scale data, the integrated learning strategy has a significant computing overhead; it also depends on the quality and variety of the base classifiers and has a long training period.

2.2 Overview of dynamic fuzzy neural network

Excellent performance in handling uncertainty, ambiguity, and complex datasets is shown by DFNN, a potent model combining fuzzy logic with neural network approaches. Particularly shows great degree of accuracy and adaptability in classification tasks, DFNN is able to efficiently cope with the restrictions of conventional neural networks in handling fuzzy input. DFNN is fundamentally based on the introduction of a fuzzy inference mechanism using fuzzy rules with affiliation functions to handle the ambiguity of input data and subsequent rule modification depending on neural network learning capacity to maximise the decision-making process.

Three fundamental layers define its structure: the layer of fuzzification, the layer of rule inference, and the defuzzification layer.

First, the layer of fuzzification converts the input data into fuzzy affiliation values. By means of the affiliation function, defuzzification maps the input features to predefined fuzzy sets and ascertains the degree of membership of the input features to a certain fuzzy set (Pazhoumand-Dar, 2019). For instance, the affiliation function $\mu_A(x)$ of an input data point x shows the degree of its belonging to the fuzzy set A. This mechanism enables the network to keep a high degree of resilience under unclear or partial knowledge. The affiliation value of every input feature about various fuzzy sets results from the fuzzification layer.

The rule inference layer follows, in which the DFNN makes decisions and computation using fuzzy logic inference rules. In this layer, the network reasons about the affiliation of the incoming data using fuzzy inference results are produced depending on fuzzy rules. The capacity of the DFNN to dynamically modify the rules and the affiliation function to various input data reflects in this layer its dynamics (Han et al., 2021). By means of optimal learning process, the network continuously modifies the fuzzy rule parameters, therefore enhancing the performance of the model. When confronted with various datasets, this function lets the DFNN dynamically change the inference rules and the affiliation function to better manage complicated data with uncertainty and ambiguity.

Conversely, the layer of defuzzification oversees turning the fuzzy inference results into definite outputs. Usually stated as affiliation degrees, fuzzy inference results are converted by the defuzzification process into either number values or category labels (de Oliveira Gomes and Basilio, 2023). The final output can be computed, for instance, using standard defuzzification methods including a weighted average method and maximum affinity approach. Commonly employed for category label prediction in classification problems, the defuzzification process marks the last stage of DFNN and generates explicit choice outputs based on fuzzy reasoning results.

Usually, the fuzzy rules of DFNN can be stated by the following mathematical formula:

$$R_i : \text{IF } x_1 \text{ is } A_1 \text{ AND } x_2 \text{ is } A_2 \text{ THEN } y_i = w_1 \cdot x_1 + w_2 \cdot x_2 \tag{1}$$

where R_i indicates the i^{th} fuzzy rule; x_1 and x_2 are the input features; A_1 and A_2 are the fuzzy sets matching the input features; y_i is the inference result; w_1 and w_2 are the weight coefficients of the rules. Based on the weight of the rules and the affiliation of the input features, this formula explains how the fuzzy rules generate the ultimate output. DFNN can produce reasonable classification results depending on the vagueness and uncertainty of the input data by means of these fuzzy rules (Yazdinejad et al., 2023).

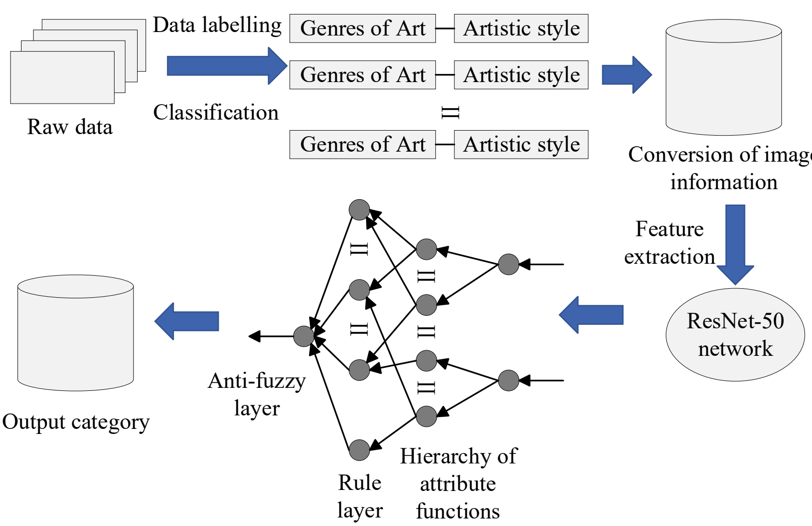
Apart from the fuzzy rules, the DFNN possesses neural network characteristics which enable it to be trained by a back-propagation technique to maximise the weights of the fuzzy rules and the network parameters. By reducing the error function, the DFNN changes the parameters of the network during the training process therefore enabling the network to better fit the characteristics and patterns of the data input (Data and Aritsugi, 2021). Although DFNN uses the principle of fuzzy inference in the training process, which makes it able of handling more complicated fuzzy input, this procedure is similar to conventional neural network training.

Generally speaking, DFNN is an intelligent model that combines the benefits of fuzzy logic and neural networks to efficiently handle complicated and fuzzy data; it is particularly appropriate for handling classification problems including uncertainty and fuzzy transitions.

3 Design of an intelligent classification method for oil painting styles

There are four layers to this clever classification system for oil painting techniques; see Figure 1. First is the layer of data preparation in charge of image improvement and standardisation. The layer of feature extraction comes next, using convolution and pooling to extract the image's colour, texture, and other elements. The layer of style recognition and classification follows to arrange the obtained features into styles. At last, there is the result output layer, which converts the classified data into particular style labels. By means of cooperation among these four levels, intelligent classification of oil painting techniques is accomplished.

Figure 1 Oil painting style intelligent classification method (see online version for colours)



3.1 Data preprocessing layer

The intelligent classification approach for oil painting styles depends critically on the data preprocessing layer, which mostly processes the input oil painting photos to guarantee that the images can be adjusted to the subsequent feature extraction and classification procedure. To increase the consistency, robustness, and diversity of the image data, one must perform a sequence of operations on the image including resizing, normalisation and enhancement since the quality of the preprocessing stage directly influences the training effect of the model and the classification accuracy.

Image resizing is the first fundamental phase of data preparation. All oil painting photos must be downsized to the same size since neural networks often want input images to have similar proportions. Resizing successfully helps the model to process all photos with the same input data and avoids the issue of inconsistent sizes that would hinder the model from processing them by reducing the variations between images.

Picture standardisation is also another important operation meant to normalise the pixel values of a picture so that they have uniform distribution features, therefore accelerating the neural network's training process and enhancing the training results. Two typical approaches define normalisation usually: one is to scale the pixel values to the range of [0, 1], and the other is to use Z-Score normalisation to convert the data into a distribution with mean 0 and standard deviation 1 (Friedman and Komogortsev, 2019). One can obtain the first approach with the following equation:

$$X_{\text{scaled}} = \frac{X}{255} \tag{2}$$

where X_{scaled} is the scaled pixel value and X denotes the image's pixel value. This approach limits the range of pixel values to between [0, 1], thus enabling constant scaling of the input data, so accelerating network training and enhancing model convergence. Z-Score normalisation with the following formula is another standardisation technique:

$$X_{\text{norm}} = \frac{X - \mu}{\sigma} \tag{3}$$

where the mean value of the picture data is μ; the standard deviation is σ; the pixel value following normalisation is X_{norm}. This approach can eliminate the bias in the data, make the pixel values in the dataset more consistently distributed, and prevent elements including brightness and contrast of various photos influencing the learning process of the model.

Another crucial preprocessing stage towards increasing the generalisation capacity of the model is data augmentation. By means of rotational, translational, flipping, cropping, etc., data augmentation transforms the original image to produce several variants of the image, therefore increasing the diversity of the dataset (Shorten and Khoshgoftaar, 2019). The improved images can prevent the model from overfitting issues during training and enable it to better learn the characteristics of several styles of oil paintings. For instance, the rotation transformation can be written as follows equation:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{4}$$

where (x, y) is the point's location in the image; (x', y') is its new location upon rotation; θ is the rotation angle. Rotating the picture helps the model to learn how the oil painting technique is portrayed from several angles, thereby improving its capacity to adjust to style variations. By use of these techniques, the intelligent classification system for oil painting styles may be taught more effectively and exhibit higher accuracy and resilience in pragmatic uses.

3.2 Feature extraction layer

Extraction of discriminative features from oil painting images by means of the ResNet-50 model is the essential phase in the intelligent classification approach for oil painting styles. Resizing the image to fit the network input requirements and pixel normalisation to guarantee that all input images have the same mean and variance helps to improve the stability of the training first, before the input image is fed into the network.

Once preprocessed, an image is sent into the ResNet-50 network, a deep CNN mostly extracting picture characteristics via several convolutional and pooling layers (Wen et al., 2020). From low-level edges and corner points and more complex texture, form, and even style aspects, the convolutional algorithms in every layer oversee extracting various levels of features from the image. Whereas a deeper convolutional layer will be able to catch brushstrokes, brushwork, and the subtle layers of an oil painting, a primary convolutional layer will capture the fundamental edge and texture information in an oil painting image. The convolution operation has as its mathematical formula:

$$F = C_n\left(C_{n-1}\left(\ldots C_1(I)\right)\right) \tag{5}$$

where F is the extracted feature map; I is the input canvas image; C_n is the individual convolutional layer from input to output, each of which responds to a small area of the image by weighted summation, therefore capturing information at different levels.

ResNet-50 overcomes the gradient vanishing issue in addition to the convolutional layers by adding residual connectivity when the network's depth rises, therefore enabling the network to learn intricate visual features in ever greater depth. This approach guarantees that even if the network structure is somewhat deep, it can still efficiently learn the higher-order elements of a picture, especially when handling delicate and complicated images such oil paintings, to extract more expressive style features.

ResNet-50 creates a high-dimensional feature vector including information on the features at all levels in the image following the image has been extracted through the convolution and pooling layers (Kılıçarslan et al., 2023). Next classification activities will draw on this feature vector. Integrating these elements is the responsibility of the completely linked layer, which generates a feature vector reflecting the painting's style at last. The feature vector is produced with this formula:

$$F_{\text{final}} = W \cdot F + b \tag{6}$$

where F_{final} is the last feature vector following the fully connected layer; F is the intermediate feature extractive from the convolutional layer; W and b are the weight and bias of the fully connected layer, respectively. This feature vector combines the texture, colour, structural and style information in the oil painting image, therefore adequately expressing the artistic qualities of the oil painting and offering enough discriminative information for the next classifiers.

3.3 Style recognition and classification layers

By means of DFNN, this layer achieves important style identification and classification. First, the DFNN is fed the high-dimensional feature vectors obtained from the previous layer. Its foundation is the fundamental idea of building a set of fuzzy rules based first on the features retrieved from the preceding layer. Usually in the form of a rule stating, if the picture characteristics adhere to a given pattern, then its style is of a certain category, each fuzzy rule explains the style of an oil painting image depending on its features. These guidelines reason regarding the input features using a fuzzy affiliation function, which measures the fuzzy metric of every feature to derive a fuzzy output. One may visualise the inference process as follows:

$$\mu_i(x) = \frac{1}{1 + e^{-(x - c_i)/\sigma_i}} \tag{7}$$

where c_i is the centre of the rule; $\mu_i(x)$ is the affiliation of input feature x with fuzzy rule i; σ_i is the width of the fuzziness. This affiliation role enables DFNN to evaluate the degree of match between the input features and every fuzzy rule.

These fuzzy outputs will then be input into the neural network for training; the output of the network is the prediction result of style categorisation at last. One may show the neural network's processing as follows:

$$Y_{\text{class}} = W \cdot \mu\left(F_{\text{feature}}\right) + b \tag{8}$$

where Y_{class} is the style classification result; W is the weight in the neural network; $\mu(F_{\text{feature}})$ is the affiliation degree derived following fuzzy inference; b is the bias term. This formulation allows the DFNN to combine the benefits of fuzzy rules and neural networks to offer accurate classification in the challenging job of oil painting style classification.

The DFNN produces ultimately a classification result indicating oil painting styles that will be mapped to oil painting style categories (e.g., Impressionist, Abstract, etc.). By means of this method, the system completes the duty of style recognition and categorisation and can precisely assign related style labels to every oil painting image.

3.4 Result output layer

The result output layer in the intelligent classification method of oil painting style is in charge of mapping the outcomes of the previous layer of style recognition and classification to oil painting style categories and producing the final classification results. Based on the feature vectors and classification results generated from the previous layer, the system will produce the final style classification labels in this layer using appropriate post-processing procedures (Sajid et al., 2019). Usually involving translating the identified style categories to predefined oil painting style labels, this process outputs them to the user or other systems for next use.

The DFNN produces a feature vector or probability distribution via a classification network in the output of the style recognition and classification layer, therefore reflecting the likelihood of every style category. This leads the resulting output layer to choose the category with the highest probability, hence guiding the final style classification choice. The maximum probability selection allows one to depict the final classification result assuming that the output of the system is a vector P with the probability of every style category:

$$P = \left[p_1, p_2, ..., p_k\right] \tag{9}$$

$$Y_{\text{final}} = \arg\max_i\left(p_i\right) \tag{10}$$

where p_i is the likelihood of belonging to category i; arg max is the choice of the category index with highest probability; Y_{final} is the final output classification result, hence, the style category label of the oil painting.

Furthermore, the system can employ a soft output approach to create the probability distribution of every category and apply the cross-entropy loss function to maximise the classification impact so guaranteeing the correctness and stability of the outcomes. With this formula, the difference between the real labels with the cross-entropy loss function and the probability distribution output by the model is measured:

$$L = -\sum_{i=1}^{k} t_i \log\left(p_i\right) \tag{11}$$

where L is the loss value; t_i is the one-hot encoding of the actual label; p_i is the model's projected probability value. Reducing the loss function helps the system to progressively improve the classifier thereby guaranteeing more accurate final style classification results (Jiang et al., 2021).

By means of these two formulations, the system not only precisely detects the painting's style but also constantly enhances the classification accuracy via optimisation procedure. The output layer will eventually provide a clear oil painting type label, guaranteeing the stability and efficiency of the overall categorisation system.

4 Experimental results and analyses

4.1 Experimental data

The experimental dataset for this work was selected from the WikiArt collection for the job of oil painting style classification. Particularly suited for style identification and classification activities, the WikiArt dataset includes artworks from several genres and styles. Most of the items in the dataset are labeled with style tags; they comprise works from many historical eras and artistic genres. Among the labels are, but are not limited to, impressionism, realism, abstraction, expressionism, etc. The dataset spans several genres, hence there could be discrepancies or several classifications for the stylistic categorisation of some works. The dataset helps to evaluate the efficacy of the suggested strategy in practical problems and facilitates efficient training of multi-class stylistic categorisation.

Table 1 lists some oil paintings in the WikiArt collection together with their fundamental details.

Table 1 WikiArt dataset

Artist	*Style*
Claude Monet	Impressionism
Pablo Picasso	Cubism
Vincent van Gogh	Post-impressionism
Edgar Degas	Realism
Jackson Pollock	Abstract expressionism
Henri Matisse	Fauvism

4.2 Methodological training and evaluation

Several rounds of training and optimisation were first carried out during the model development and evaluation phase to guarantee that the model could efficiently understand the aspects of oil painting techniques. Combining a cross-entropy loss function with an Adam optimiser to modify the network weights and data augmentation, early halting strategy and L2 regularisation to prevent overfitting, the training process was run. With a 70% 15% ratio, the dataset comprised a training set, a validation set, and a test set. Model training uses the training set; hyperparameter tweaking makes use of the validation set; final evaluation of the model performance comes from the test set. Before entering the model to guarantee data consistency, all photos were consistently scaled and normalised.

Both quantitative and qualitative evaluations were applied in the model assessment period. Two focused metrics are first computed in the quantitative evaluation to extensively examine the model performance in the task involving oil painting style classification.

Particularly in assignments with a high degree of style overlap, the Class Difference metric helps to evaluate the variability between several style groups and indicates whether the model can clearly separate between them (Rutherford et al., 2022). Usually, this statistic is computed by averaging the Euclidean distances or similarity between samples from several groups:

$$\text{Class Difference} = \frac{1}{N}\sum_{i,j}\left\|C_i - C_j\right\| \tag{12}$$

where N is the overall count of categories, C_i and C_j correspondingly represent the centroids of several categories.

The degree of Style Confusion the model causes in classification of styles is measured. Calculating the chance of misclassification between every category helps one to spot circumstances where style limits are blurring (Morgan, 2018). Style Confusion can expose which styles are most likely to be misclassified in the classification process for oil paintings, therefore guiding model optimisation:

$$\text{Style Confusion} = \frac{\sum_{i,j}\text{Confusion}(i, j)}{N} \tag{13}$$

where N is the total number of categories; Confusion (i, j) is the frequency of category i being misclassified as category j.

By means of a combination of quantitative and qualitative evaluations, the performance of the model in the oil painting style classification task is thoroughly investigated. This not only guarantees the accuracy of the model but also highlights its shortcomings in handling similarities between sophisticated styles, so offering a useful basis for later model optimisation.

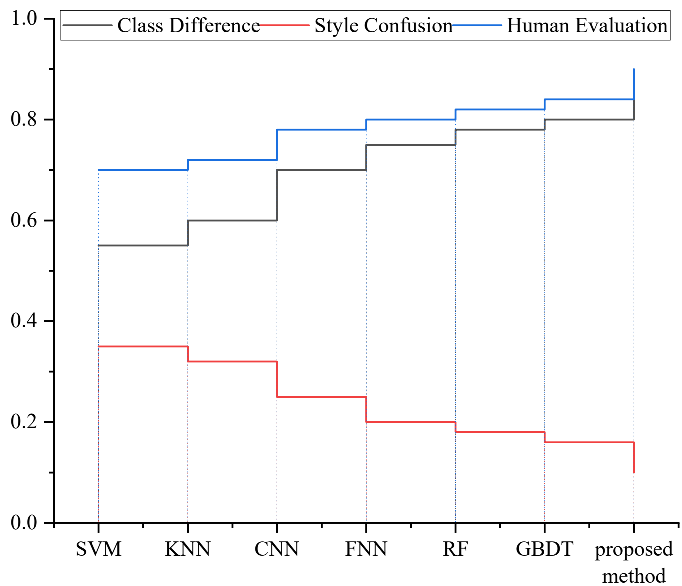
4.3 Experimental results and performance analysis

This paper's method's classification accuracy in the oil painting style classification task is first evaluated, then compared with six other conventional or fusion methods to confirm its generalisation capacity.

Among the selected for comparison are SVM, KNN, CNN, FNN, RF, and GBDT. These techniques have some benefits and are extensively applied in picture classification challenges. These techniques are evaluated against DFNN in oil painting style classification to assess DFNN performance.

Every technique is first trained, and the model's parameters are adjusted with reference to the training set data throughout the trials. The model's performance is then first assessed on the validation set to choose the optimal hyperparameters. On the test set, a last assessment of the models was conducted recording Class Difference, Style Confusion, and Manual Evaluation outcomes. Figure 2 presents the outcome of Experiment 1.

Figure 2 Results of the classification task experiment (see online version for colours)

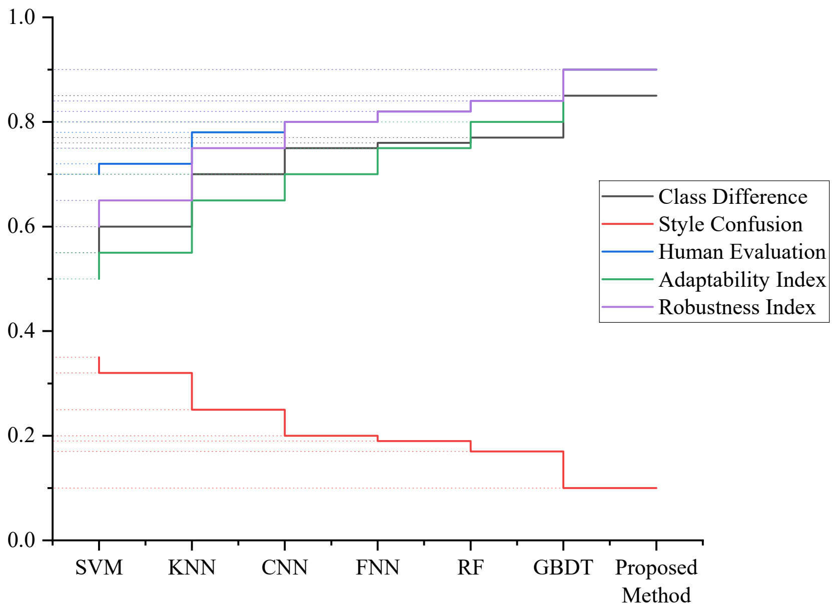


The experimental results reveal that the approach of this work works satisfactorily in the categorisation task of oil painting style. Regarding Class Difference, this approach achieves 0.85, much higher than previous approaches, suggesting that it has great benefits in feature extraction and classification capacity and can clearly differentiate several techniques of oil paintings. Regarding Style Confusion, this paper's approach is only 0.10, far less than previous approaches, however it shows great performance in classification accuracy, thereby reducing misclassification. Furthermore, in the manual evaluation, the accuracy of this paper's approach is as high as 90%, so confirming its dependability and accuracy in useful applications particularly in the context of fuzzy style borders, thus displaying greater adaptability.

In this work, the performance advantage of the strategy is more clearer than in other approaches. With 0.55 and 0.55 in Class Difference and 0.35 and 0.32 in Style Confusion respectively, the conventional SVM and KNN approaches show somewhat poor performance. Though better than the conventional techniques in terms of performance, even the most sophisticated CNN, FNN, RF and GBDT methods have a Class Difference between 0.70 and 0.80 and Style Confusion between 0.16 and 0.25, which are lower than the approaches in this study. These techniques have likewise lower manual evaluation accuracy, ranging from 70% to 84%. Taken together, the approach of this work not only performs well on quantitative measures but also is quite appreciated in qualitative assessments by specialists, so providing a dependable answer in the task of oil painting style classification.

Experiment 2 splits the Impressionist styles found in the WikiArt collection into two subsets: early and late Impressionism. The model is trained using early impressionist data; late impressionist data is utilised to assess model dynamic adjustment capacity. To evaluate the models' resilience, noisy data including blurring and light fluctuations are also included in the test set. Six conventional approaches (SVM, KNN, CNN, FNN, RF, GBDT) as well as the approach in this work are compared in the trials. Figure 3 shows the experimental findings.

Figure 3 Results of the dynamic adjustment capability experiment (see online version for colours)



Experiment 2 results reveal that the approach of this work shows notable benefits in terms of new style and evolution of oil painting technique. Regarding Class Difference, this paper's approach achieves 0.85, far higher than previous approaches, suggesting its better capacity in differentiating oil paintings of several genres. Regarding Style Confusion, this paper's approach has only 0.10, far less than other approaches yet shows better classification accuracy. This paper's method is 90% accurate in the manual evaluation, greater than other approaches, so confirming its dependability and accuracy in useful application. With a 0.90 adaptability index, this paper's approach indicates that it can more rapidly adjust to new trends. This work presents a method with a robust index of 0.90, greater than existing approaches, so displaying better anti-interference capacity.

This work is outstanding in dynamic adjustment ability and resilience when compared with conventional approaches. In Class Difference and Style Confusion, conventional techniques such SVM and KNN show rather poor performance; the accuracy of manual judgment is similarly low. Although better than the conventional approaches in performance, even the more sophisticated CNN, FNN, RF and GBDT methods have lower adaptability and robustness indexes than this paper's solution. These results confirm that the approach of this work not only shows better adaptability and stability in the face of style variations and noisy data, but also has an advantage in classification accuracy, so validating its possible use in the field of artwork classification and analysis.

Experiment 1 and Experiment 2 findings reveal that the approach in this work works satisfactorially in the task of classifying oil paints. In terms of classification accuracy and generalisation capacity, experiment 1 finds that the approach beats several conventional and state-of-the-art techniques. Experiment 2 shows even more its great flexibility and stability when addressing noisy data and style evolution. These findings taken together confirm the efficiency and quality of the approach in this work on the topic of artistic classification.

5 Summary and outlook

5.1 Summary of the study

Aiming to solve the constraints of conventional classification methods in handling the diversity, complexity and fuzziness of oil painting styles, this work proposes a DFNN-based intelligent classification method. This work effectively generates an efficient and strong oil painting style classification model by closely analysing the visual and stylistic aspects of oil painting images and combining the adaptive capacity and fuzzy processing mechanism of DFNN.

This work initially clarifies the origins and relevance of oil painting style classification, examines the inadequacies of conventional techniques, and suggests an original solution based on DFNN in the research process. The special benefits of DFNN in handling the problem of oil painting style categorisation are confirmed by means of comparison among several classification approaches. This work also presents a dynamic learning method, which helps the model to dynamically modify its structure and parameters in response to changes in training data, therefore enabling better handling of the evolution and uncertainty of oil painting styles.

Experiments 1 and 2 fully assess the performance of the method of this study in the categorisation task on oil painting style. Experiment 1 concentrates on classification accuracy and generalisation ability; the results show that the method of this paper performs better than the six compared methods in three main criteria, namely Class Difference, Style Confusion and Manual Evaluation, and shows great classification accuracy and generalisation ability. Experiment 2 investigates the dynamic adjustment capacity and robustness of this paper's method in the face of the evolution of oil painting styles and new styles, and the results once more show that this paper's method preserves its advantages in other indexes as well, so stressing its great adaptability and stability in handling stylistic changes and noisy data. These two tests jointly confirm the efficiency and superiority of the approach of this research in the field of oil painting style classification, so supporting strongly technically for artwork classification and analysis.

5.2 Problems and directions for improvement

Although the intelligent categorisation approach for oil painting styles suggested in this study has achieved impressive results in numerous aspects, some issues were still detected during the research process and these concerns also present directions for improvement in next studies.

First of all, especially in large-scale datasets with high computing resource consumption and long training time, the training process of the DFNN model is rather complicated. This is mostly because DFNN must simultaneously optimise the parameters of fuzzy rules and neural networks, therefore complicating the model. Future research should investigate more effective optimisation techniques including enhanced genetic algorithms or particle swarm optimisation algorithms in order to cut training time and resource expenditure. Furthermore, looked at are methods like quantisation and model pruning to optimise the DFNN's structure and raise model operation's efficiency.

Second, the interpretability of the model is still restricted in some situations even if DFNN performs well in handling ambiguity and uncertainties in oil painting techniques. Especially when considering intricate art style elements, the model's decision-making process is challenging to grasp intuitively. An attention mechanism can be included in the future to help the model to become more interpretable by highlighting the image areas that are fundamental for the classification process, therefore offering a more natural justification for art style classification (Kamakshi and Krishnan, 2023). Simultaneously, more study can be done on how to more effectively include the knowledge of art historians into the model to improve the capacity of the model to grasp and describe artistic forms.

At last, even although the present DFNN model has some dynamic adjustment capacity when considering the evolution of oil painting styles and new styles, the adaptability of the model still has to be enhanced when dealing with drastic stylistic shifts or totally unknown new styles. This suggests that the generalising capacity of the model still needs work. More style development data can be taken into account in the future to be included to further enhance the dynamic adaptation capacity of the model via means of augmented learning. Furthermore, one can investigate how to apply cross-domain knowledge transfer methods to oil painting style classification so that the model might better adjust to fast style changes and the arrival of new trends.

Declarations

All authors declare that they have no conflicts of interest.

References

Bengamra, S., Mzoughi, O., Bigand, A. and Zagrouba, E. (2024) 'A comprehensive survey on object detection in visual art: taxonomy and challenge', *Multimedia Tools and Applications*, Vol. 83, No. 5, pp.14637–14670.

Castellano, G. and Vessio, G. (2021) 'Deep learning approaches to pattern extraction and recognition in paintings and drawings: an overview', *Neural Computing and Applications*, Vol. 33, No. 19, pp.12263–12282.

Data, M. and Aritsugi, M. (2021) 'T-dfnn: an incremental learning algorithm for intrusion detection systems', *IEEE Access*, Vol. 9, pp.154156–154171.

de Oliveira Gomes, A. and Basilio, J.C. (2023) 'A fuzzy inference model to identify the current industry maturity stage in the transformation process to Industry 4.0', *IEEE Transactions on Automation Science and Engineering*, Vol. 21, No. 2, pp.1607–1622.

Du, C., Wang, Y., Wang, C., Shi, C. and Xiao, B. (2020) 'Selective feature connection mechanism: concatenating multi-layer CNN features with a feature selector', *Pattern Recognition Letters*, Vol. 129, pp.108–114.

Fakayode, S.O., Mehari, T.F., Fernand Narcisse, V.E., Grant, C., Taylor, M.E., Baker, G.A., Siraj, N., Bashiru, M., Denmark, I. and Oyebade, A. (2024) 'Microplastics: challenges, toxicity, spectroscopic and real-time detection methods', *Applied Spectroscopy Reviews*, Vol. 59, No. 9, pp.1183–1277.

Friedman, L. and Komogortsev, O.V. (2019) 'Assessment of the effectiveness of seven biometric feature normalization techniques', *IEEE Transactions on Information Forensics and Security*, Vol. 14, No. 10, pp.2528–2536.

Gultepe, E., Conturo, T.E. and Makrehchi, M. (2018) 'Predicting and grouping digitized paintings by style using unsupervised feature learning', *Journal of Cultural Heritage*, Vol. 31, pp.13–23.

Han, Y., Huang, G., Song, S., Yang, L., Wang, H. and Wang, Y. (2021) 'Dynamic neural networks: a survey', *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 44, No. 11, pp.7436–7456.

Jiang, S., Li, J. and Fu, Y. (2021) 'Deep learning for fashion style generation', *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 33, No. 9, pp.4538–4550.

Kamakshi, V. and Krishnan, N.C. (2023) 'Explainable image classification: the journey so far and the road ahead', *AI*, Vol. 4, No. 3, pp.620–651.

Kılıçarslan, G., Koç, C., Özyurt, F. and Gül, Y. (2023) 'Breast lesion classification using features fusion and selection of ensemble ResNet method', *International Journal of Imaging Systems and Technology*, Vol. 33, No. 5, pp.1779–1795.

Kim, J., Jun, J.Y., Hong, M., Shim, H. and Ahn, J. (2019) 'Classification of oil painting using machine learning with visualized depth information', *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. 42, pp.617–623.

Kumar, M.P., Poornima, B., Nagendraswamy, H. and Manjunath, C. (2019) 'A comprehensive survey on non-photorealistic rendering and benchmark developments for image abstraction and stylization', *Iran Journal of Computer Science*, Vol. 2, pp.131–165.

Morgan, D.L. (2018) 'Living within blurry boundaries: the value of distinguishing between qualitative and quantitative research', *Journal of Mixed Methods Research*, Vol. 12, No. 3, pp.268–279.

Pazhoumand-Dar, H. (2019) 'FAME-ADL: A data-driven fuzzy approach for monitoring the ADLs of elderly people using Kinect depth maps', *Journal of Ambient Intelligence and Humanized Computing*, Vol. 10, pp.2781–2803.

Pezeshki, Z. and Mazinani, S.M. (2019) 'Comparison of artificial neural networks, fuzzy logic and neuro fuzzy for predicting optimization of building thermal consumption: a survey', *Artificial Intelligence Review*, Vol. 52, No. 1, pp.495–525.

Rutherford, S., Kia, S.M., Wolfers, T., Fraza, C., Zabihi, M., Dinga, R., Berthet, P., Worker, A., Verdi, S. and Ruhe, H.G. (2022) 'The normative modeling framework for computational psychiatry', *Nature Protocols*, Vol. 17, No. 7, pp.1711–1734.

Sajid, S., Hussain, S. and Sarwar, A. (2019) 'Brain tumor detection and segmentation in MR images using deep learning', *Arabian Journal for Science and Engineering*, Vol. 44, pp.9249–9261.

Shorten, C. and Khoshgoftaar, T.M. (2019) 'A survey on image data augmentation for deep learning', *Journal of Big Data*, Vol. 6, No. 1, pp.1–48.

Wen, L., Li, X. and Gao, L. (2020) 'A transfer convolutional neural network for fault diagnosis based on ResNet-50', *Neural Computing and Applications*, Vol. 32, No. 10, pp.6111–6124.

Yazdinejad, A., Dehghantanha, A., Parizi, R.M. and Epiphaniou, G. (2023) 'An optimized fuzzy deep learning model for data classification based on NSGA-II', *Neurocomputing*, Vol. 522, pp.116–128.

Zhao, Y., Ren, D., Chen, Y., Jia, W., Wang, R. and Liu, X. (2022) 'Cartoon image processing: a survey', *International Journal of Computer Vision*, Vol. 130, No. 11, pp.2733–2769.

Zheng, Y., Xu, Z. and Wang, X. (2021) 'The fusion of deep learning and fuzzy systems: a state-of-the-art survey', *IEEE Transactions on Fuzzy Systems*, Vol. 30, No. 8, pp.2783–2799.