Facial Beauty Prediction via Local Feature Fusion and Broad Learning System

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ABSTRACT Facial beauty prediction (FBP), as a frontier topic in the domain of artificial intelligence regarding anthropology, has witnessed some good results as deep learning technology progressively develops. However, it is still limited by the complexity of the deep structure network in need of a large number of parameters and high dimensions, easily leading to a great consumption of time. To solve this problem, this paper proposes a fast training FBP method based on local feature fusion and broad learning system (BLS). Firstly, two-dimensional principal component analysis (2DPCA) is employed to reduce the dimension of the local texture image so as to lessen its redundancy. Secondly, local feature fusion method is adopted to extract more advanced features through avoiding the effects from unstable illumination, individual differences, and various postures. Finally, extensional feature eigenvectors are input to the broad learning network to train an efficient FBP model, which effectively shortens operational time and improve its preciseness. Extensive experiments with the proposed method on large scale Asian female beauty database (LSAFBD) can be conducted within 13.33s while sustaining an accuracy of 58.97%, impressively outstripping other state-of-the-art methods in training speed.

INDEX TERMS Facial beauty prediction (FBP), local feature fusion, broad learning system (BLS).

I. INTRODUCTION

Facial beauty prediction (FBP) \cite{1} is a significant scientific research direction in machine vision and artificial intelligence, favored by many domestic and foreign researcher. Exploring how to interpret, quantify, and predict beauty better will offer people a more scientific perspective on beauty, thus promoting the development of the cross-research direction of FBP. There will be different answers to the evaluation of human appearance based on different aesthetics. Therefore, assisted with artificial intelligence in anthropology, psychology, and public aesthetics to predict human facial beauty, a relatively scientific and objective judgment standard can be obtained. In the past decade, a series of research outcomes have been achieved in the field \cite{1}–\cite{3}. The theoretical results of FBP research have been widely adopted in practice, such as social applications, cosmetic surgery, and beauty product shopping guides. However, FBP still suffers from issues including unclear evaluation indicators, massive time consumption of deep networks training, and lack of high-performance equipment.

Deep learning has fully displayed its strengths in the field of FBP in the past decade \cite{4}–\cite{6}. Compared with conventional machine learning approaches, deep learning networks can automatically extract higher-level features from facial data \cite{7}. Although deep learning has realized excellent prediction results in FBP, its imperfections \cite{8} can never be underestimated: (1) time-consuming and costly training process due to a great deal of parameters; (2) poor model generalization \cite{9} arisen from deep learning’s greater sensitivity to image texture features than to image shape features; (3) huge calculation needed resulting from the complex structure of deep learning network. It requires highly configured equipment to complete model training, further increasing the economic burden.

To overcome the issues of deep learning above, this paper proposes a fast training method based on local feature fusion and broad learning system (BLS) \cite{10}. Above all,
different local texture feature methods are employed to extract features of face images. Because of the need of feature fusion and it will lead to significantly grow of data dimension, a two-dimensional principal component analysis (2DPCA) [11] is designated to reduce each kinds of texture images dimension. Compared with other dimensional reduction methods, 2DPCA excels in extracting more advanced facial features, while improving the computer's operating efficiency and model recognition accuracy.

Texture invariance is acquired by fusing different kinds of local texture features to constrain the bias of the texture. Geirhos R et al. [9] proved that the neural network is strongly biased in recognizing the texture of the images rather than the shape of the images. Hence, enhancing the ability of the neural network to learn the texture of the images can strengthen the robustness of the network. Simultaneously, local feature fusion can make up for the disadvantage of single local features to improve the robustness of image features.

Broad learning system (BLS) is adopted as a rapid and simple classifier algorithm for FBP task. It is based on the random vector functional-link neural network (RVFLNN) [12]–[14] structure. Compared with the “depth” structure, the “width” structure is simpler because there is no layer-to-layer coupling. When the network’s accuracy cannot meet the requirements, it can be improved by broadening the “width” of the network. Similarly, because of no multi-layer connection, the broad learning network can rapidly be remodeled in an incremental way without complete retraining process. Besides, compared with the time-consuming training demanding high-performance equipment in deep learning, BLS can be quickly established in a few minutes with a normal PC.

The primary contributions in this paper can be summarized as follows:

- This is the first time for broad learning to be incorporated in overcoming the FBP training problems, which has ensured a promising performance for model learning speed and accuracy.
- A texture-based local feature fusion method combined with the 2DPCA is proposed to improve the model’s semantic representation and transform the bias from texture to shape.
- An efficient and simple FBP network is introduced in this paper. Experimental results prove that this network can be easily constructed in an expeditious way even with general equipment.

The layout of this paper is arranged as follows. Section 2 provides an overview of the related works of this paper while Section 3 elaborates the method and algorithm process. Experimental results are explained in Section 4, followed by discussions and conclusions of this paper in Section 5.

II. RELATED WORKS

Since the proposed method is based on local feature fusion and broad learning to solve the problem of FBP, this section will introduce the related works in FBP as well as in local feature fusion and broad learning.

A. FACIAL BEAUTY PREDICTION

Conventional FBP largely focuses on geometric features, enabling it to collect key points on the face. It operates with the calculation of the Euclidean distance of the key point and the ratio vector between them and then inputs the obtained distance data into the classifier for learning. In 2006, Eisenthal et al. [15] utilized support vector machine and the K nearest neighbor algorithm to predict the facial beauty on 100 frontal face images, while based on which Fan et al. [16] adopted higher-dimensional geometric features for traditional supervised classification. Compared with geometric features, texture features have more robust characterization capabilities and fewer restrictions on face poses. Geometric features are only suitable for face beauty research under general conditions. Hence, Yan et al. [17] proposed a cost-sensitive sequence regression (CSSR) FBP method, through extracting and testing the original pixels and texture features, successfully counter the problem of unbalanced data set categories, reaching a classification accuracy of 52.12%. Furthermore, an extensive database named large scale Asian female beauty database (LSAFBD) was established by Zhai et al. [18] to settle the problem of insufficient facial data via applying apparent multiscale features to FBP. The above experiments reveal that if the texture feature uses the part of the whole face as the feature extraction object, it can substantially reduce manual intervention and improve model calculation efficiency.

In recent years, some new methods for studying facial beauty [7] have sprung up in neural networks and deep learning. Gan et al. [19] employed the deep convolutional network model for feature learning with a correlation of 0.739 while Jie et al. [20] established a psychologically stimulated convolutional neural network model to predict facial beauty, achieving a correlation of 0.87. In the same year, Gan et al. [21] adopted a deep convolutional network, with which the accuracy of male and female FBP could reach 52.30% and 55.24% respectively based on LSAFBD. After that, Gan et al. [22] introduced a research on FBP based on deep convolutional features of dual activation layers which vastly outperformed the previous methods both in classification and regression prediction. It possessed better real-time performance and accuracy in mainstream CNN models.

At present, although methods based on deep learning can theoretically extract the in-depth features of face images, limited results in this regard gained by scholars have told a different story. For one thing, the main reason belongs to not enough exploration about the prediction model training for the optimal hierarchical structure. For another, deep learning with numerous parameter designs involved can lower operating efficiency. Therefore, reducing the network model’s scale and improving training efficiency are the core of the research with important scientific significance and research value.
B. LOCAL FEATURE FUSION

Local feature fusion [23] is a classic computer vision concept, which has been widely used in biometrics identification [24]. The traditional method is to use single local feature to train neural network to realize biometric recognition. The difference between the traditional method and local feature fusion lies in the existence of complementary advantages between different features in the latter one, which can make up for the shortcomings of a single feature and enhance the robustness of image features. Yu et al. [25] realized the recognition of human ears by extracting the texture feature and edge feature of the image separately by histogram of oriented gradient (HOG) for local feature fusion. Min et al. [26] verified the effectiveness of the multi-feature fusion algorithm in enhancing the model performance in the details of the VR panoramic image more than the single-feature fusion algorithm. Yu et al. [27] suggested an emotion recognition model algorithm focusing on long short-term memory (LSTM) with the fusion of different local facial features, which acquired a 24.38% higher accuracy compared with the typical method.

Since both texture information and semantic information play crucial roles in FBP tasks, the proposed method in this paper using local feature fusion. Experimental results verify the effectiveness of the proposed method in favorably fulfilling FBP tasks.

C. BROAD LEARNING SYSTEM

BLS is an expeditious model without the need of deep network. This system first transfers the original images and places them in the feature node as a mapping feature, followed by the extensive expansion of the structure in the enhanced node. If the network deems to be expanded, incremental learning algorithms are developed for fast remodeling in broad expansion without a retraining process. It can improve the training speed while ensuring the accuracy of the model.

Many scholars have verified the effectiveness of broad learning in the field of image recognition through experiments. For example, Zhang et al. [28] provided evidence about how face recognition with the help of BLS could remain unaffected by the number of facial features with intense illumination and occlusion and meanwhile maintaining a prominent accuracy. Chen et al. [29] unraveled the superiority of BLS and its variants to several existing learning algorithms in time series prediction and performance regression on face recognition database. Compared with other classic structures, the efficiency and effectiveness of the BLS variants have been fully testified. What is more, Xu et al. [30] raised a new adaptive neural control framework based on broad learning, giving birth to a better human neuromotor system than conventional adaptive neural control did.

This is the initial attempt for the BLS to serve as an FBP classifier in FBP tasks. Through substantial experiments, it is certified that BLS performs outstandingly in optimizing FBP training efficiency and the final prediction accuracy.

III. PROPOSED METHOD

In this paper, we proposed an effective and simple FBP system with the participation of local feature fusion and BLS. To begin with, pre-process the images in the LSAFBD, followed by the utilization of different local texture feature including LBP [31], [32] LPQ [33], [34], and LMP [35] methods to extract facial features. Secondly, 2DPCA [11] is adopted to achieve dimensional reduction of texture images. After that, the texture images are processed with local feature fusion method. At last, input the fused feature eigenvectors into BLS to predict facial beauty. Fig. 1 displays the whole processing of the proposed method in this paper.

A. FACIAL IMAGE PRE-PROCESSING

Facial detection and key point detection are both performed on the face images. The key point method of the face is estimated by the three-level convolutional neural network, while the key point prediction equation of the face is based on the multi-level regression:

$$\sum_{i=1}^{n} x_i^{(k)} + \sum_{k=2}^{l} \Delta x_i^{(k)} - \frac{1}{l_i}$$

where for n-level cascade, x represents the input value of the key points of human face. There is a prediction at level k, among which the first level prediction refers to the absolute value prediction bit and the next level prediction serves as an adjustment to realize the detection of key points of the face. A red frame indicates the detected face area, and green dots locate the five key points of the detected eyes, nose, and mouth corners, as shown in Fig. 2.

Owing to the detrimental factors such as deflection and tilt in the face images of the original database, it is of urgent necessity to perform operations such as alignment on the detected face. Firstly, use the key points at the center of the left and right eyes to calculate the connecting line and horizontal line angle so that the images can be aligned horizontally in case of posture deflection. Then, fix the pixels of the center point of the eyes and the center point of the mouth to 48 pixels with the normalization of scale following. Finally, image with a size of 144 × 144 can be obtained as the input of the network shown in Fig. 3.

B. LOCAL FEATURE FUSION

1) LOCAL DESCRIPTORS

Compared with global feature fusion, local feature fusion contains richer features and lower correlation between features. In the case of occlusion, the detection and matching of other features will not be affected by the disappearance of some features. In recent years, local features [36] have been widely used in face recognition, three-dimensional reconstruction, target recognition, and panoramic image stitching. In this paper, we incorporate three efficient local texture feature methods to complete the local feature fusion operation.

Local Binary Patterns (LBP) has long been applied to face image analysis, including face detection and recognition, and
Local Phase Quantization (LPQ), whose principle share similarities with LBP, mainly obtains image features by using the local discrete Fourier transform (DFT) of the image. LPQ with the use of the image frequency domain feature information engenders a better feature invariance effect on the image interfered by blur. It means that LPQ features have good blur invariance and consequently, when using LPQ to extract the blurred image’s texture information, it produces superior results. Compared with LBP, despite the LPQ feature image tends to lose more details, it still owns the competitive edge of being insensitive to blur. Hence when indefinite blurred and disturbing images are to be encountered in practice, LPQ can be helpful in enhancing the robustness of the algorithm.

Local Monotonic Pattern (LMP) mainly extracts specific micro-pattern facial features from face images with its operator applied to the image pixels. This method converts by finding the monotonic intensity of adjacent pixels with different radius, tiling the image and obtaining each tile histogram. Then through spatial information enhancement to find smaller texture features, the final feature vector is obtained from the histogram. The discriminate power of the LMP operator assists the successful integration of multiple adjacent pixel radius in the micro-pattern and the
histogram of spatial encoding. The psychological experiment of Bassili [37] shows that facial features can be recognized more accurately from sequence images than from a single image. The performance of local texture feature extraction is given in Fig.4.

2) LOCAL FEATURE FUSION METHOD WITH 2DPCA DIMENSIONAL REDUCTION

Feature fusion is basically an intermediate level process of extracting feature information from original information for comprehensive analysis and processing. The extracted feature information is a sufficient representation or statistics of the original data fusion initial information, and the multi-source information is classified and integrated accordingly. Simultaneously, multi-feature extraction can provide more feature information of the recognition target than single feature extraction, which can better build up the dimension of feature space. This paper mainly focuses on local texture feature fusion for LBP, LPQ and LMP, three of which will extract image feature information from different angles, and then fuse them to obtain a new eigenvector as the feature vector for subsequent recognition.

Before local feature fusion, 2DPCA is implemented to reduce the dimension of local texture images. If \( \{B_1, B_2, \ldots, B_p\} \) are the training texture images, compute the covariance matrix of the training images

\[
Q = \sum_{i=1}^{p} (B_i - \bar{B})^T (B_i - \bar{B})
\]

where \( i = 1, 2, \ldots, p, \) and \( \bar{B} = \frac{1}{p} \sum_{i=1}^{p} B_i. \)

Then, select the eigenvectors relevant to the \( k \) largest positive eigenvalues to form the transformation matrix \( B_i \).

If \( B_i \) represents training sample, its feature matrix will be

\[
G_i = (B_i - \bar{B})V_{row}
\]

If \( T \) represents testing sample, its feature matrix will be

\[
G = (T - \bar{B})V_{row}
\]

In 2DPCA, the covariance matrix can be directly established by using the original matrix. Its main advantages are: (1) the correlation of the row eigenvectors or column eigenvectors of the image removed; (2) less time spent in calculating the eigenvalue eigenvector.

Assume that different kinds of local texture feature matrix after dimension reduction are \( A \) and \( B \). When performing feature fusion, first, obtain a \( d \)-dimensional eigenvector \( F_A \) and an \( x \)-dimensional eigenvector \( F_B \) representing its characteristics. Then, normalize the feature eigenvectors to \( F_A \) and \( F_B \) according to the principle of maximum and minimum for \( F_A' \) and \( F_B' \):

\[
F_A' = \frac{F_A - \min(F_A)}{\max(F_A) - \min(F_A)}
\]

\[
F_B' = \frac{F_B - \min(F_B)}{\max(F_B) - \min(F_B)}
\]

where \( F_A = \{F_{p1}, F_{p2}, \ldots, F_{pn}\} \), and \( F_B = \{F_{q1}, F_{q2}, \ldots, F_{qd}\} \).

Finally, perform a weighted cascade fusion to the two features after normalization abovementioned

\[
F = \begin{bmatrix} w_1 F_A' \\ w_2 F_B' \end{bmatrix}
\]

In which, \( w_1 \) and \( w_2 \) are obtained through training, and \( w_1 + w_2 = 1 \) while the fusion ratio is directly assigned to 1:1. The fused feature \( F \) will be the final face feature.

C. BROAD LEARNING SYSTEM

1) BASIC THEORY OF BROAD LEARNING

This part will introduce the basic theory of broad Learning. BLS is based on the traditional random vector functional-link neural network (RVFLNN) [39], [40]. For the basic network in general classification tasks shown in Fig. 5 (a). It is simpler and easier to update this network than the traditional model.

Assume that \( A_n \) represents an \( n \times m \) pattern matrix. It is the same as adding a new column to the input matrix \( A_{n+1} \), represented as

\[
A_{n+1} \Delta [A_n|a]
\]
The novel pseudo-inverse $A_{n+1}^+$ is equals to

$$
\begin{bmatrix}
A_n^+ - db^T \\
b^T
\end{bmatrix}
$$

(9)

where $d = A_n^+ a$

$$
b^T = \begin{cases} 
(c)^+ & \text{if } c \neq 0 \\
(1 + d^T d)^{-1} d^T A_n & \text{if } c = 0 
\end{cases}
$$

(10)

And $c = a - A_n d$. So we can get the new weights below:

$$
W_{n+1} = \begin{bmatrix}
W_n - db^T Y_n \\
b^T Y_n
\end{bmatrix}
$$

(11)

where the weights are $W_{n+1}$ and $W_n$. They represent the weights before and after adding new enhanced nodes, respectively. In this way, by calculating only the pseudo inverse of the corresponding added node, the new weight can be readily updated.

If $A_n$ is full rank and $c=0$, the pseudo-inverse $A_n^+$ and the weight $W_n$ will be quickly updated. A novel node was added to the network is given at Fig. 5 (b). Where $A$ represents the extended input matrix composed of feature nodes and enhancement nodes. A dynamic system is designed to update the weight of the model immediately for the newly added model and enhancement node.

Based on pseudoinverse and ridge regression learning algorithms, we have

$$
W_m = (\lambda I + AA^T)^{-1} A^T Y
$$

(12)

Specifically, we have that

$$
A^+ = \lim(\lambda I + AA^T)^{-1} A^T
$$

(13)

where value $\lambda$ denotes the further constraints by summarizing the squared weights, $W$.

2) BROAD LEARNING SYSTEM MODEL

The BLS effectively reduces the training time of classifier, and possesses generalization ability in background of modeling and control. In this section, we mainly introduce the structure of the broad learning network. This system needs to map the inputs to construct a set of mapped features at first. And then combine incremental learning algorithms that can update the system dynamically. Fig. 6 shows the basic structure of BLS.

Assume that input feature eigenvectors as $F \in R$. For $n$ mapping features, $m$ enhancement nodes can be generated. The input $F$ is projected and the group $i$ of feature nodes is generated; then the first mapping feature can be expressed as

$$
Z_i = \varphi(FW_{ei} + \beta_{ei})
$$

(14)
where \( Z_i, i = 1, 2, \ldots, n \). \( W_{ei} \) and \( \beta_{ei} \) stand for random matrix and bias respectively. All feature nodes can be represented as \( Z^n = [Z_1, \ldots, Z_n] \). \( \varphi(\cdot) \) is an activation function. So, the \( m \) group of enhancement nodes can be denoted as

\[
H_j \equiv \xi(Z^nW_{hj} + \beta_{hj})
\]

(15)

where, \( W_{hj} \) and \( \beta_{hj} \) represent random matrix and bias, respectively. All enhancement nodes can be represented as \( H^m = [H_1, \ldots, H_m] \). \( \xi(\cdot) \) is an activation function.

The combined matrix obtained by connecting the enhancement node and feature node is used as BLS’s the new input.

\[
Y = [Z^nH^m]W^m
\]

(16)

Combining with the \( W^m = (\lambda I + AA^T)^{-1}A^TY \), and according to the pseudo-inverse and ridge regression learning algorithm, we have

\[
A^+ = \lim(\lambda I + AA^T)^{-1}A^T
\]

(17)

where \( A^+ = [Z^nH^m]^+ \). This formula can be derived from the above derivation

\[
W^m = [Z^nH^m]^+Y
\]

(18)

which is the connection weight of the broad learning network model. The model overall construction and learning procedure of FBP via local feature fusion and broad learning is listed in Algorithm 1.

### IV. EXPERIMENTAL RESULTS & ANALYSIS

Experimental results are given to confirm the effectiveness of FBP network. The database we used in this experiment certifies this method’s effectiveness in the LSAFBD containing 10,000 face images. There are 5 labels in LSAFBD, which are ugly, unattractive, ordinary, beautiful and glamorous. We have performed equalization processing based on this database. Fig. 7 presents the data distribution of each category in the LSAFBD. The horizontal axis denotes database label, while the vertical axis as the percentage of each category of data. Fig. 8 refers to a sample of each category labels in the database.

Comparisons are conducted between the prediction ability of our FBP network with those of the existing mainstream approaches. The experiments are equipped with a 32GB memory, Inter-i5 3.6 GHz CPU laptop on MATLAB software platform.

#### A. EXPERIMENTS ON SINGLE LOCAL FEATURE & BLS

This section will combine the broad learning network with the single local feature extraction method to build a robust model that can achieve beautiful face prediction. Table 1-4 are the FBP results of LBP, LPQ, LMP and the original pixels under different feature nodes and enhancement nodes in the BLS separately while in table 5 a comparison among different dimensional reduction methods can be found. We reduced the dimension of PCA to a one-dimensional feature eigenvector 784, whereas 2DPCA calculated the eigenvectors of a 48×48 matrix.

Concluding from repeated experiments and demonstrations, we set the attenuation coefficient of the enhanced node to 0.3 and the regularization parameter of the sparse area to

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**Algorithm 1** Facial Beauty Prediction via Local Feature Fusion and Broad Learning System

**Input:** training samples set \( X, Y \); \( Y \) is the output matrix; \( x \) represents one of the samples; \( (x_c, y_c) \) and \( g_c \) represents the center pixel; \( i_c \) is grayscale value; \( n_1 \) represents gray value of adjacent pixels; \( s \) represents a symbolic function; \( q_i(X) \) are binary coding integer values; \( g_{p1} \) and \( g_{p2} \) respectively correspond to the intensity values \( F \) equally spaced pixels on the circle with radius \( R1 \) and \( R2 \).

**Output:** \( W \)

for \( k=0; k \leq n; \)

- Facial detection and key point detection;
  - Calculate \( \sum X = \frac{\sum_{i=1}^{p} s(i_p - i_c); \quad \text{Calculate } \sum_{j=1}^{8} q_j(X) 2^{-j};} {p=0} \)
  - Calculate LMPF, R1, R2 \( (x, y) = \sum_{p=0}^{p-1} s(g_{p1} - g_c) \land s(g_{p2} - g_{p1}) 2^{-p}; \)
  - Calculate the covariance matrix \( Q = \sum_{i=1}^{p} (B_i - \bar{B}^T(B_i - \bar{B}); \)
  - Calculate \( G_i = (B_i - \bar{B})V_{row} \) and \( G = (T - \bar{B})V_{row}; \)
  - Assume that local feature fusion methods are A and B;
  - Calculate \( F_A = \frac{\max(F_{A} \text{min}(F_{A})}{\min(F_{A})}; \quad F_B = \frac{\max(F_{B}) \text{min}(F_{B})}{\min(F_{B})}; \)
  - Calculate \( F = \frac{w_1 F_A}{w_2 F_B}; \)
  - for \( i = 0; i \leq n; \)
  - Random \( W_{hj}, \beta_{hj}; \)
  - Calculate \( Z_i = \varphi(FW_{ei} + \beta_{ei}); \)
  - end
  - Set \( Z^n = [Z_1, \ldots, Z_n]; \)
  - for \( j = 1; j \leq m; \)
  - Random \( W_{hj}, \beta_{hj}; \)
  - Calculate \( H_j \equiv \xi(Z^nW_{hj} + \beta_{hj}); \)
  - end
  - Set \( H^m = [H_1, \ldots, H_m]; \)
  - Calculate \( A^m \) and get \( (A^m)^+ \) with \( A^+ = \lim(\lambda I + AA^T)^{-1}A^T; \)
  - Calculate \( W^m = [Z^nH^m]^+Y; \)
  - if \( \text{training error} \geq \text{threshold}; \)
  - Add \( p \) enhancement nodes or \( n+1 \) feature mapping;
  - Update parameters;
  - end
  - Set \( W; \)

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TABLE 1. Performance of LBP with 2DPCA.

| Feature nodes | Enhancement nodes | Accuracy (%) | Training time (s) | Testing time (s) |
|---------------|-------------------|--------------|-------------------|------------------|
| 100           | 500               | 43.75        | 9.10              | 0.87             |
| 100           | 900               | 43.87        | 6.17              | 1.02             |
| 100           | 1500              | 44.81        | 5.10              | 0.84             |
| 100           | 3000              | 45.96        | 9.04              | 0.99             |
| 100           | 3500              | 45.69        | 7.91              | 0.82             |
| 300           | 3000              | 45.76        | 8.55              | 0.91             |
| 500           | 3000              | 46.33        | 7.80              | 0.86             |
| 700           | 3000              | 45.92        | 9.91              | 1.22             |
| 800           | 3000              | 45.20        | 10.84             | 1.28             |

TABLE 2. Performance of LPQ with 2DPCA.

| Feature nodes | Enhancement nodes | Accuracy (%) | Training time (s) | Testing time (s) |
|---------------|-------------------|--------------|-------------------|------------------|
| 100           | 500               | 52.68        | 9.36              | 1.04             |
| 100           | 900               | 52.31        | 8.88              | 1.08             |
| 100           | 1500              | 52.06        | 7.88              | 1.06             |
| 100           | 3000              | 52.10        | 8.64              | 0.50             |
| 100           | 3500              | 53.78        | 7.07              | 0.91             |
| 300           | 3500              | 53.73        | 10.49             | 0.96             |
| 500           | 3500              | 53.67        | 8.99              | 1.57             |
| 700           | 3500              | 54.32        | 9.38              | 0.95             |
| 800           | 3500              | 54.07        | 11.77             | 1.56             |

TABLE 3. Performance of LMP with 2DPCA.

| Feature nodes | Enhancement nodes | Accuracy (%) | Training time (s) | Testing time (s) |
|---------------|-------------------|--------------|-------------------|------------------|
| 100           | 500               | 50.51        | 6.54              | 0.65             |
| 100           | 900               | 50.04        | 7.16              | 1.6              |
| 100           | 1500              | 51.44        | 8.61              | 1.56             |
| 100           | 2000              | 51.98        | 9.41              | 0.96             |
| 100           | 3000              | 51.51        | 10.08             | 0.95             |
| 300           | 2000              | 51.77        | 11.38             | 1.66             |
| 500           | 2000              | 52.00        | 10.50             | 1.89             |
| 700           | 2000              | 52.02        | 9.54              | 0.92             |
| 800           | 2000              | 51.87        | 9.23              | 1.82             |

FIGURE 7. LSAFBD data distribution histogram.

2e-20 in this experiment, which were conducive to the birth of the best test accuracy. The test accuracy result was the average value of 50 training times. Training time and testing time corresponded to the values when the accuracy was average.

It can be seen from the above experimental results that when LBP, LPQ, and LMP are used for feature extraction and original pixels as input, the accuracies of FBP are 43.09%, 52.98%, 50.19% and 54.88%, respectively. Among these subjects, LBP has the worst effect when used as feature extraction, and the prediction accuracy of original pixels remains the highest. The experiment also shows that single local feature cannot achieve robust facial feature extraction. Simultaneously, the original image as training data retains more advanced facial features, such as skin fineness and facial details leading to better prediction.

Known from the tables, based on 2DPCA the training time of LBP, LPQ, LMP and original pixels are 7.80s, 9.38s, 9.54s, and 16.24s respectively. The experiment result shows that the training speed of broad learning witnesses a geometric increase different from deep network. This corroborates the effectiveness of broad learning as a classification network.

In addition, we also compared the impact of different dimensional reduction methods on prediction performance. Table 5 tells the influence of 2DPCA, PCA and no operation on the predicted network performance. And performance results proved that 2DPCA exceeds PCA and no-operation in facial beauty prediction. After researches conducted on these two algorithms, the following conclusions can be drawn.
B. EXPERIMENTS ON LOCAL FEATURE FUSION & BLS

The following experiments will perform local feature fusion on the acquired data to further improve the prediction accuracy. Local feature fusion mainly conducts more advanced feature extraction by cascading the generated feature eigenvectors of the face image.

Due to the large size of data dimension after cascade, inputting it directly into the broad learning network will raise the training time and reduce the classification accuracy affected by background noise, light and other factors. Therefore, after local texture feature extraction process, 2DPCA need to invite again to reduce high-dimensional data. Table 6-8 are the prediction results of different numbers of feature nodes and local texture features under enhanced nodes after dimensional reduction and fusion. Table 9 also compares the experiment results among dimensional reduction methods. The dimensional reduction of PCA and 2DPCA remained the same as experiment A.

In this experiment, the attenuation coefficient of the enhanced node set to 0.3, and the regularization parameter of the sparse area set to $2e^{-7}$, which could optimize the experimental results. The test accuracy result was the average value of 50 training times. Training time and testing time corresponded to the value when the accuracy was the average.
Compared with the prediction results in Table 5, the prediction performance of FBP based on local feature fusion is much higher than that of single local feature. This method can reach the prediction accuracy at 58.97% in 13.33s. Through local feature fusion, texture invariance is achieved. Also, the influence of background noise is avoided and redundant features are removed, preserving more advanced facial features. From the comparison results in Table 9, 2DPCA proves its effectiveness again in improving FBP accuracy and robustness. 2DPCA is capable of projecting the original features to the dimension with as much information as possible through reducing the dimension of the original features.

### C. PERFORMANCE COMPARISON WITH SVM CLASSIFIER

In this section, the traditional methods support vector machine (SVM) [18], a generalized linear classifier, is taken as classifier performance comparison to ensure fair conclusion in this experiment, because broad learning is also based on linear features mapping. The results of performance
comparison between BLS and SVM can be referred to Fig. 9 and Fig.10.

Fig.9 and Fig.10 compare the training time and prediction accuracy of BLS and SVM, showing that BLS greatly shortens the training time while improving the prediction accuracy compared with SVM. This outcome consolidates the effective status of BLS as a classifier. In addition, we can also find that whether it is with SVM or BLS, local feature fusion with 2DPCA can obtain the best results in FBP accuracy.

**D. PERFORMANCE COMPARISON WITH DEEP LEARNING METHODS**

To corroborate the effectiveness of our method, we choose five kinds of well-performed deep networks to constitute comparison with our method. These five state-of-the-art deep learning methods [42]–[46] can even produce satisfying outcomes even under the ImageNet challenge; however, they demand deep structure and high-performance computer in their operations. In this section, related experiments about CNN needs to be tested on a V ARM 5G, Intel-i7 64GB memory computer with 8G GPU.

According to table 10, although broad learning only performs linear feature extraction, it still obtains better prediction results and consumes less time than some popular deep learning methods did. Besides, compared with hours of training time equipped with high-performance PC in deep network, our methods enable the establishment of a high accuracy FBP model in a normal laptop within a few minutes.
V. CONCLUSION

In this paper, a novel method is proposed based on local feature fusion and broad learning for FBP task. Unlike other models for FBP, BLS as a simple and fast network is adopted to predict for improving the training speed while ensuring prediction accuracy, successfully providing an alternative for deep learning structure. Experiments verify that broad learning can efficiently update and reshape the model on a regular computer. Furthermore, local feature fusion with 2DPCA dimensional reduction is designed to extract highly discriminative features specific to facial images, improving the model’s semantic representation and transforming the bias from texture to shape.

In this work, comparisons have been conducted between the accuracy and training time of the proposed method and other state-of-the-art approaches so as to demonstrate its validity. The experiments on LSAFBD confirm the effectiveness and the efficiency of the proposed FBP model, which obviously outperforms the existing deep neural network in terms of training speed. However, in view of the serious labeling errors on FBP task, efforts will be further devoted into the exploration of new methods that can satisfactorily solve the cost-sensitive problem of facial beauty in the future.

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