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The Editor-in-Chief and the publisher have retracted this article, which was submitted as part of a guest-edited special section. An investigation uncovered evidence of systematic manipulation of the publication process, including compromised peer review. The Editor and publisher no longer have confidence in the results and conclusions of the article.

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Mural digital image restoration technology and stitching evaluation model based on machine learning

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Abstract. Mural painting refers to art on the wall, which has high aesthetic value. However, due to its vulnerability to damage, digital image restoration and stitching techniques are now used to permanently preserve mural images. The purpose of our study is to select a more suitable specific calculation method by studying machine learning (ML) methods and conduct in-depth research on mural digital image restoration technology and stitching evaluation, so that it can better serve the restoration and splicing of the current mural digital images. Based on the experiments, it can be seen that the respondents in hall A had a high degree of recognition for digital image restoration and stitching technology. There were 176 respondents, and only 29 people believed that digital image restoration was not important; respondents in hall C did not agree with the digital image restoration technology as much as hall A, only 132 people thought it was important, and 64 people thought it was not important. It can be seen that the model establishment of mural digital image restoration technology and splicing evaluation is deeply affected by the knowledge level of the evaluator. The experimental results of our study showed that the research process of mural digital image restoration technology and stitching evaluation based on ML method was more effective than other methods of analyzing experimental data. © *2022 SPIE and IS&T* [DOI: 10.1117/1.JEI.32.3.031806]

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1 Introduction

The development of the intelligent era has promoted the development of related intelligent information technology and greatly improved the convenience of public life. As the demand for data analysis continues to increase in the era of big data in various industries, efficient knowledge acquisition through machine learning (ML) has gradually become the main driving force for the development of ML technology today. ML in the era of big data emphasizes "learning itself as a means," and ML becomes a support and service technology. Therefore, ML is developing more and more in the direction of intelligent data analysis and has become an important source of intelligent data analysis technology. In addition, in the era of big data, as the rate of data generation continues to accelerate, the volume of data has increased unprecedentedly, and new types of data that need to be analyzed are emerging, such as text understanding, text sentiment analysis, image retrieval and understanding, and graphical and web data analysis. This makes intelligent computing technologies, such as big data ML and data mining (DM), extremely important in the application of intelligent analysis and processing of big data. ML algorithm is a comprehensive information processing tool, involving many disciplines, including but not limited to the fields of introductory science and statistics, and belongs to the core of the field of artificial intelligence. Due to the wide range of uses of ML algorithms, generally, induction and synthesis were generally used.

Because murals have high aesthetic and artistic value, in the era of electronic data storage, the behavior of digital image restoration and splicing to save murals has become an inevitable trend

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in the intelligent age. Mural painting is an important archaeological material for our understanding of history, and culture provides an important basis. Frescoes are an important part of the world's culture, a cultural heritage belonging to the whole of humanity. Although cultural products have regional and national distinctions, the cultural values contained in these products belong to the entire human race and the entire world. Therefore, these murals are not just the private property left by one person or some people, but the wealth that belongs to the whole human civilization. There were many scholars, who analyzed mural restoration and splicing restoration work, and many scholars conducted research on mural restoration work from the field of digital images, but few scholars analyzed it from the perspective of ML. Based on the ML method, this paper analyzed the repair and splicing of murals in the field of digital images. The development of mural preservation technology in the age of intelligence was explored, and research methods in this direction were broadened. They provided a feasible method for the formulation of mural digital image restoration technology and splicing evaluation model, which had certain practical significance.

The innovation of this paper is that it is based on ML algorithm to analyze the mural digital image restoration technology and stitching evaluation model.

2 Related Work

Mural painting is essentially the art on the wall. It takes the form of direct painting on the wall and is a part of the building, so it has high artistic value. Therefore, there are many scholars who study and discuss it. The purpose of Veneranda et al.'s[1] research was to investigate the biodegradation process that destroyed the frescoes preserved in the Ariadne house. Shuai et al.[2] believed that solving the current problems of digital product piracy and copyright disputes was a top priority. On this basis, a digital watermarking algorithm was developed, which can encode private images, and used a variety of attack methods to conduct experiments on carrier images. Yue and Wei believed that digital image authentication involved related technologies, such as tamper-proof, copyright protection, or access control. Through the development of a large number of digital image authentication (DIA) techniques to authenticate digital images, the general framework and techniques of image watermarking were described in this paper, and potential issues for future research directions were also discussed.[3] Zhang et al.[4] proposed that the choice of subset size was very important for the accuracy of DIC. Therefore, an adaptive bidirectional dynamic subset selection algorithm was proposed, which enabled each subset size to be optimal. Peng et al.'s experiment proposed a method for determination that combined dispersive liquid–liquid microextraction with digital scanning image analysis, using orthogonal experiments to optimize reagent concentrations. Orthogonal experiments were used to optimize the reagent concentration, and they were successfully applied to the analysis of total iron in water and food samples, which had a potential industrial impact on the development of related enterprises.[5] These scholars are very keen on the research and discussion of digital images of murals, and some use digital image technology as a research method, which is widely used in experiments. However, there are few discussions on the repair technology and splicing evaluation of digital images of murals, and few scholars have conducted researches combined with ML algorithms.

ML is a multidisciplinary science, and the main research is in the field of artificial intelligence. There is a wide range of applications, so the academic community has been keen to explore the specific role of ML. Buczak and Guven studied the literature related to ML and DM methods. To support network analysis for intrusion detection, some typical datasets for ML/DM were therefore briefly presented and some suggestions for the use of the given methods were provided.[6] The main purpose of ML proposed in Jiang et al.'s[7] research is to support smart radio terminals, enabling smart 5G systems to autonomously access the most valuable spectrum bands with its help, and to adjust the transmission protocol on the basis of controlling the transmission power. Voyant et al.'s research mainly expounded the method of predicting solar radiation using ML methods and compared methods, such as neural network and supported vector regression many times in the text. However, due to the diversity of indicators, such as datasets, the prediction errors of such methods are comparable.[8] Kavakiotis et al.[9] believed that in the face of the increase of health information data, the application of ML in biological sciences became more important and indispensable, and data related to diabetes were studied. Liu et al.[10] believed that the method of interactive model analysis was very important for users to effectively solve artificial intelligence problems and divide related work into three categories: understanding, diagnosis, and refinement. Potential future research opportunities were explored. These scholars are very keen to widely apply ML technology to specific experimental research, but they mainly involve the field of artificial intelligence. Few studies have been done on ancient frescoes, such as digital image restoration techniques and stitching evaluation of frescoes studied in this paper.

3 Mural Digital Image Restoration Technology and Stitching Evaluation Method Based on Machine Learning

3.1 *Digital Image Restoration Technology and Stitching Evaluation of Murals*

3.1.1 *Murals*

A mural is a finished product after painting on the wall, with great aesthetic value, a precious cultural heritage in human history, and an artistic treasure. As an important carrier reflecting historical civilization, it bears the painstaking efforts of the painter and the hidden traces of the times.[11] Figure 1 shows a display of exquisite murals.

3.1.2 *Digital image restoration technology*

Image restoration is an ancient technology that originated in the Renaissance period. With the advent of the digital age, digital image technology has been widely used in various fields.

Fig. 1 Exquisite mural display.

Fig. 2 Display of the restored mural image.

However, because the technology is easily affected by multiple factors, restoration and stitching of digital images has become a hot research topic of current scholars, and digital image restoration technology has emerged.[12] Digital image restoration technology is widely used in various fields of life, such as restoration of ancient murals, film, and television special effects production.[13] In the process of virtual restoration of murals, the digital image information of ancient murals is generally collected first, and then digital image restoration technology is used to restore the lost or occluded parts of the murals, so as to restore the original appearance of the virtual murals.[14] Figure 2 shows a display image after image restoration.

3.1.3 *Evaluation of digital image stitching*

Digital image stitching is a kind of image restoration technology, which is generally to digitally shoot a certain image.[15] For the obtained captured images to accurately reflect the original content, the overlap of photos taken at each adjacent part should be at least 50% higher.[16] Due to various factors, the stitched image would produce unsatisfactory results, such as blurring and many noise points, which would easily affect the subsequent image stitching work. Therefore, how to objectively evaluate the quality of digital images is also a big problem. At present, the quality evaluation methods for digital image stitching are subjective qualitative evaluation and objective quantitative evaluation.[17]

3.2 *Machine Learning*

ML is a subject involving many fields, such as approximation theory and probability theory. It uses computers as a research tool and uses it to simulate the way of human learning in real time, so as to improve its own learning efficiency and optimize the performance standards of computer programs.[18] However, the earliest idea of ML is to imitate the human thinking mode, as shown in Fig. 3.

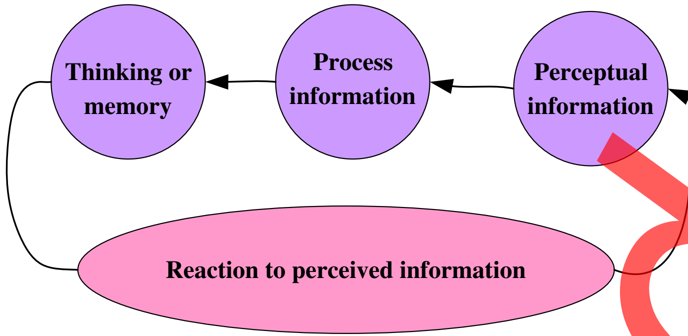

Fig. 3 Cognitive processes in the human brain.

ML in the big data environment can use distributed and parallel computing to avoid the interference caused by noisy data.[19] In the data age, ML is an important support for data analysis. For example, text comprehension and image retrieval analysis are a major object of analysis today. Figure 4 shows a beautiful picture of some classic ML.

Back propagation (BP) neural network is a multifeedforward neural network, which is composed of multiple layers and connected by weights. Differentiable functions are generally used as transfer functions, which are usually learned using an error back-propagation algorithm.[20] Figure 5 shows a schematic diagram of a three-layer BP neural network.

BP neural network is a multilayer feedforward neural network composed of input layer, hidden layer, and output layer. In the typical three-layer BP neural network diagram in Fig. 5, N is set as the number of neurons in the input layer, K is the number of neurons in the hidden layer, and L is the number of neurons in the output layer. The n neuron in the input layer is written as A_n, the k neuron in the hidden layer is written as I_k, and the l neuron in the output layer is written as B_l. The connection weight between A_n and I_k is set to w_{kl}.

It can be clearly seen from this figure that there are two kinds of signals propagating between the layers of the neural network. One is the working signal, that is, the output layer receives a vector of length N, and the output layer outputs a vector of length L. Among them, p represents the input of each layer, and q represents the output of each layer, and then the actual output of the network is

Fig. 4 Beautiful ML diagram.

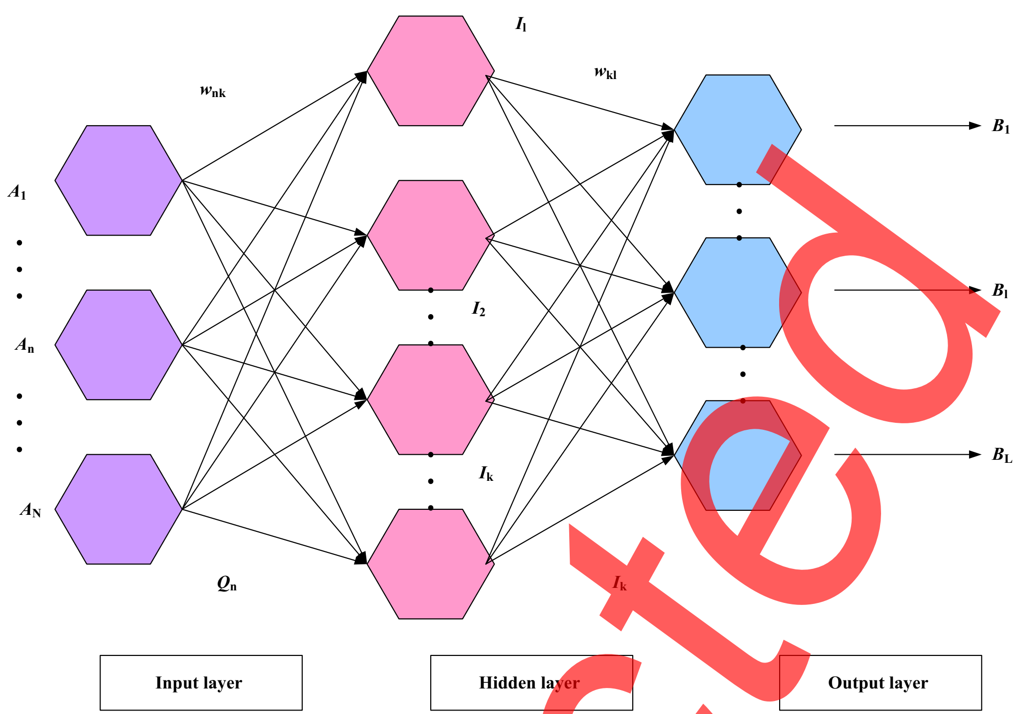

Fig. 5 Schematic diagram of a typical three-layer BP neural network.

$$B(m) = [q_l^1, q_l^2, \cdots q_l^l]. \tag{1}$$

The expected output is

$$t(m) = [t_1, t_2, \cdots, t_l]. \tag{2}$$

The second is the error signal.

The error signal after m iterations is defined as

$$e_l(m) = t(m_l) - B(m_l). \tag{3}$$

Error energy is defined as

$$e(m) = \frac{1}{2}\sum_{l=1}^{l} e_l^2(m). \tag{4}$$

Since the BP network algorithm is a supervised learning algorithm, the derivation process of a three-layer BP neural network is as follows.

(1) Forward-passing working signal

That is, the output of the input layer is equal to the input signal of the entire network:

$$q_N^n(m) = a(m). \tag{5}$$

The input of the k neuron in the hidden layer is equal to the weighted sum of $q_N^n(m)$:

$$p_K^k(m) = \sum_{n=1}^{N} w_{nk}(m) q_N^n(m). \tag{6}$$

$f(*)$ is set as the sigmoid function, and then the output of the k neuron in the hidden layer is

$$q_K^k(m) = f(p_K^k(m)). \tag{7}$$

Then the input value of the l neuron in the output layer is equal to the weighted sum of $q_K^k(m)$:

$$p_K^k(m) = \sum_{k=1}^{K} w_{kl}(m) q_K^k(m). \tag{8}$$

Then the output of the l neuron in the output layer is equal to

$$q_L^l(m) = \mathrm{g}(p_L^l(m)). \tag{9}$$

Among them, the error of the l neuron in the output layer is

$$e_l(m) = t_l(m) - q_J^j(m). \tag{10}$$

Among them, the error of the l neuron in the output layer is

$$e(m) = \frac{1}{2} \sum_{l=1}^{L} e_l^2(m). \tag{11}$$

(2) Adjustment of the weight change and the back-propagation of the error signal by the steepest descent method:

a. Weights w_{kl} between the hidden layer and the output layer are adjusted.

According to the steepest descent method, the gradient $\frac{\partial e(m)}{\partial wkl(m)}$ of the error with respect to w_{kl} is calculated and adjusted in the opposite direction:

$$\Delta w_{kl}(m) = -\gamma \frac{\partial e(m)}{\partial w_{kl}(m)}, \tag{12}$$

$$w_{kl}(m+1) = \Delta w_{kl}(m) + w_{kl}(m). \tag{13}$$

The gradient value is

$$\frac{\partial e(m)}{\partial w_{kl}(m)} = \frac{\partial e(m)}{\partial e_l(m)} \cdot \frac{\partial e_l(m)}{\partial q_L^l(m)} \cdot \frac{\partial q_L^l(m)}{\partial p_L^l(m)} \cdot \frac{\partial p_L^l(m)}{\partial w_{kl}(m)}. \tag{14}$$

The definition of local gradient is introduced

$$\delta_L^l = -\frac{\partial e(m)}{\partial p_L^l(m)} = e_l(m) g'(p_L^l(m)). \tag{15}$$

The weight correction value is

$$\Delta w(m_{kl}) = \gamma \delta_L^l q_L^l(m). \tag{16}$$

The local gradient can clearly represent the required change in weights, which is equivalent to the product of the neuron's error signal and the derivative of the transferred function. $g'(p_L^l(m)) = 1$ is substituted into Eq. (16) to obtain:

$$\Delta w_{kl}(m) = \gamma e_l(m) p_L^l(m). \tag{17}$$

b. The error signal propagates forward along the neural network and continuously adjusts the weight w_{kl} between the input layer and the hidden layer:

$$\Delta w_{kl}(m) = \gamma \delta_K^k q_N^n(m). \tag{18}$$

δ_K^k is the local gradient, so

$$\delta_K^k = -\frac{\partial e(m)}{\partial p_K^k(m)} = \frac{\partial e_l(m)}{\partial p_K^k(m)} f'(p_K^k(m)). \tag{19}$$

Since the hidden layer is invisible, the partial derivative $\frac{\partial e_l(m)}{\partial q_K^k(m)}$ of the error to the output value of the layer cannot be directly obtained, so the local gradient of the output layer node is obtained by combining the formula:

$$\frac{\partial e_l(m)}{\partial q_K^k(m)} = \sum_{l=1}^{L} \delta_L^l w_{kl}. \tag{20}$$

So

$$\delta_K^k = f'(p_K^k(m)) \sum_{l=1}^{L} \delta_L^l w_{kl}. \tag{21}$$

4 Experiment of Mural Digital Image Restoration Technology and Stitching Evaluation

4.1 *Scheme Design of Mural Digital image Restoration Technology and Stitching Evaluation*

As a treasure representing national culture and world civilization, murals have great aesthetic and artistic value. However, because the preservation technology of murals has always been defective, and the work of restoring and reproducing them has become a major difficulty at present, therefore, based on the development of the digital age, it is very important to apply ML to mural digital image restoration and stitching technology. It is also conducive to fully presenting the original appearance of murals hundreds, thousands, or even tens of thousands of years ago with the technical help of scientific intelligence and can effectively draw the key points of this paper. This experiment uses ML technology as the main experimental method, specifically involving the BP neural network algorithm, and distributes 900 questionnaires to the visitors of the three museums in City G. The basic information is shown in Table 1.

Since only 931 valid questionnaires were recovered by volunteers, the valid recovery rate of this questionnaire survey was 92.3%. It can be seen from Table 1 that there are 289 people in museum A, 267 people in museum B, and 275 people in museum C in this valid questionnaire. Among them, museum A has the largest number of men, with 160 people, accounting for 19.3% of the valid questionnaires; and museum C has the largest number of women, with 151 people, accounting for 18.2% of the valid questionnaires.

4.2 *Discussion on the Results of Mural Digital Image Restoration Technology and Stitching Evaluation*

This questionnaire mainly asks questions about "respondents' understanding of the restoration of digital images of murals" and their basic attitudes.

Table 1 Basic information of respondents.

	Female	Male	Total
A	129	160	289
B	135	132	267
C	151	124	275

Table 2 Statistics on the educational level of respondents.

	A	B	C
Primary school	83	51	113
Middle school	125	96	76
University	81	120	86

4.2.1 *Educational level of the respondents*

Analysis of the educational level of the respondents who participated in this questionnaire can help to analyze the digital image restoration technology and splicing evaluation of murals. Table 2 shows the statistics of the educational level of the respondents.

It can be seen from Table 2 that 297 respondents are middle school graduates, accounting for 35.7% of the valid questionnaires; followed by university graduates, with 287 respondents, accounting for 34.5% of the valid questionnaires; only 247 people have primary school education, accounting for 29.7% of the valid questionnaires. Among the respondents, in hall A, the number of people with secondary school education is the largest, with 125 people, and the number of people with university education is the least, only 81 people, accounting for 15% and 9.7% of the valid questionnaires, respectively; in hall B, the number of people with university education is the largest, with 120 people, and the number of people with primary school education is the smallest, only 51 people, accounting for 14.4% and 6.1% of the valid questionnaires, respectively; and in hall C, the number of people with primary school education is the largest, with 113 people, and the number of people with middle school education is the smallest, with only 76 people, accounting for 13.6% and 9.1% of the valid questionnaires, respectively.

4.2.2 *Whether the murals viewed are believed to have been restored*

This questionnaire is mainly aimed at evaluating and judging the digital image restoration and splicing technology of murals. Therefore, whether the respondents can clearly recognize whether the murals have been restored can provide scientificity and reliability for the reference data of this experiment, and it is also conducive to the answering and analysis of follow-up questions. Figure 6 shows the respondents' perception of the murals they watched.

As can be seen from Fig. 6, 483 respondents believed that the murals they watched were restored, accounting for 58.1% of the valid questionnaires; 348 respondents believed that the

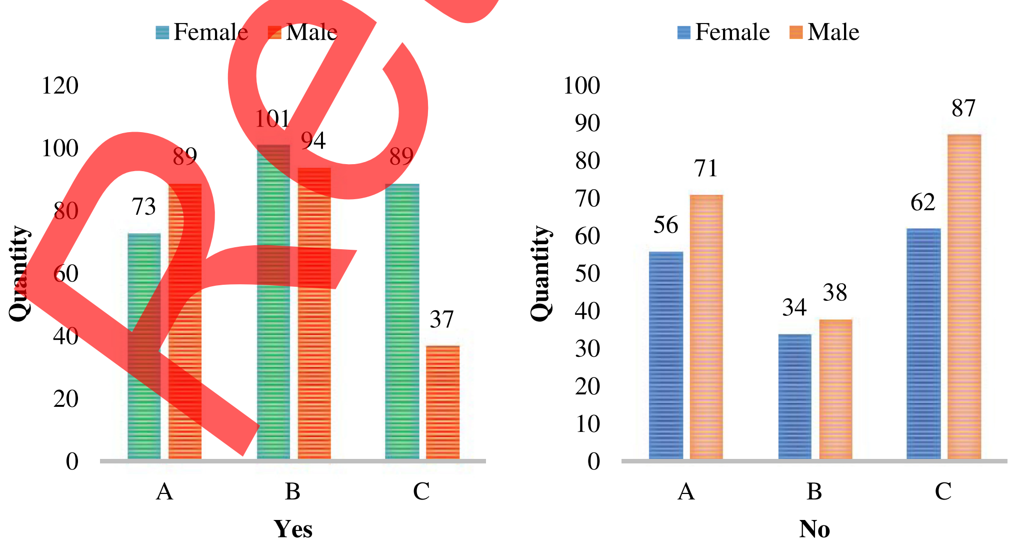

Fig. 6 Respondents think whether the murals they viewed have been restored.

murals they watched were unrestored, accounting for 41.9% of the valid questionnaires. From the comparison in Fig. 6, it can be seen that hall B has the largest number of people who agree with 104 people; among the respondents who disagree, there are only 72 people in hall B with 149 people.

4.2.3 *Whether digital image restoration technology is understood*

Whether the respondents understand the analysis of digital image restoration technology is conducive to making an accurate judgment on the evaluation of mural digital image restoration technology. Figure 7 shows whether the respondents understand the specific situation of digital image restoration technology.

As can be seen from Fig. 7, most of the respondents do not understand digital image restoration technology, there are 484 respondents, accounting for 58.2% of the valid questionnaires. In particular, there are 195 respondents in hall A, accounting for 23.5% of the valid questionnaires, including 120 men and 75 women. Relatively speaking, there are 151 respondents in hall B who are relatively familiar with digital image technology, accounting for 18.2% of the valid questionnaires, including 70 men and 81 women.

4.2.4 *Whether digital image stitching technology is understood*

Whether the respondents understand the analysis of digital image splicing technology is helpful for making accurate judgments on the evaluation of mural digital image splicing technology later. The specific situation is shown in Fig. 8.

According to the statistical results, whether the respondents understand the digital image stitching technology is more consistent with whether the respondents understand the digital image restoration technology. Most of the respondents did not know much about digital image stitching technology. The number of people in this part reached 510, accounting for 61.4% of the valid questionnaires; only 321 respondents were relatively familiar with digital image restoration technology, accounting for 38.6% of the valid questionnaires. The responses of the entire questionnaire were combined to show that the number of visitors with a university degree who knew about the restoration technology of digital images of murals was more than the number of people with a primary school education and a junior high school education. It can be seen that it is very meaningful to ask questions about the educational level of the respondents in the questionnaire.

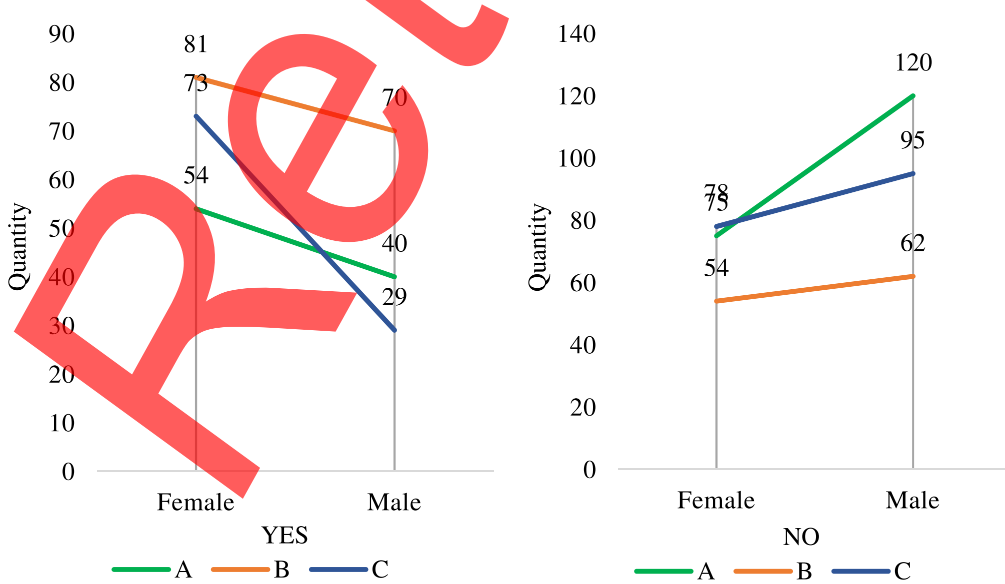

Fig. 7 Whether respondents understand digital image restoration techniques.

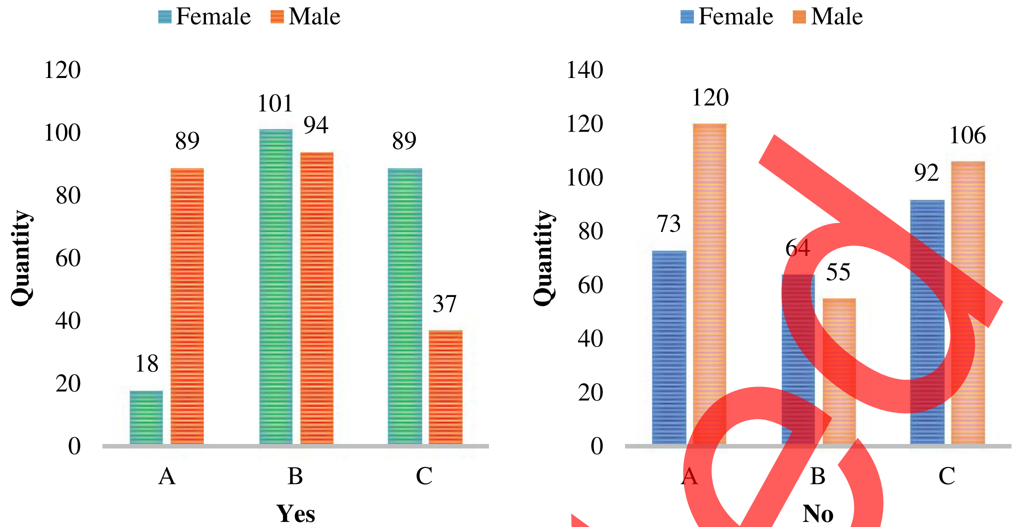

Fig. 8 Whether respondents understand digital image stitching technology.

4.2.5 *Satisfaction with the murals after digital image restoration and stitching*

The discussion of visitors' satisfaction with the murals after digital image restoration and splicing can directly show the respondents' evaluation of the mural digital image restoration technology and splicing, which can enrich the experimental results of this paper. The details are shown in Table 3.

It can be seen from Table 3 that 708 respondents are satisfied or neutral with the restored murals, accounting for 85.2% of the valid questionnaires. Only a small part of the respondents are dissatisfied; there are 123 people, accounting for 14.8% of the valid questionnaires. Since the mural itself is a kind of highly aesthetic work of art, it can be seen from the relevant survey that the respondents with a satisfied or neutral attitude can simply appreciate the artistic value expressed by the mural. Except for some visitors who are highly professional in appreciation, most of those who are dissatisfied are because their personal appreciation of murals is weak and it is difficult to understand the artistic value of murals.

4.2.6 *Most important factor in digital image stitching*

The important factors in the digital image stitching technology proposed in this questionnaire are all selected from the relevant literature, involving four aspects: image preprocessing, image noise reduction, image registration, and image fusion. Since the understanding of these factors requires a high degree of professionalism of the respondents, when answering this question, the staff who distributed the questionnaires explained the respondents in detail to ensure the reference of the data. The details are shown in Table 4.

According to Table 4, the most people think that image noise reduction and image registration are the most important factors in digital image stitching, 242 and 239, respectively, accounting for 29.1% and 28.8% of the valid questionnaires. Followed by the image fusion technology, there are 182 people, accounting for 21.9% of the valid questionnaires. The number of people

Table 3 Satisfaction with the murals after digital image restoration and stitching.

	A	B	C
Satisfied	130	112	89
Neutral	102	131	144
Dissatisfied	57	24	42

Table 4 Factors considered most important in digital image stitching.

	A	B	C
Image preprocessing	51	61	56
Image noise reduction	84	74	84
Image registration	73	77	89
Image fusion	81	55	46

who chose image preprocessing is the least, with 168 people, accounting for 20.2% of the valid questionnaires. It shows that most of the respondents believe that the most important elements in digital image stitching should be the elements that can improve the clarity of the image and can perfectly match the incomplete image stitching, emphasizing the restoration of the image.

4.3 *Application of Machine Learning to Mural Digital Image Restoration Technology and Stitching*

Based on the above analysis, it can be seen that the respondents' understanding and cognition of digital images of murals are relatively lacking, and digital image restoration technology is a widely used technology in the data age. Therefore, it is helpful to enrich the experimental data of this paper to explore the respondents' cognition of the importance of digital image restoration and stitching technology to the restoration of murals. The specific situation is shown in Fig. 9.

Among the subjects of this questionnaire survey, the visitors of hall A are the subjects of the experimental group of this paper, and the visitors of halls B and C are the subjects of the control group of this paper. Since there are many visitors with elementary school education in hall C, the respondents in hall C are used as an experimental comparison for the importance of digital image restoration technology to murals. It is clear from Fig. 9 that the respondents in hall A have a high degree of recognition of the technology, 176 people think it is important, and only 29 people think it is not important. It can be seen that the recognition degree of hall C is not as high as that of hall A, only 132 people think it is important, and 64 people think it is not important. It can be seen that the establishment of models for mural digital image restoration technology and splicing evaluation is deeply affected by the knowledge of the evaluators.

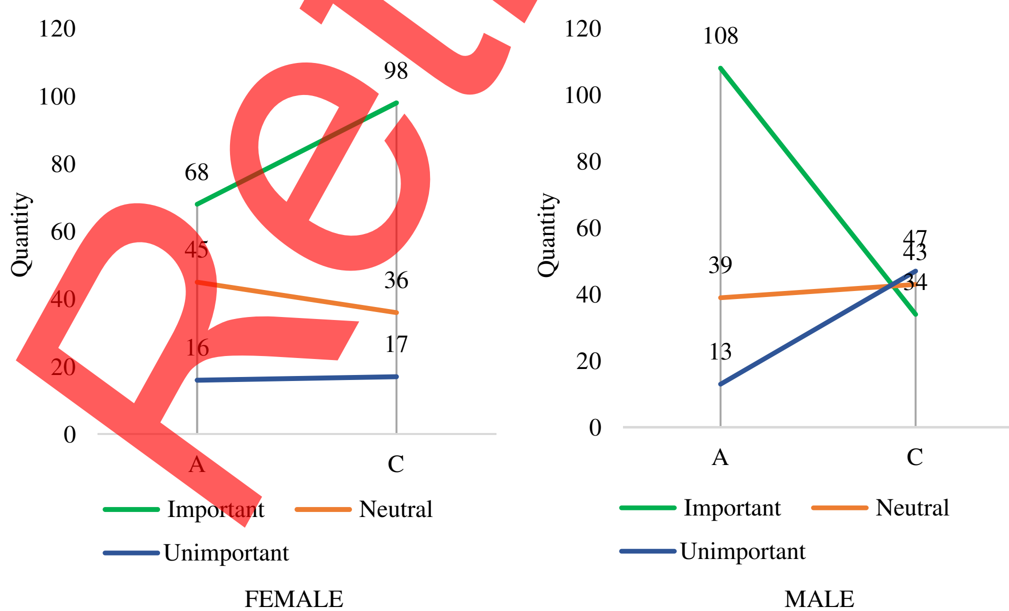

Fig. 9 Importance of digital image restoration and stitching technology for mural restoration.

Based on the above analysis, it can be seen that ML technology can be well combined with mural digital image restoration technology and stitching evaluation model. The development of digital information has made the digital image restoration technology of murals analyzed in many aspects, which can show the good development prospects of digital image restoration technology and stitching technology in the ML field from multiple angles. However, due to the lack of in-depth knowledge of ML and technology, this experiment only used the visitors of the three museums in city G as the experimental objects to conduct questionnaire analysis and did not conduct separate analysis on students or experts majoring in digital image restoration, although the presentation of the results would be more complete.

5 Discussion

Through the analysis of this case, it can be seen that the method of analyzing mural digital image restoration technology and splicing evaluation model based on ML technology is more scientific than the traditional method. The researchers use ML technology to further explore the development direction of mural digital image restoration technology and stitching technology and optimize the algorithm in the specific experimental process. Finally, the best solution for this experiment is obtained.

6 Conclusions

Through the analysis of this case, the following conclusions can be drawn: ML technology is an efficient data processing technology, which can bring different analysis angles to the research of mural digital image restoration and provide great advantages for the analysis and research of mural digital image restoration technology and splicing evaluation model. Through the questionnaire analysis of 900 visitors, this paper drew some reference conclusions about the research on mural digital image restoration technology and stitching evaluation model. Of course, to effectively restore cultural relics and murals, it is inseparable from the further improvement of digital image restoration technology. The restoration of digital images still requires further efforts by researchers, which is very important to improve the accuracy and restoration of cultural relics. Digital image restoration is not only a research hotspot now but also in the future. This is a major measure for cultural inheritance and appreciation, and it is necessary to continuously improve and enrich analysis methods to promote image restoration work development.

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