

Multi-source Heterogeneous Data Mining for the Interpretation of Ink Experimental Visual Language

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Abstract. This paper first discusses the classification of ink experiment visual language and analyzes its basic features and functional value. Secondly, the residual network is utilized to represent the visual features of ink experimental images, and the BP neural network is introduced as the basis for the construction of a feature-level fusion network. Then the DS evidence theory is used for the decision-making of ink experimental visual feature images, and then the multi-source heterogeneous data fusion model is constructed. Finally, the training accuracy is tested and empirically analyzed for the multi-source heterogeneous data fusion model. The results show that the testing time of the multi-source heterogeneous data fusion model based on the BP neural network is 0.52s, which is 0.24s and 0.15s higher than the original VGG19 and VGG16 networks and the interpretation of the visual language of the ink experiment is mainly based on the static ink, dynamic ink and interactive ink. This shows that the interpretation of ink experimental visual language can be realized through multi-source heterogeneous data, which also provides a new direction for the innovative development path of ink art.

1. Introduction

Traditional ink art, with profound cultural meaning and spiritual connotation, is a category of Chinese national art aesthetic ideal and one of the most characteristic art forms of Chinese culture [1-2]. In the early 1990s, under the influence of the “85 art trend”, the ink and wash experiments came into being. The emancipation of ideas and the influx of Western art and culture had a great influence on traditional ink and wash and enlightened the mind, although it has a deep historical foundation [3-4]. However, in the past, ink and wash art only stayed in the internal circle of artists and did not enter the life of the Chinese public, and the profit-seeking purpose embedded in Western art would inevitably cause disturbances to the Chinese culture, economy, and ideology, etc. [5-6]. Artists no longer indulge in the fun and visual changes of the brush and ink itself but continue to explore the boundaries of ink expression through experimentation. They try to combine traditional ink and modern social art forms, find emotional entry points with the

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public, resist the invasion of foreign cultures, strengthen the national cultural identity and firm cultural confidence through the connected cultural lineage [7-8].

But “water” and “ink” are essentially just substances as painting materials. Like other materials, they do not have a kind of nationalistic or ethnic qualities, and their value and significance lie in the concepts or ideas given to the materials by the artists rather than in the essentialist qualities of the materials themselves [9-10]. The reason why “ink language” has been used as a carrier to express China’s unique cultural ideas for thousands of years is that the information conveyed by the visual effect is difficult to be replaced by other media. The attention paid to the “ink experiment” nowadays is an opportunity for Chinese ink art to show its character and value to the world [11-12]. Therefore, openly exploring the visual language of ink and wash, rigorously summarizing the rules of its production, and cautiously using the appropriate means of expression are the only ways to better highlight the core meaning of the most valuable Chinese ink and wash.

The ink art has a strong oriental charm and cultural connotation, and it responds to the trend of contemporary consumers’ pursuit of diversified visual styles with its unique visual performance. Literature [13] utilizes the ink art style simulation model and three-dimensional technology to realize the construction of ink three-dimensional virtual reality scenes and the construction of ink brushstroke models through metacellular automata so as to obtain the most realistic ink painting art effect. Literature [14] analyzed the development situation of Chinese contemporary ink artworks in the international art world as an example and inverse, indicating that ink art culture has uniqueness and can realize cross-cultural communication, and also provides a medium for globalized art exchange. Literature [15] takes the art exhibition of the Metropolitan Museum of Art in New York as an example, analyzes the importance of the experimental art language of Chinese ink and shows that the development of ink and wash art cannot be separated from the cultural context, and it needs to be rooted in the culture in order to realize the innovative development.

In addition, literature [16] argues that the development of ink art in China is not only a result of history but also closely related to philosophy in practice. It discusses the innovative ways of ink art practice and makes ink art more intuitive to show its specific meaning through natural elements. Literature [17] introduces modern science and technology to digitally display the stylized drawing of ink painting; through the process of drawing ink paintings and canvas texture and other perspectives can realize digital ink painting stylization and promote the digital development of ink painting style. Literature [18] used discrete cosine transform and convolutional neural networks to construct a framework for analyzing the artistic style of ink painting, and the framework was verified and analyzed through the dataset, and the results showed that the framework could realize the classification of the artistic style of ink painting.

This paper takes the classification of ink experiment visual language as the entry point, discusses its artistic connotation and functional value, and uses the residual network to realize the visual feature representation of ink experiment images. The BP neural network is used as the basis for the construction of a feature-level fusion network, and the DS evidence theory is introduced to construct the decision-level fusion model, and then the structure of the multi-source heterogeneous data fusion model is given. In order to verify the deductive form of multi-source heterogeneous data in mining ink experimental visual language, the constructed model was tested and analyzed empirically. The results show that the ink experimental visual language interpretation form is mainly based on technology fusion, which in turn provides a new development path for the development of ink art and also promotes the immersive sensory experience of ink art.

2. Characteristics and Value of Ink Experimental Visual Language

2.1. Classification of the visual language of ink experiments

Ink Experiment is the product of contemporary ink artists’ exploration of Chinese ink art, a revolutionary creation of ink art. Its style is rich and varied, the choice of media is more diverse, and its expression is no longer confined to flat paper. Ink experimentation is bred in the background of the era of global information development and integration, out of ink and from ink. The language of ink experimentation is roughly categorized into three kinds: first, graphic language. Second, cross-border media language. And third,

narrative language. The forms of visual language, the development of thinking, and the spirit of the times that these inks have coincide with cultural thought. Ink experiment has never stopped exploring the visual language in the process of development. In the new era of rapid development of technology, ink experiment wants to explore the unique visual language and still need to continue to look for answers in ink art, one can extend the vitality of Chinese ink, and the other can be a better development of the visual language of ink experiment. The visual language of ink experiments is categorized as shown in Figure 1.

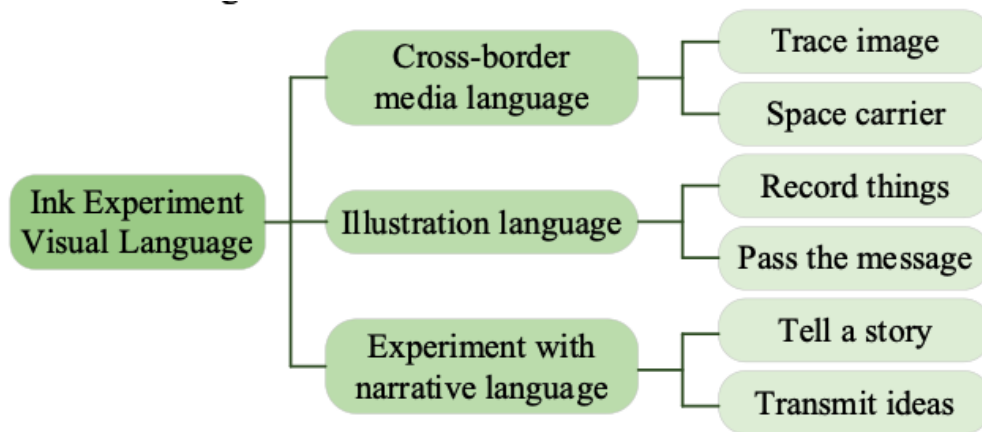


Figure 1: The visual language of ink experiments

2.2. Characterization of the visual language of ink experiments

Ink and wash experimentation is a typical art form in contemporary Chinese art, and the art form is highlighted in the experimental innovation of painting medium and the exploration and research of image expression, and the formation of a systematic discourse system. In interpreting the works of ink and wash experiments, it is necessary to involve the basic level of the referential system - the media elements. The artistic styles formed by different media tools such as topography, collage and inkjet in the ink and wash experiments have become the attempts of Chinese painting art in modern transformation, expanding the texture and spatiality of artistic creation. Accompanied by the exploration of the transformation of media elements, the ink experiment combines localized traditional painting materials with Western conceptual art, resulting in ink forms mainly represented by abstract ink, conceptual ink, installation ink, and performance ink, forming a unique visual language representation. Figure 2 shows the visual language representation of the ink experiment.

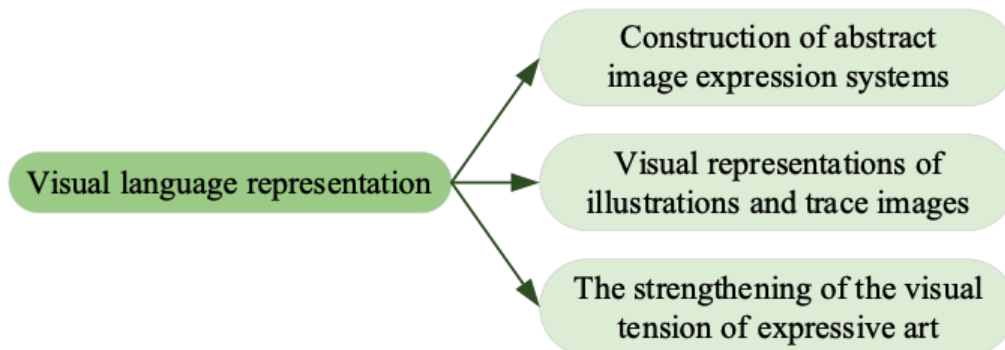


Figure 2: Visual language representation of ink experiments

2.3. The Value of Experimental Ink Visual Language

Chinese ink art uses paper and silk as its medium, utilizing the water-absorbing, fusing and percolating properties of rice paper to naturally form layers of light and dark and changes in block surfaces. At the same time, it does not seek resemblance but emphasizes the expression of imagery, focuses on the expression of emotions at the spiritual level, and has a strong subjective abstraction. The application of ink visual language in contemporary art has the function of inheriting traditional Chinese culture vertically, disseminating information horizontally, and creating beauty and bringing people aesthetic experience individually. These functions reflect the different attributes of the experimental ink visual language to meet the needs of ink art, which directly determines the value of the experimental ink visual language in contemporary ink art. The value conveyed by the experimental ink visual language is shown in Figure 3.

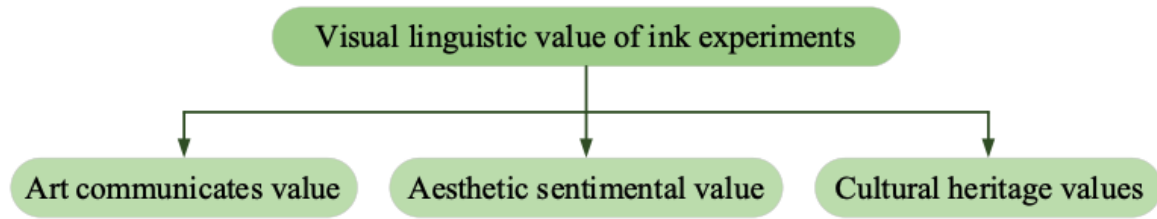


Figure 3: The value of visual language for ink experiments

In summary, the application of ink experimental visual language in ink art can meet the needs of artistic creation, play the function of artistic content and artistic form innovation, gradually complete the function of cultural inheritance, dissemination and aesthetics, and create a new design direction in the field of ink art design.

3. Multi-source Heterogeneous Data Fusion for Visual Characterization of Ink Experiments

In order to realize the effective fusion of ink experimental visual features, this chapter fuses the BP neural network, image feature fusion network and D-S evidence theory for multi-source heterogeneous data acquisition of ink experimental visual features. It provides effective technical support for the interpretation of ink experimental visual features with multi-source heterogeneous data fusion to be carried out later.

3.1. Visual feature representation network for ink experimental images

According to the principle of convolution in deep learning theory, to a certain degree, the deeper the number of network layers, the greater the number of parameters contained in the model, and the more combinations of image features can be fitted, learning a variety of different image features need to correspond to the use of enhanced mapping relationships, and thus improve the performance of the algorithm. However, there will also be a large number of image detail features that can not be effectively recognized; thus, the design idea of the residual network is proposed to obtain more accurate images.

The essence of the residual network is a convolutional neural network with deep network layers stacked by a large number of residual blocks. The residual block is the core module that constitutes the residual network; the basic structure of the residual network is shown in Figure 4.

x shows the input information of the residual block, and $F(x)$, $Y(x)$ shows the output of the middle convolutional layer of the residual block and the output information of the residual block, respectively. The main improvement work of the residual block is to add a jump connection between the cascaded convolutional layers, which connects the shallow network to the deep network directly. Thus the input-output relationship of the residual block can be expressed as:

$$X_d = X_s + \sum_{i=s}^{d-1} F(X_i, W_i) \quad (1)$$

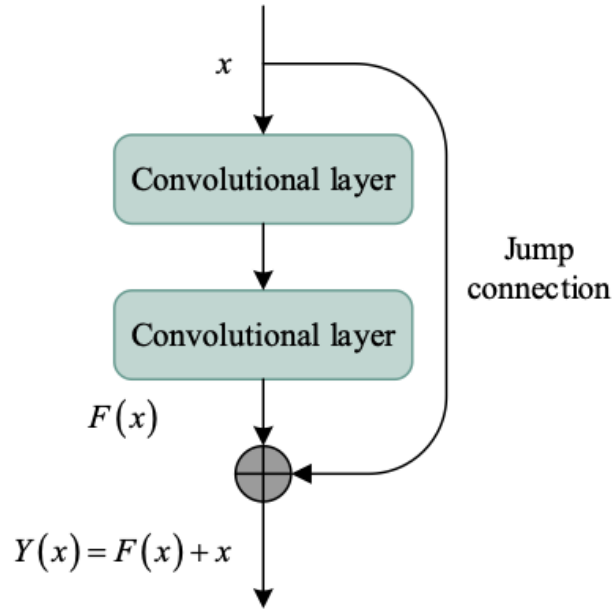


Figure 4: The basic structure of a residual network

Where X_s denotes the shallow network information, i.e., the input of the residual block, X_d denotes the deep network information, i.e., the output of the residual block, and $F(X_i, W_i)$ denotes the convolution operation of the i th convolutional layer. After introducing the residual idea, the gradient propagated to the shallow network out can be expressed as:

$$\frac{\partial \theta}{\partial X_s} = \frac{\partial \theta}{\partial X_d} \frac{\partial X_d}{\partial X_s} = \frac{\partial \theta}{\partial X_d} \left(1 + \frac{\partial}{\partial X_s} \sum_{i=s}^{d-1} F(X_i, W_i) \right) \quad (2)$$

Where θ is the loss value calculated based on the loss function and the actual output of the network model, d, s is the convolutional layer number, and $F(X_i, W_i)$ is the convolution operation of the i rd convolutional layer.

The addition of residual blocks allows both the shallow and deep layers of the network to obtain appropriate gradient information to update the parameters, ensuring that the network can still operate effectively after stacking a large number of layers. The introduction of this structure in the convolutional neural network when performing visual feature representation of ink experimental images can more accurately ensure that the details of the ink experimental images can be recognized and the visual features are more distinct.

3.2. Structure of the multi-source heterogeneous data fusion model

Feature fusion generally includes state data fusion and feature data fusion. For target state monitoring, parameter correlation and state vector estimation are mainly applied to target state data fusion, which contains multi-source data with descriptive data sources. The feature data fusion of the target, which is closely related to pattern recognition technology, contains multi-source data with non-imaging data sources and imaging data sources such as radar images and infrared imaging. In this paper, we explore the feature fusion of different structural data for the feature fusion of ink experimental vision, and the feature fusion structure is shown in Figure 5.

Decision fusion will be the data obtained from different sensors where feature extraction and identification or decision-making judgment, respectively, the corresponding results were obtained, the use of decision

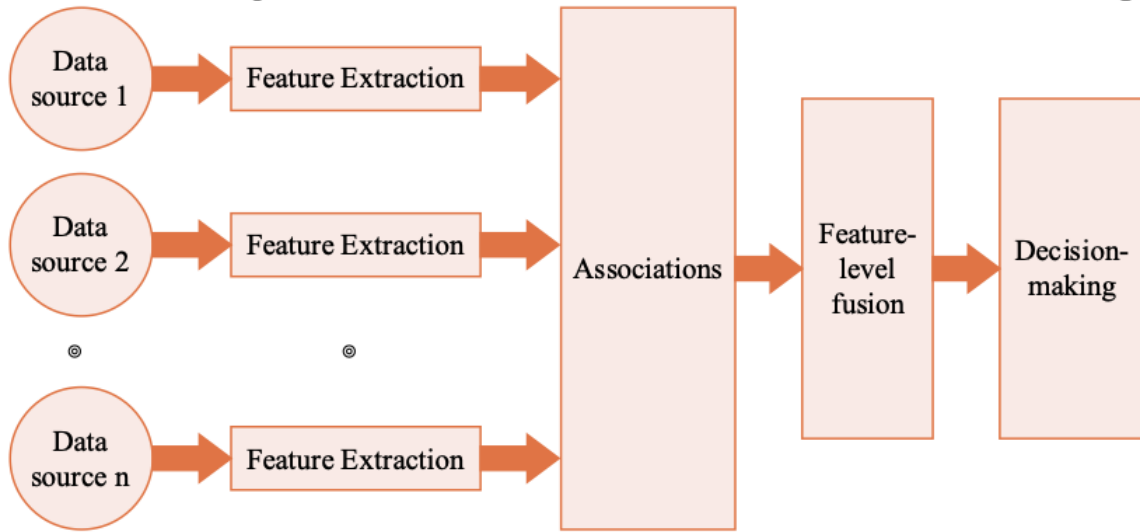


Figure 5: The structure of feature fusion

fusion algorithm for fusion, the final result is the globally optimal result, the decision fusion structure is shown in Figure 6.

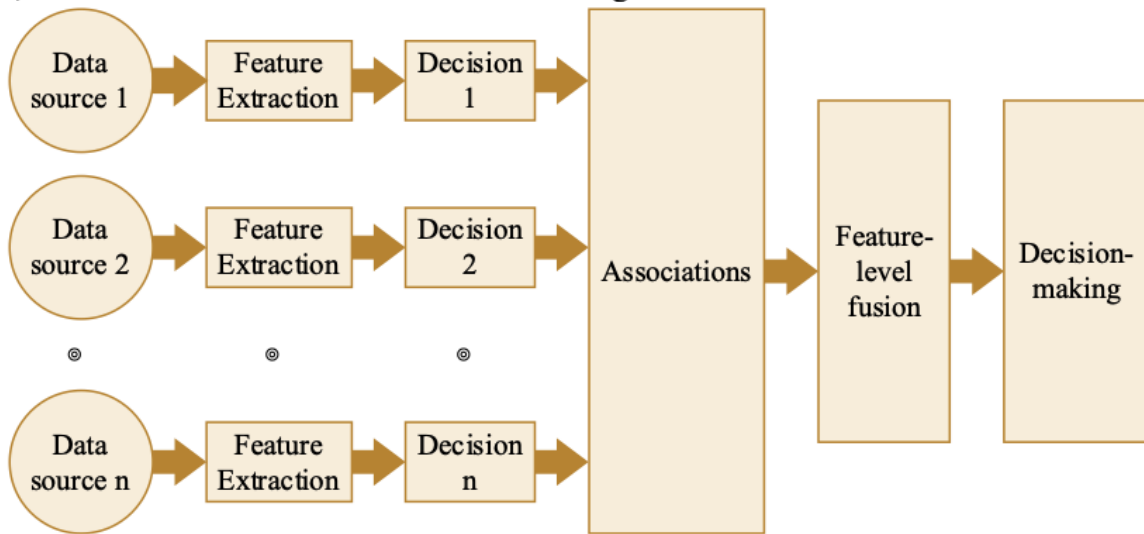


Figure 6: The structure of decision fusion

Hybrid fusion mainly designs the model structure according to the requirements. This paper combines feature fusion and decision fusion to improve the performance of the fusion model. The hybrid fusion structure is shown in Figure 7.

Both feature fusion and decision fusion have the disadvantage of poor robustness, information is easily lost during processing, resulting in incomplete data, and the uncertainty of the data affects the accuracy of the results. In contrast, hybrid fusion fuses the results of data from different sensors after feature-level fusion with the results of separate decision-making judgments, which improves robustness and flexibility.

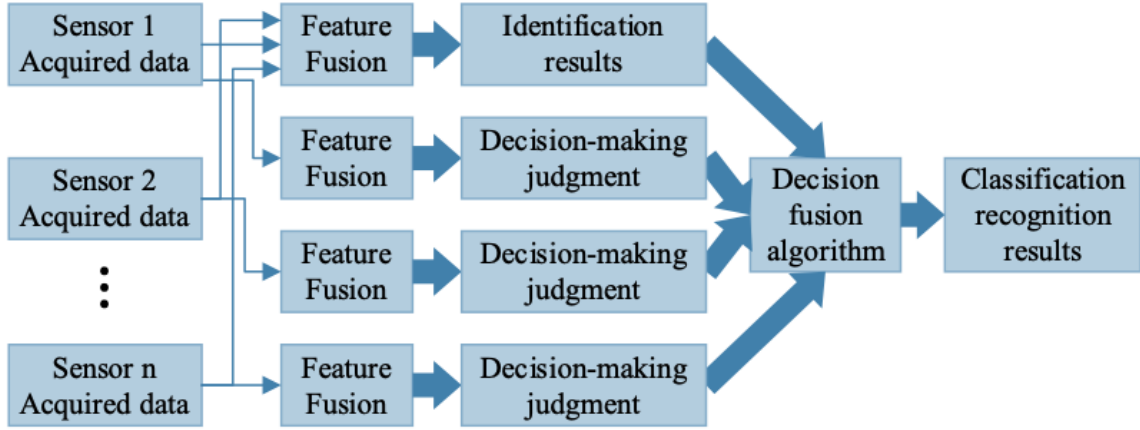


Figure 7: The structure of the hybrid fusion

3.2.1. Feature-level ink experiment visual feature fusion

Feature level fusion in this paper uses multiple convolutional neural network models to analyze the feature mappings of the ink experiment images fused through the BP neural network to obtain the classification recognition of the target. The classification probability of the visual features of the ink experiment is obtained through multiple forward and backward propagation iterations of the BP neural network. The specific network structure of the feature-level fusion model is shown in Fig. 8.

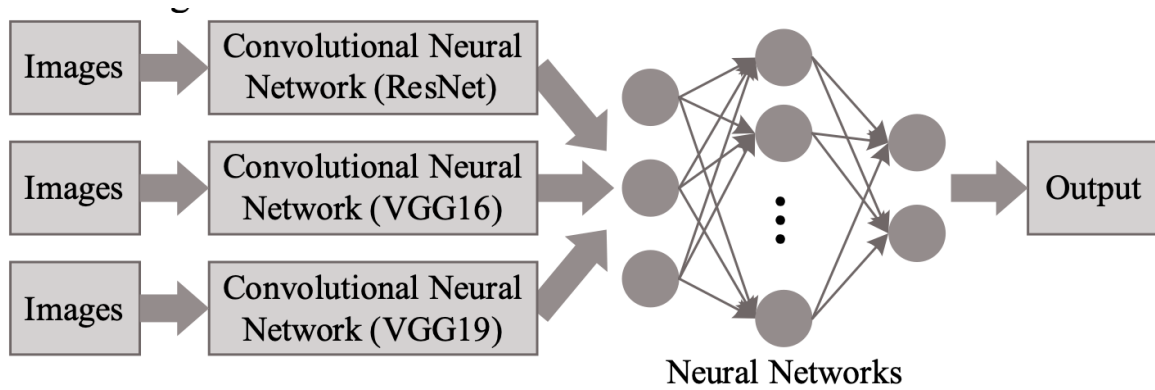


Figure 8: Feature-level fusion networks that fuse BP neural networks

In the BP algorithm, given the input layer input vector is $X = \{x_1, x_2, \dots, x_i, \dots, x_m\}$, the l nd hidden layer vector is $H^l = (h_1^l, h_2^l, \dots, h_j^l, \dots, h_{s_l}^l)$, and the output layer output vector is $Y = \{y_1, y_2, \dots, y_n\}$, let w_{ij}^l be the bias of the j th neuron from the $l - 1$ th layer. Then:

$$h_j^l = f(\text{net}_j^l) \quad (3)$$

$$\text{net}_j^l = \sum_{i=1}^{s_{l-1}} w_{ij}^l + b_j^l \quad (4)$$

Where net_j^l is the input to layer l , the j rd neuron, and $f(\cdot)$ is the activation function.

The sum of squares of the difference between the output and the expected value is used as the error function in the model, which is expressed as:

$$e = \frac{1}{2} \sum_i (X_i^m - Y_i)^2 \quad (5)$$

The error for all training samples is:

$$E_{total} = \frac{1}{N} \sum_{i=1}^N E(i) \quad (6)$$

In the above equation, Y_i represents the expected value of the output result, while X_i^m represents the actual value of the output.

3.2.2. Decision-level ink experiment visual feature fusion

Decision level fusion in the ink experimental image data as an example of the model is introduced for the ink experimental image data training convolutional neural network to get to make classification and recognition decisions on multi-class targets. The corresponding a priori knowledge base is established to make classification judgments on the multi-class targets. These judgments are then fused to obtain the final target classification recognition result.

In this paper, DS evidence theory is used as a decision-level fusion algorithm. The metric of DS evidence theory is the trust function, which is obtained by constraining the probability of the target, which gives it a strong ability to deal with unambiguous information. The allocation of the basic credibility of DS evidence theory becomes a difficult point when it is used for target recognition, and the combination with neural networks just solves the problem of the allocation of credibility. By training the neural network, the basic credibility of each recognized target is assigned, and then the DS evidence theory is used for fusion to obtain the fusion result.

1. Basic elements of DS evidence theory. In DS evidence theory, define a set of propositions Θ , which contains all possible outcomes of a certain decision problem, which is non-empty and all elements in the set are mutually exclusive, and call Θ an identification frame. Define an identification frame Θ as:

$$\Theta = \{A_1, A_2, \dots, A_i, \dots, A_N\} \quad (7)$$

Where A_i denotes the i nd proposition of the recognition framework as an element or an event, N denotes the total number of set propositions, and $i = 1, 2, \dots, N$.

In the recognition framework Θ , the basic probability distribution function is defined as:

$$m : 2^\Theta \rightarrow [0, 1] \quad (8)$$

Its representation m is a mapping from the power set 2^Θ to $[0, 1]$ which satisfies the following condition, viz:

$$\begin{cases} m(\emptyset) = 0 \\ \sum_{A \subseteq \Theta} m(A) = 1 \end{cases} \quad (9)$$

Where m is the probability distribution function on 2^Θ , and $m(A)$ denotes the underlying probability distribution function of A , which indicates the degree of trust in proposition A .

Assuming $B \subseteq A \subseteq \Theta$, the trust function is defined in the identification framework Θ :

$$Bel : 2^\Theta \rightarrow [0, 1] \quad (10)$$

Its representation is a mapping from the power set 2^Θ to $[0, 1]$ which satisfies the following condition, viz:

$$Bel(A) = \sum_{B \subseteq A} m(B) \quad (11)$$

$Bel(A)$ as a trust function for A .

Assuming $A \subseteq \Theta$, the likelihood function is defined in the identification framework Θ :

$$Pl : 2^\Theta \rightarrow [0, 1] \quad (12)$$

Its representation is a mapping from the power set 2^Θ to $[0, 1]$ which satisfies the following condition, viz:

$$Pl(A) = 1 - Bel(\bar{A}) \quad (13)$$

$Pl(A)$ as a trust function of A .

2. *Synthesis rules for DS theory.* Suppose that for a given recognition framework Θ there are two evidences, m_1, m_2 are two basic probability assignment functions on Θ , and the focal element is A_i, B_j . If $A_i \cap B_j = A \subset \Theta$ and $m_1(A_i)m_2(B_j)$, then $\sum_{A_i \cap B_j = A} m_1(A_i)m_2(B_j)$ denotes the partial probability assigned to A , and the total probability eventually assigned to A is:

$$\sum_{A_i \cap B_j = A} m_1(A_i)m_2(B_j) \quad (14)$$

But when $A = \emptyset$, an irrationality arises, viz:

$$\sum_{A_i \cap B_j = \emptyset} m_1(A_i)m_2(B_j) > 0 \quad (15)$$

So a normalization factor is introduced, i.e.:

$$\left(1 - \sum_{A_i \cap B_j = \emptyset} m_1(A_i)m_2(B_j) \right)^{-1} \quad (16)$$

Such that the sum of the probabilities at $A \neq \emptyset$ is 1.

The DS synthesis rule for two shreds of evidence is:

$$m(A) = m_1(A) \oplus m_2(A) = \begin{cases} \frac{\sum_{A_i \cap B_j = A} m_1(A_i)m_2(B_j)}{1 - K}, & A \neq \emptyset \\ 0, & A = \emptyset \end{cases} \quad (17)$$

$$K = \sum_{A_i \cap B_j = \emptyset} m_1(A_i)m_2(B_j) \quad (18)$$

Where K is defined as a conflict function.

Analogously to the synthesis rule for two pieces of evidence, the synthesis rule for multiple pieces of evidence can be derived. Suppose that for a given identification framework Θ there is more than one piece of evidence whose corresponding underlying probability assignment function is $m_1, m_2, \dots, m_n$. Assuming that they are not completely conflicting and independent of each other, the synthesis rule for more than one piece of evidence can be expressed as follows:

$$m(A) = \begin{cases} \frac{\sum_{A_1 \cap \dots \cap A_n = A} m_1(A_1) \cdots m_n(A_n)}{1 - K}, & A \neq \emptyset \\ 0, & A = \emptyset \end{cases} \quad (19)$$

$$K = \sum_{A_1 \cap \dots \cap A_n = \emptyset} m_1(A_1) \cdots m_n(A_n) \quad (20)$$

In $m(A) = m_1(A) \oplus m_2(A) \oplus \cdots \oplus m_n(A)$, the process of multiple evidence synthesis, the order of evidence synthesis can be changed.

For the ink experiment visual features, which have more variables, the synthesis of multiple pieces of evidence is mainly applied to realize the effective fusion of features. The DS evidence theory can effectively provide enough training samples for the parameter update of the BP neural network, which in turn promotes the effectiveness of the decision-level fusion network results.

4. Multi-source Heterogeneous Data Fusion Model in Ink Experiment Visual Feature Interpretation

In order to seek the effective development and deduction path of ink experimental visual features, this chapter analyzes the validity of the multi-source heterogeneous data fusion model constructed in the previous section and unfolds the analysis of ink experimental visual features as an illustration of ink experimental visual features deduction.

4.1. Training and Analysis of Multi-source Heterogeneous Data Fusion Models

For the ink experiment's visual features, mainly contains the beauty of mood, spirituality and harmony. In this section, the original VGG16, VGG19, ResNet34 network and BP neural network are used to train the multi-source heterogeneous data fusion model, respectively, and the optimizer of the model is Adam with the learning rate of 0.0001, and analyze the training accuracy of the model, the loss value, and the test of each model time are shown in Table 1.

Table 1: Training accuracy, loss and test time of the model

Model	Accuracy	Loss	Epochs	Batch size	Test time (s)
Original VGG19 network	95.68%	0.05	20	128	0.28
The original VGG16 network	91.92%	0.18	20	128	0.37
The original ResNet34 network	83.67%	0.24	20	128	3.65
BP network	99.89%	0.01	20	128	0.52

From the training results of the four networks on the multi-source heterogeneous data fusion model, the accuracy of the BP neural network in the training set is 99.89%, which is improved by 4.21%, 7.97%, and 16.22% compared with the other three networks, respectively. This shows that the multi-source heterogeneous data fusion model based on BP neural network given in this paper has good training ability, which is due to the simple structure of the BP neural network and the application of DS evidence theory to realize the effective updating of BP neural network parameters. The test time of the BP neural network-based multi-source heterogeneous data fusion model is 0.52s, which is 3.13s lower than the original ResNet34 network, but 0.24s and 0.15s higher than the original VGG19 and VGG16 networks. Although the test time of the BP neural network is comparatively long, the improvement in accuracy is negligible. This indicates that the BP neural network-based multi-source heterogeneous data fusion model has good training accuracy and can effectively realize the extraction of visual features for ink experiments.

In order to further analyze the effectiveness of the multi-source heterogeneous data fusion model, the BP neural network is used to test the training effect for the visual features of the ink experiment. The training effect of the multi-source heterogeneous data fusion model on the ink experiment visual features is shown in Figure 9.

From the training effect of the multi-source heterogeneous data fusion model on the visual features of the ink experiment, the accuracy of this paper's model for the visual features of the ink experiment in terms of the beauty of meaning, the beauty of spirituality, and the beauty of harmony are steadily increasing with the increase in the number of iterations. For contextual beauty, when the number of iterations is 100, its

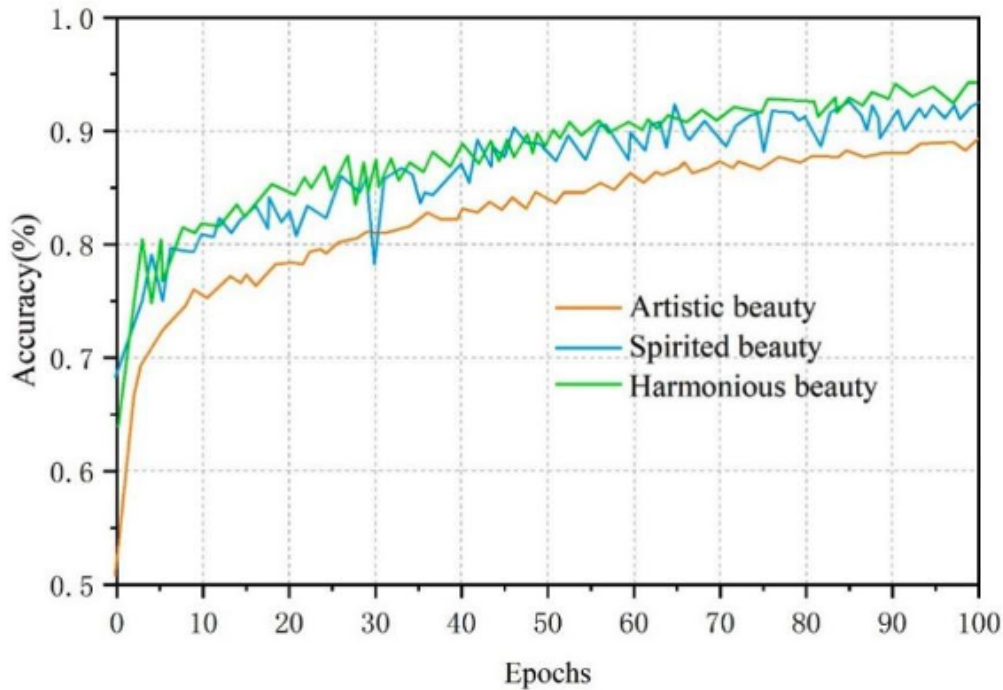


Figure 9: Training effect of multi-source heterogeneous data fusion model

feature extraction accuracy is 89.72%. For dynamic beauty, the feature extraction accuracy is 91.04% when the number of iterations is 100. For harmonious beauty, when the number of iterations is 100 times, its feature extraction accuracy is 93.52%. This shows that the multi-source heterogeneous data fusion model constructed in this paper can effectively realize the extraction of visual features of the ink experiment, and the accuracy of the model can be better guaranteed by the effective parameter update iteration.

4.2. Ink experiment visual language interpretation expression form analysis

The medium of communication is an important factor contributing to the development of ink art, as well as an important carrier in the creative process, and also influences the expression of the ink language. The traditional ink and wash media depend on hard media such as pen, ink, paper, ink stone or other natural manufacturing materials to keep the surface. This kind of primitive media has the characteristics of not being easy to circulate and being fragile. The experimental visual language of ink and wash relies on modern technology to better access the expressive form of ink and wash art and promote the interpretation of the experimental visual language of ink and wash. This section analyzes the existing ink experimental artworks based on the multi-source heterogeneous data fusion model constructed in the previous section, and the results of the quantitative analysis of its deductive expression form are shown in Table 2.

From the viewpoint of the interpretive expression forms of ink artworks, it is mainly dominated by static ink, dynamic ink and interactive ink, with its A rating accounting for 39.97%. This shows that more people recognize that these three forms of expression belong to the development of the experimental visual language of ink and also believe that these three forms of expression can better promote the interpretation of the experimental visual language of ink and promote its innovation. Among them, for the static ink forms, more people tend to favor ink experimental painting and ink experimental photography, with 86.66% of the evaluation above a C grade. This indicates that the experimental ink painting expresses the rhythm of ink art, while the experimental ink photography can further create the spirit of ink. The form of dynamic ink and wash, experimental ink and wash animation and experimental ink and wash film and television

Table 2: Ink experiment visual language deduction expression form

Deductive representation		A	B	C	D
Static ink	Ink experimental painting	43.84%	21.15%	19.57%	15.44%
	Ink experiment photography	44.74%	26.46%	17.56%	11.24%
Dynamic ink	Ink experiment animation	33.82%	41.04%	14.78%	10.36%
	Ink experiment film and television	45.48%	21.59%	14.07%	18.86%
Interactive ink	Ink experiment game	34.36%	33.07%	19.08%	13.49%
	Ink experiment experience	37.59%	29.61%	18.25%	14.55%

are its main forms of expression, with a D-grade evaluation of 14.61%. Although there are some artists who deny the expression form of dynamic ink experiment, it cannot be denied that dynamic ink gives more possibilities to the visual language of ink art, changes the way of appreciating ink art in the past, and gives people new visual experiences. In terms of the interactive ink form, the percentage of its C grade or above evaluation is 85.98%. This shows that the experimental ink visual language has begun to better combine with the real technology to realize the real-time interaction between the works and the senses, which can better achieve the whole body and mind, immersive art experience.

In summary, the analysis of the interpretation form of the ink experimental visual language realized through the multi-source heterogeneous data fusion model shows that the ink experimental visual language needs to be more combined with the real technology. It can effectively enhance the inheritance and development of ink art and also provide people with more diversified ways of feeling.

5. Conclusion

This paper starts from the classification of ink experimental visual language, analyzes its basic features and functional value, and in order to be able to better explore the deductive form of ink experimental visual language, a multi-source heterogeneous data fusion model is constructed using BP neural network and DS evidence theory. An empirical analysis was carried out for the deduction of ink experimental visual language, and the following conclusions were drawn:

1. The accuracy of the multi-source heterogeneous data fusion model constructed based on the BP neural network for the ink experimental visual language features of the beauty of meaning, spirituality and harmony increases steadily with the increase in the number of iterations. When the number of iterations reaches 100, the accuracy of extracting the features of contextual beauty, dynamic beauty and harmonious beauty is 89.72%, 91.04% and 93.52%, respectively. This shows that the multi-source heterogeneous data fusion model constructed in this paper can effectively mine the features of the ink experiment visual language and provide effective technical support for analyzing its deductive form.
2. From the perspective of the interpretation of ink experimental visual language, it mainly focuses on static ink, dynamic ink and interactive ink, and the proportion of its A-level evaluation is 39.97%. This shows that the current ink experimental visual language gradually began to integrate with modern science and technology so that it can better bring immersive experience for the public and also help the innovation and inheritance of ink art.

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