Modeling the Participation in Decision-Making Mechanism of Party Organizations in Vocational Colleges Based on Digital Art Transformation of Image Text Feature Recognition

Yonghong Wang[1*]

[1]Jiangsu Vocational College of Information Technology, Wuxi, Jiangsu, China ,710100

Corresponding author: Yonghong Wang, wyh7704@126.com

Abstract. At present, party organizations in vocational colleges have certain drawbacks in participation in decision-making. In order to improve the accuracy and scientific nature of participation in decision-making of party organization in vocational colleges, based on image text feature recognition technology, this paper constructs a support system for participation in decision-making of party organizations in party universities based on image text feature recognition. Moreover, this article uses image text feature extraction technology to perform data analysis and obtain reliable results through system analysis. In addition, this paper combines the DCT and pixel flip strategy methods to propose a dual-domain combination of multi-contour pixel flip text image feature recognition algorithm, improves the text feature recognition effect of party organization documents in vocational colleges, and enhances the robustness of text features in the case of visibility. Finally, this paper designs experiments to verify the performance of the model constructed in this paper. The research results show that the model constructed in this paper has a certain practical effect and can be applied to the decision-making of party organizations in vocational colleges.

Keywords: Image text; feature recognition; vocational colleges; party organization; decision-making mechanism; digital art transformation
DOI: https://doi.org/10.14733/cadaps.2024.S2.1-18

1 INTRODUCTION

In the face of the development and changes of the world, the country, the party, and the school, the historical opportunities and challenges faced by the party building of private colleges and universities are unprecedented. The practical innovation, theoretical innovation, and system innovation of party building are constantly advancing. The "Outline of Education Development" clearly proposes to strengthen party building in private schools and actively explore ways and methods for party organizations to play a role. In order to cope with the diversification of social ideology and culture and the rapid development of emerging media such as the Internet, starting from the reality of private education, to study how to establish the political core position of the party and how to truly play the role of party organization and other in-depth issues, to ensure scientific analysis of the party building laws in vocational colleges, and to realize the scientific approach of party building has become a very important task for practitioners and researchers of party building work in vocational colleges [24].This study grasps the importance of party building on the basis of correctly interpreting the characteristics and laws of private colleges and universities, and combines the commonality of party building work and the individuality of private colleges to explore the problems and solutions of party building in private colleges. Judging from the available data, this is one It is a work that few people dabble in, so this research will have breakthrough and pioneering theoretical innovation value. Strengthening the party building work in private colleges and universities is to implement the requirements of the "Several Opinions on Strengthening the Party Building Work in Private Colleges and Universities" by the Party Group of the Ministry of Education of the Central Organization Department. Although the party building work in private colleges also has some common features in the party building work of public colleges, it does not have public colleges. That kind of longer history and richer experience has its own particularity,The research analyzes party building issues from the perspective of caring about the development of the party's education and the development of vocational colleges, and strives to reach a higher level in terms of theory, reality and operability. The research results can be a useful reference for the education administration departments to carry out work, and have important practical guiding significance for the party building work of vocational colleges. The application of the results will help the healthy and stable development of the education of private colleges and universities [3].Digital art transformation can impact decision-making mechanisms in various fields by providing new tools and technologies, improving the accuracy of information, and enhancing the learning experience.

Party building is a dynamic development process. The connotation of party building is very rich, encompassing all aspects of party building work, and has a distinct party and practical nature. Therefore, party building in vocational colleges is an inseparable and important part of the party building of the Chinese Communist Party. The guiding ideology, goals, tasks and main contents of party building stipulate the basic framework of the guiding ideology, goals, tasks and main contents of party building in vocational colleges [11].The guiding ideology of party building in vocational colleges should embrace the integration of digital art as a means to promote innovation, creativity, and cultural development. By leveraging digital tools and techniques, party building efforts can become more dynamic and engaging, attracting the attention and participation of students.

Based on network data, this article combines the image and text recognition technology to model the participation in decision-making mechanism of the party organization in vocational colleges, analyzes its process, and proposes corresponding decision-making suggestions on this basis.

2 RELATED WORK

The transform domain method [12] transforms the pixel value to a certain transform domain. For example, discrete cosine transform, discrete Fourier transform), discrete wavelet transform, etc. embed features by modifying the transform domain coefficients [18]. This method is robust, but the features embedded through the transform domain are easily lost in the process of text binarization.

The spatial domain method [4] is to directly modify the pixel value to embed features. This type of method can be divided into methods based on text structure [14], methods based on character features [16] and methods based on pixel flipping [19]. The method based on text structure embeds features by changing the structure of the text (line, character, paragraph, etc.). For example, it embeds features by moving the line up and down [5] or moving the position of the character left and right [2], and extracts the feature based on the centroid of the line or character. The algorithm of this type of method is simple, but the format modification is easy to cause the loss of features, and the robustness is low [8].The method based on character feature embeds the feature by modifying the character's feature (size, stroke, position, brightness, etc.).For example, it embeds features by splitting the characters of the left and right or up and down structures [6], and embeds the features by adjusting the curvature of the strokes [10].This type of method has high concealment and strong ability to resist printing and scanning attacks, but it is difficult to achieve blind feature extraction, and this type of method is often designed based on a specific language. The method based on pixel flipping embeds features by changing the selected pixels and adjusting the relationship between the number of black and white pixels. The pixels with strong visual concealment are selected for modification through the pixel flip strategy. This type of feature has good invisibility, strong resistance to printing and scanning attacks, and can achieve blind feature extraction. When the feature is embedded by modifying the pixel, if the text undergoes various attacks to change the pixel, the feature will be changed. Therefore, the robustness of spatial domain features is lower than that of transform domain methods [17].

In order to make the features not only applicable to binary text images, but also to have excellent resistance to various attacks, researchers have proposed a dual-domain combination method [7]. The dual-domain combination method not only uses various transform domain methods, but also uses spatial domain methods to directly modify text pixels. For example, it modifies the DCT coefficient of the matrix constructed by the ratio of the number of black pixels in each block of the text image according to the characteristics, and then uses the pixel flip strategy to modify the ratio of the number of black pixels in the block [21].It uses the ratio of the number of black pixels in the text to the average number of black pixels in each character to construct a matrix, modifies the DCT coefficient of the matrix according to the characteristics, and then uses the pixel flip strategy to modify the number of black pixels in each character [9].In addition, it uses DFT to describe the outline of the character, modify the outline of the character according to the characteristics, and select the flipped pixels through the difference between the new and the old outlines [13].

In the dual-domain combination method, features are often embedded in a single time. When the feature is embedded only once, the feature error rate is high after various attacks. Secondly, the existing pixel flip strategy can be divided into single pixel flip strategy and single contour flip strategy [23]. The single-pixel flip strategy scores the flipping of each pixel based on the visual impact of flipped pixels, and selects pixels with small visual differences after flipping to perform flipping. Although this strategy considers the visual impact of flipped pixels when selecting flipable pixels, the evaluation of a single pixel flip can easily introduce concave and convex points on the character stroke boundary and reduce the invisibility of features [20].In order to solve this problem, a single contour flip strategy was proposed [15]. This strategy modifies the outermost contour of the character according to certain rules, and selects flipped pixels according to the difference between the old and new contours. Since the human eye is less sensitive to contour changes than a single pixel change, this strategy is more in line with the characteristics of human vision [1]. However, this strategy is easy to embed wrong features, and after embedding features, it may disrupt the order of features and reduce the robustness of features.

Digital feature technology uses a specific algorithm to hide copyright information in digital media content (carrier), and the copyright information hidden in digital media content is the feature. The goal of digital features is to protect the rights of the owner of the carrier file. Even if the carrier file with embedded features is copied or slightly modified without authorization, the owner can still extract the feature information in the carrier file and verify the copyright owner of the carrier file [22]. This technology is an important means to identify the ownership of digital media content and ensure information security.

3 TEXT IMAGE FEATURE RECOGNITION IN TRANSFORM DOMAIN

The text image feature in the transform domain transforms the pixel value into a transform domain such as DCT, DFT, DWT, singular value decomposition, etc., and then modifies the transform domain coefficient embedding feature according to specific rules. When embedding features, one or more transformation domains are used for one or more transformations, and different transformation regions are selected to embed features.

(1) Discrete Fourier transform

In image processing, discrete Fourier transform is generally used. The calculation process of the one-dimensional discrete Fourier transform is shown in formula (1).

$$f_k = \sum_{n=0}^{N-1} x_n \exp\left(-\frac{2\pi i}{N}kn\right), k = 0, \cdots, N-1 \tag{1}$$

Among them, x is the original data, N is the number of original data, n is the variation range of the original data, f is the value mapped to the transformation domain, and k is the variation range of the transformation domain value.

The two-dimensional discrete Fourier transform is a one-dimensional discrete Fourier transform in both directions, and the calculation process is shown in formula (2).

$$f_{k_x,k_y} = \sum_{n_x=0}^{N_x-1}\sum_{n_y=0}^{N_y-1} x_{n_x n_y} \exp\left(-\frac{2\pi i}{N_x}k_x n_x\right)\exp\left(-\frac{2\pi i}{N_y}k_y n_y\right) \tag{2}$$

Among them, f is the value mapped to the transform domain, x is the original data, N_x and N_y are the number of original data in two directions respectively, n_x and n_y are the variation range of original data in two directions, k_x and k_y are the variation range of transformation domain value respectively.

(2) Discrete cosine transform

Discrete cosine transform is widely used in image processing. There are many forms of one-dimensional discrete cosine transform. The following formula represents a form with simple operation and wide application range.

$$f_u = c_u \sum_{n=0}^{N-1} x_n \cos\left[\frac{(n+0.5)\pi}{N}u\right] \tag{3}$$

Among them, f is the transformed coefficient, x is the original data, N is the number of original data, n is the original data transformation range, and c_u is the compensation coefficient. The calculation formula is shown in the following formula.

$$c_u = \begin{cases} \sqrt{\frac{1}{N}}, u = 0 \\ \sqrt{\frac{2}{N}}, u \neq 0 \end{cases} \tag{4}$$

The two-dimensional discrete cosine transform is performed on the basis of the one-dimensional discrete cosine transform again. The calculation formula is shown in the following formula.

$$f_{u_x,u_y} = c_{u_x} c_{u_y} \sum_{n_x=0}^{N_x-1}\sum_{n_y=0}^{N_y-1} x_{n_x n_y} \cos\left[\frac{(n_x+0.5)\pi}{N_x}u_x\right]\cos\left[\frac{(n_y+0.5)\pi}{N_y}u_y\right] \tag{5}$$

Among them, f is the transformed coefficient, x is the original data, N_x and N_y respectively are the number of the original data in two directions, and n_x and n_y are the change ranges of the original data in the two directions, respectively.

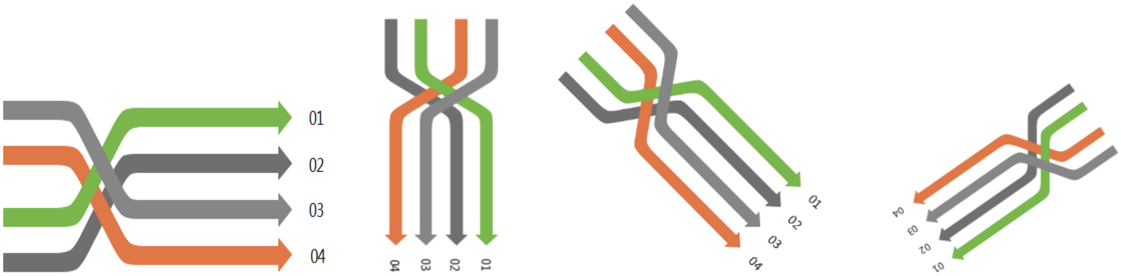
In actual use, in order to facilitate calculations, the image is usually divided into blocks, each block is divided into blocks, and then the blocks are merged. Usually, $8*8$-size blocks are used.

The text image features in the transform domain are robust. However, since the pixel gray value is 0~255 after the feature is embedded in the transform domain, the text image needs to be binarized again. The feature information embedded in the binarization process may be lost. Therefore, it is not considered to directly embed features into binary text images through transform domain methods.

In the spatial domain text image feature method, the method based on pixel flip has a wide range of applications and stronger robustness. In the method based on pixel flipping, the pixel flipping strategy selects pixels in the text that have little visual impact to flip. Since there are only two types of black pixels in a text image, either black or white, any pixel in the text may cause visual perception after inversion. In addition, there are a lot of blank areas in the text image, and there are few redundant data, which makes it difficult to embed features. Therefore, the pixel flip strategy plays an important role in feature invisibility and robustness. The pixel flip strategy should flip as many pixels as possible, and the flipping will not cause human eyes to perceive it.

Pixel flip strategy can be divided into single pixel flip strategy and contour flip strategy. The single-pixel flip strategy takes each pixel as an evaluation object independently, and selects flipped pixels in the text image by evaluating a single pixel. The smoothness of a pixel refers to how the pixel and its surrounding pixels change. In a binary text image, the pixel value only contains 0 and 1, and the change is only 0 to 1 or 1 to 0.For a pixel P, there are usually 8 adjacent pixels, which are located in four directions: vertical, horizontal, diagonal, and anti-diagonal, as shown in Figure 1.The smoothness of pixels is calculated from the changes of pixels in these 4 directions. The calculation is as follows:

$$\begin{cases} N_h(i,j)=\sum_{k=-1}^{1}\sum_{l=-1}^{0} I\left(\left\{p_{i+k,j+l} \neq p_{i+k,j+l+1}\right\}\right) \\ N_v(i,j)=\sum_{k=-1}^{1}\sum_{l=-1}^{0} I\left(\left\{p_{i+l,j+k} \neq p_{i+l+1,j+k}\right\}\right) \\ N_d(i,j)=\sum_{k,l\in(-1,0)} I\left(\left\{p_{i+k,j+l} \neq p_{i+k+1,j+l+1}\right\}\right) \\ N_{bd}(i,j)=\sum_{k\in(0,0) l\in(-1,0)} I\left(\left\{p_{i+k,j+l} \neq p_{i+k-1,j+l+1}\right\}\right) \end{cases} \tag{6}$$



(a) (b) (c) (d)

Figure 1: The neighborhood pixel direction of the center pixel:(a) Horizontal direction, (b) Vertical direction, (c) Diagonal direction, (d) Anti-diagonal direction.

Among them N_h is the smoothness in the horizontal direction, N_v is the smoothness in the vertical direction, N_d is the smoothness in the diagonal direction, N_{bd} is the smoothness in the anti-diagonal direction, P is the central pixel, and i and j are the horizontal and vertical coordinates of the pixels, respectively.

$$p_a = p_b, I\{p_a, p_b\} = 0; p_a \neq p_b, I\{p_a, p_b\} = 1 \tag{7}$$

The connectivity of a pixel refers to the number of connected regions within 8 neighborhoods of the pixel. Connected areas refer to areas with equal pixel values and adjacent pixels. The 8-neighborhood of P pixels is shown in Figure 2. It contains 2 white connected regions (as shown in Figure 3) and 1 black connected region (as shown in Figure 4), so the connectivity of pixel P is 3.

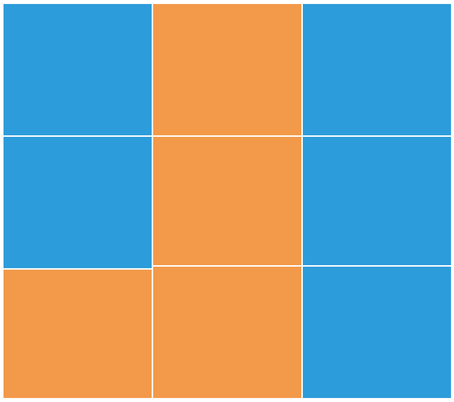


Figure 2: 8-neighborhood of P pixels.

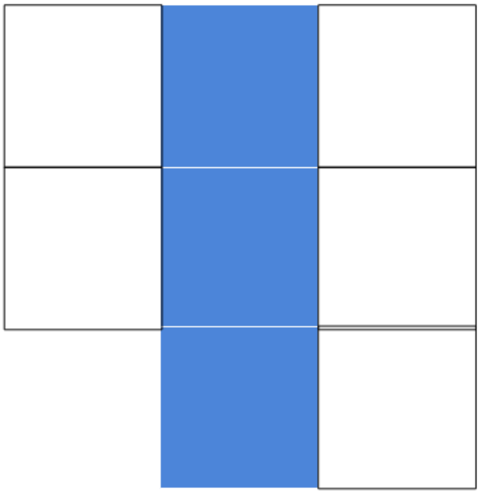


Figure 3: White connected areas.

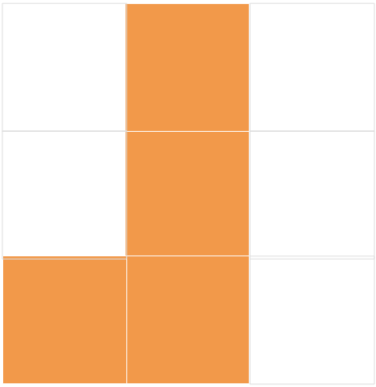


Figure 4: Black connected areas.

After obtaining the smoothness and connectivity of the pixels, calculate the reversible score of each pixel through some rules:

- If the horizontal or vertical smoothness is 0 or 0, the pixel cannot be flipped.
- If the smoothness in the diagonal or anti-diagonal direction, that is, or is 0, the reversible score remains unchanged; if it is not 0, the reversible score increases;
- If the smoothness of the pixel remains unchanged after the pixel is flipped, the pixel's reversible score is increased; if the smoothness of the pixel is reduced by more than the threshold after the flip, the pixel's reversible score is reduced.
- If the connectivity of the pixel changes after the pixel is flipped, reduce the flipped score; otherwise, the flipped score will increase. This method selects flipped pixels through the final flipable score, and the pixels with high flipped scores are flipped first, which reduces the visual difference brought by flipped pixels to the text image, and is a good pixel flip strategy. However, evaluating and flipping a single pixel can easily introduce concave and convex points on the boundary of the character stroke, reducing the invisibility of features.

The contour flip strategy does not evaluate the reversibility based on a single pixel. By modifying the overall outline of the character to flip pixels, not only the number of flipped pixels is increased, but the visual perception of boundary modification is effectively reduced.

The Fourier descriptor is used to represent the outermost contour of the character. The Fourier descriptor is a classic and effective shape description operator. The connected component I with the black pixel flip rate α is extracted from the text. Its closed boundary is composed of N vertices, and the coordinates of these N vertices are used to construct a complex function $z(n)$, and $z(n)=x(n)+i\cdot y(n)$.Among them, $x(n)$ and $y(n)$ are the abscissa and ordinate, respectively, and $n=0,1,\cdots,N-1$.The new character contour is obtained by modifying the Fourier descriptor, and the pixels to be flipped are selected according to the difference between the new and old character contours. When DFT is performed on $z(n)$, the coefficient $Z(k)$ is obtained as shown in the following formula.

$$Z(k)=\frac{1}{N}\sum_{n=0}^{N-1}z(n)e^{\frac{-j2\pi kn}{N}} \tag{8}$$

Among them, $k \in [0, N-1]$. $Z(k)$ is the Fourier descriptor of the connected component.By modifying the coefficient of the high-frequency region of the Fourier descriptor to 0, a new connected component profile is obtained through the new Fourier descriptor, and the connected component I' is obtained by filling.

The connected component I_0 obtained by the formula is shown in the following formula.

$$I_0 = \begin{cases} I \cap I', \alpha < 0 \\ I \cup I', \alpha > 0 \end{cases} \tag{9}$$

When $\alpha < 0$, the number of black pixels of I_0 is $\beta_\cap$ .When $\alpha > 0$, the number of black pixels of I_0 is $\beta_\cup$ .The number of black pixels of I is β .If $|\beta_\cap - \beta|/\beta \ge |\alpha|$ or $|\beta_\cup - \beta|/\beta \ge |\alpha|$, then $I = I_0$ .Otherwise, the zero-setting range of the Fourier descriptor high-frequency coefficients is expanded, and new connected components are reconstructed.

The following formula represents the printing and scanning process.

$$F_w(x) = KF(x) \tag{10}$$

Among them, F and Fw are the images before and after printing and scanning of a certain character, x represents the pixels of the text image, and K is the influence of the printing and scanning process. If I is a certain character image area, the following formula can be obtained.

$$\int_I F_w(x)\,dx = \int_I K dx \int_I F(x)\,dx \tag{11}$$

Among them, $\int_I F_w(x)\,dx$ is the number of black pixels contained in the original image of the character, $\int_I K dx$ is the number of black pixels contained in the character after printing and scanning, and $\int_I K dx$ is a constant. If A and AW are respectively the number of black pixels contained in each character in the text image, the following formula can be obtained.

$$\frac{\int_I F(x)\,dx}{A} = \frac{\int_I F_w(x)\,dx}{Aw} \tag{12}$$

It can be concluded that before and after the printing and scanning process, the ratio of the number of black pixels in each character in the text image to the average number of black pixels in each character is unchanged.

The print scan invariant represents the part of the image that remains unchanged before and after the print scan. The invariant is used to embed features to ensure that the features can still be extracted correctly after the print scan attack.

Feature embedding and extraction Feature embedding algorithm embeds features into the redundant data of the text image without being noticed by human eyes, and feature extraction algorithm extracts the features embedded in the text image. The transform domain feature is not suitable for binary text images, and the robustness of spatial domain features is not ideal. The dual-domain combined feature is not only suitable for binary text images, and the ability to resist attacks is relatively high.

The current dual-domain combined features are less resistant to print scan attacks, which hinders the practical application of text image features that resist print scans. In order to improve the feature's resistance to printing and scanning attacks, this paper proposes an optimized text image feature embedding and extraction algorithm based on dual-domain combined features. When feature embedding, the feature image is preprocessed first, and then the print scan invariant embedding feature of the connected components of the text image is modified by DCT and multi-contour flip strategy. The extraction algorithm is designed according to the embedded algorithm.

In order to improve the feature robustness, this paper designs an optimized dual-domain combined feature embedding algorithm based on print scan invariant, combined with DCT and multi-contour flip strategy. The print scan invariant of the connected components of the text image is used to perform embedding features. According to the characteristic information, the DCT coefficients of the characteristic matrix constructed by the modified printing scan invariant are obtained, and the modified invariant is obtained through inverse transformation. Then, the multi-contour flip strategy is used to modify the pixels of the connected components, so that the print scan invariant of the connected components becomes the print scan invariant of the embedded features. The design ideas are as follows:

(1) Extract connected components

The connected components in the text image after binarization are extracted. The threshold value t of the number of black pixels of the connected component is set. In order to dynamically adjust the value of t according to the text and filter out the too small connected components in the text, the algorithm in this paper determines t by the average number of black pixels in each connected component in the first line of the text, and the calculation formula is shown in the following formula.

$$t = \frac{\sum_{1}^{D_0} x_{i0}}{D_0} \times v \tag{13}$$

Among them, D_0 is the number of connected components in the first row, x_{i0} is the number of black pixels in each connected component, and v is a decimal number from 0 to 1.

Then, the connected components whose number of black pixels are less than t are filtered out.

(2) Construct feature matrix

The algorithm in this paper uses the first line of text to calculate the average number of black pixels of a single connected component, and the rest of the lines except the first line of text are embedded. The print scan invariant of the connected component of the embedded part is calculated as shown in the following formula.

$$e_i = \frac{x_i}{M} \times A \tag{14}$$

Among them, x_i is the number of black pixels in each connected component, A is the power of 10, which is a precision adjustment parameter to avoid excessive loss of black pixels, and M is the average number of black pixels of the connected components of the first line of the filtered text, as shown in the following formula.

$$M = \frac{\sum_{1}^{D} x_i}{D} \tag{15}$$

Among them, D is the number of connected components in the first row after filtering.

The printing scan invariant e_i of the connected components is used to construct the $8*8$ characteristic matrix $E_j, j=0,1,\cdots,k-1$. This article uses row precedence to construct the matrix.

(3) Calculate the number of feature embedding c and expand the feature

In order to improve the robustness of the feature, the algorithm in this paper embeds the feature multiple times, and the number of embedding c is dynamically determined by the total embedding capacity of the text. In each feature matrix E_j, p-bit features are embedded in every 64 connected components. Then, the calculation formula for the number of repeated embedding times c in the text image is shown in the following formula.

$$c=\frac{p\times k}{y} \tag{16}$$

Among them, p is the number of features embedded in each feature matrix, k is the number of feature matrices, and y is the feature length.

The feature sequence is expanded c times. For example, if the original feature sequence is 010 and c is 3, the feature sequence will be expanded to 000111000.

(4) Modify the characteristic matrix coefficients

Modify the DCT coefficients of the feature matrix according to the extended feature sequence. In the DCT coefficients, when the features are embedded in the low-frequency region, the robustness is strong but the invisibility is poor. When the features are embedded in the high-frequency region, the text change is small but the features are easily destroyed. The algorithm in this paper embeds the features into the intermediate frequency region of the DCT coefficients, starting with the s-th coefficient in the reverse "Z" arrangement of the DCT coefficients. If the feature bit is 1, the modification coefficient is T. If the feature bit is 0, the modification coefficient is $-T$ .T is an integer in the range of $[1,5000]$ .Then, the new feature matrix E'_j is obtained by inverse DCT. When T takes different values, E'_j is different. In order to reduce the number of flipped pixels of connected components and improve feature invisibility, the gap between E_j and E'_j should be as small as possible. The difference between E_j and E'_j is compared by the correlation coefficient R and the optimal difference U. The correlation coefficient R calculation formula is shown in the following formula.

$$R=-\frac{\sum\left(E-\bar{E}\right)\left(E'-\bar{E}'\right)}{\sqrt{\sum\left(E-\bar{E}\right)^2\left(E'-\bar{E}'\right)^2}} \tag{17}$$

The optimal difference U calculation formula is shown in the following formula.

$$U=\sum\sum\left|\frac{E-E'}{E}\right| \tag{18}$$

The larger R and the smaller U, the smaller the gap between E_j and E'_j.Through multiple iterations, the minimum difference between E_j and E'_j when the value of T is within the range $[1,5000]$ is searched to determine the final value of T. At this time, E'_j is the final feature matrix.

(5) Calculate the number $x_i^{'}$ of black pixels of each connected component target

Each component $e_i^{'}$ of $E_i^{'}$ represents a printing scan invariant after a connected component is embedded with features. According to $e_i^{'}$, the target black pixel $x_i^{'}$ of each connected component can be obtained, as shown in the following formula.

$$x_i^{'} = \frac{e_i^{'} M}{A} \tag{19}$$

(6) Flip pixels

The multi-contour flip strategy is used to flip the pixels of each connected component to change the number of black pixels of the connected component from x_i to $x_i^{'}$, so as to achieve the purpose of embedding features in the text image.

The feature extraction algorithm is designed according to the feature embedding algorithm, and the design ideas are as follows:

- Binarize the printed and scanned text image, and use the Hough transform to correct the text skew caused by the printing and scanning process.
- Extract the connected components of the text, construct the feature matrix, and calculate the number of feature embedding c.
- Extract the characteristic sequence according to the DCT coefficients: After the DCT coefficients are arranged according to the inverse "Z" word, starting from the s-th coefficient, if the coefficient is positive, then 1 is extracted; if the coefficient is negative, then 0 is extracted.
- (4)A feature is determined by the mode of the consecutive c bits of the extracted sequence, and the feature sequence is obtained.
- Decompress the feature sequence using the white skipping block decoding method to obtain the feature image.

4 PARTICIPATION IN DECISION-MAKING SYSTEM OF PARTY ORGANIZATION IN PRIVATE COLLEGES

The party organization participation decision-making system of private colleges and universities constructed in this paper mainly uses the image feature recognition system to obtain effective information from various documents issued by the party organization and meeting records, and uses image text feature extraction technology for data analysis, and reliable results are obtained through system analysis.

The character area filtering of party organization documents in private colleges and universities is a binary classification problem. In this paper, an SVM classification model is trained by a sample set containing characters and pseudo-characters generated from the character candidate area, and the trained model is used to judge whether the character candidate area belongs to the text area.

After the judgment, the pseudo character area is deleted and the character area is reserved. The specific flow diagram is shown in Figure 5.

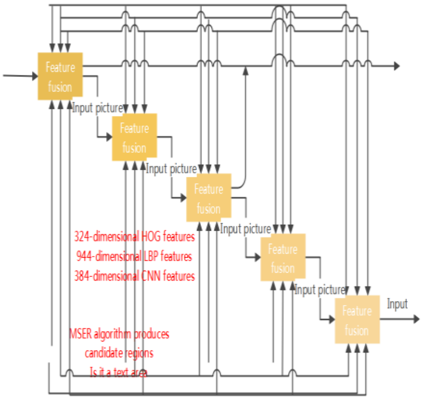


Figure 5: Schematic diagram of the file character area filtering process of the party organization in vocational colleges.

In view of the missing text detection phenomenon in the traditional MSER algorithm, improvements are made in the use of MSER, and the improved MSER algorithm is used to extract candidate regions of characters. First, the algorithm converts the original image into R, G, and B three-channel images. Then, the algorithm performs illumination equalization processing on the image under the three channels of R, G, and B respectively, which can avoid the phenomenon of missing characters due to the sensitivity of the MSER algorithm to illumination. Next, the algorithm extracts MSER connectivity areas from the three channels. The connected domains extracted by different channels can be complementary, so the detected MSER connected domains are more than the detected connected domains under a single gray channel. Finally, the algorithm merges the MSER connected regions extracted from the three channels, and uses the combined MSER connected regions as the final character candidate region. The specific algorithm flow is shown in Figure 6.

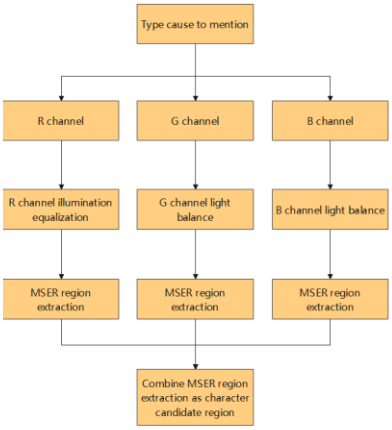


Figure 6: Schematic diagram of the algorithm flow diagram of character candidate region extraction.

The private colleges and universities based on image text feature recognition but the organizational participation decision support system mainly adopts the B/S architecture of the presentation layer, the business logic layer and the data layer.

According to needs, the support system for participation in decision-making of vocational colleges based on image text feature recognition can be divided into 7 functional modules, namely, login module, data query and input module, model solving module, result display module, database management, user information management and user feedback module.

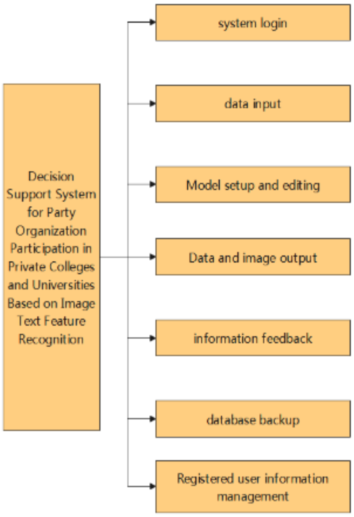


Figure 7: The support system for participation in decision-making of vocational colleges based on image text feature recognition.

5 THE EFFECT VERIFICATION OF THE PARTICIPATION IN DECISION-MAKING MECHANISM OF THE PARTY ORGANIZATION IN VOCATIONAL COLLEGES BASED ON IMAGE TEXT FEATURE RECOGNITION

This paper constructs the support system for participation in decision-making of vocational colleges based on image text feature recognition, and then performs effect verification of the system. This paper collects the participation in decision-making documents of part of the party organizations in private colleges and universities as verification materials, and divides them into groups. Moreover, this article analyzes the events of these data, and counts keywords to perform the accuracy of the event analysis, and compares them with the facts. The results are shown in Table 1 and Figure 8.

Number	*Result evaluation (%)*	*Number*	*Result evaluation (%)*	*Number*	*Result evaluation (%)*
1	*85.8*	*33*	*81.5*	*65*	*88.1*
2	*89.2*	*34*	*84.9*	*66*	*82.2*
3	*80.7*	*35*	*87.0*	*67*	*80.4*
4	*79.1*	*36*	*87.1*	*68*	*91.0*
5	*81.8*	*37*	*88.2*	*69*	*91.6*
6	*87.2*	*38*	*90.9*	*70*	*90.6*
7	*90.3*	*39*	*89.4*	*71*	*82.9*
8	*90.3*	*40*	*86.3*	*72*	*91.1*

9	*79.6*	*41*	*90.8*	*73*	*88.8*
10	*82.5*	*42*	*89.6*	*74*	*87.3*
11	*89.4*	*43*	*90.4*	*75*	*81.7*
12	*86.7*	*44*	*83.0*	*76*	*86.9*
13	*87.1*	*45*	*83.6*	*77*	*84.8*
14	*84.8*	*46*	*89.5*	*78*	*84.8*
15	*86.2*	*47*	*79.4*	*79*	*91.4*
16	*87.9*	*48*	*80.1*	*80*	*90.9*
17	*90.8*	*49*	*80.7*	*81*	*83.5*
18	*87.4*	*50*	*80.3*	*82*	*83.0*
19	*83.3*	*51*	*89.1*	*83*	*90.2*
20	*79.8*	*52*	*80.3*	*84*	*90.7*
21	*88.9*	*53*	*83.9*	*85*	*79.1*
22	*91.2*	*54*	*80.8*	*86*	*87.2*
23	*82.4*	*55*	*83.7*	*87*	*86.6*
24	*90.1*	*56*	*86.2*	*88*	*86.8*
25	*84.1*	*57*	*82.5*	*89*	*91.4*
26	*82.8*	*58*	*81.6*	*90*	*85.3*
27	*89.9*	*59*	*90.9*	*91*	*81.9*
28	*79.0*	*60*	*79.7*	*92*	*80.5*
29	*90.3*	*61*	*85.0*	*93*	*89.2*
30	*80.9*	*62*	*90.7*	*94*	*85.8*
31	*80.4*	*63*	*81.9*	*95*	*80.1*
32	*79.8*	*64*	*81.0*	*96*	*84.2*

Table 1: Statistical table of the accuracy of event analysis of the support system for participation in decision-making of vocational colleges based on image text feature recognition.

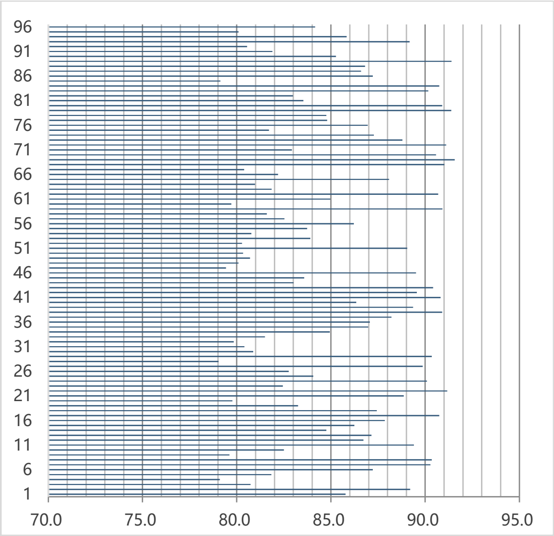


Figure 8: Statistical diagram of the accuracy of event analysis of the support system for participation in decision-making of vocational colleges based on image text feature recognition.

From the above analysis, we can see that the support system for participation in decision-making of vocational colleges based on image text feature recognition constructed in this paper has a good event analysis accuracy. After that, this article conducts the effect evaluation of strategy analysis, and the results are shown in Table 2 and Figure 9.

Number	*Scores*	*Number*	*Scores*	*Number*	*Scores*
1	*80.2*	*33*	*77.9*	*65*	*85.2*
2	*78.2*	*34*	*83.8*	*66*	*76.3*
3	*78.5*	*35*	*84.2*	*67*	*87.1*
4	*83.7*	*36*	*87.0*	*68*	*75.3*
5	*82.2*	*37*	*76.8*	*69*	*83.0*
6	*80.7*	*38*	*84.0*	*70*	*82.4*
7	*76.0*	*39*	*83.2*	*71*	*84.5*
8	*80.3*	*40*	*75.8*	*72*	*85.4*
9	*79.4*	*41*	*80.4*	*73*	*79.0*
10	*75.5*	*42*	*78.6*	*74*	*76.1*
11	*81.0*	*43*	*79.2*	*75*	*78.6*
12	*81.6*	*44*	*79.3*	*76*	*83.8*
13	*85.6*	*45*	*83.1*	*77*	*86.4*
14	*87.1*	*46*	*86.4*	*78*	*78.1*
15	*81.4*	*47*	*82.8*	*79*	*79.2*
16	*86.8*	*48*	*82.4*	*80*	*82.8*
17	*80.8*	*49*	*87.5*	*81*	*84.0*
18	*81.5*	*50*	*76.2*	*82*	*83.3*
19	*76.6*	*51*	*86.3*	*83*	*80.2*
20	*77.0*	*52*	*80.0*	*84*	*75.5*
21	*80.6*	*53*	*85.0*	*85*	*83.5*
22	*85.5*	*54*	*82.5*	*86*	*81.6*
23	*84.0*	*55*	*77.2*	*87*	*79.7*
24	*82.4*	*56*	*77.9*	*88*	*83.9*
25	*80.6*	*57*	*76.6*	*89*	*78.7*
26	*83.3*	*58*	*79.9*	*90*	*84.8*
27	*83.9*	*59*	*82.4*	*91*	*76.9*
28	*84.4*	*60*	*82.0*	*92*	*81.4*
29	*78.3*	*61*	*79.2*	*93*	*86.8*
30	*87.5*	*62*	*84.7*	*94*	*87.2*
31	*77.2*	*63*	*82.8*	*95*	*78.4*
32	*79.3*	*64*	*75.3*	*96*	*86.1*

Table 2: Statistical table of the evaluation of the strategy analysis effect of the support system for participation in decision-making of vocational colleges based on image text feature recognition.

From the chart analysis, we can see that the strategy analysis of the support system for participation in decision-making of vocational colleges based on image text feature recognition constructed in this paper is good.

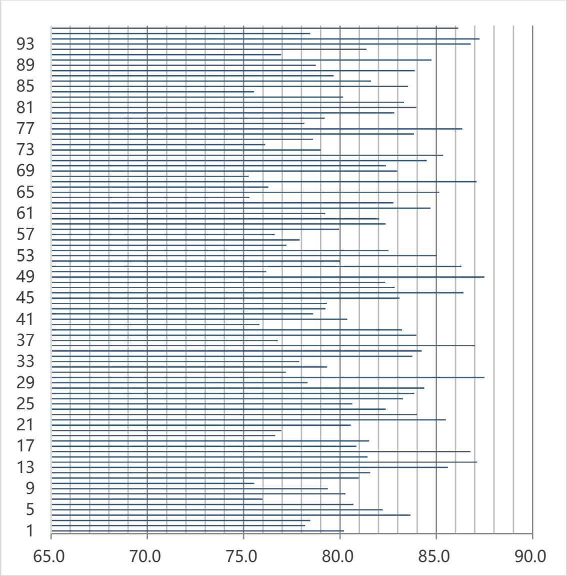


Figure 9: Statistical diagram of the evaluation of the strategy analysis effect of the support system for participation in decision-making of vocational colleges based on image text feature recognition.

6 CONCLUSION

In the face of changes in the world, national conditions, party conditions, and school conditions, the historical opportunities and challenges faced by party building in private colleges are unprecedented. In order to cope with the diversification of social ideology and culture and the rapid development of emerging media such as the Internet, starting from the reality of private education, to study how to establish the political core position of the party and how to truly play the role of party organization and other in-depth issues, to ensure scientific analysis of the party building laws in vocational colleges, and to realize the scientific analysis of party building has become a very important task for practitioners and re-searchers of party building work in vocational colleges. This paper combines image feature recognition technology to construct a support system for participation in decision-making of party organizations in vocational colleges based on image text feature recognition, and to verify and analyze the system performance. The research results show that the system constructed in this paper has obvious effects and certain practicality.

Yonghong Wang, https://orcid.org/0009-0008-0319-8717

ACKNOWLEDGEMENTS

- General Project Initiation Project of the 2019 Jiangsu Provincial Education System Party Construction Research Association: <Research on the Innovation of the Integrated Education Model of "Leading Party Construction, Coordinating Two Areas, and Educating People through Three Aspects" >(2019JSJYDJ02131).
- 2022 Jiangsu University Philosophy and Social Science Research Project Initiation Project: < Higher Vocational Colleges from the Perspective of Synergy Theory "Research on the Construction of the "Three Allures Education" Work System(2022SJSZ0429).

REFERENCES

[1] Aghdam, M. H.; Heidari, S.: Feature Selection Using Particle Swarm Optimization in Text Categorization, Journal of Artificial Intelligence & Soft Computing Research, 2015, 5(4), 2015, 38–43. https://doi.org/10.1515/jaiscr-2015-0031

[2] Beigi, A. M.; Maroosi, A.: Parameter identification for solar cells and module using a Hybrid Firefly and Pattern Search Algorithms, Solar Energy, 171(4), 2018, 435-446. https://doi.org/10.1016/j.solener.2018.06.092

[3] Benson, N. F.; Kranzler, J.H.; Floyd, R. G.: Examining the integrity of measurement of cognitive abilities in the prediction of achievement, Comparisons and contrasts across variables from higher-order and bifactor models, Journal of School Psychology, 58(3), 2016, 1-19. https://doi.org/10.1016/j.jsp.2016.06.001

[4] Brehm, M.; Imberman, S. A.; Lovenheim, M. F.: Achievement effects of individual performance incentives in a teacher merit pay tournament, Labour Economics, 44(5), 2017, 133-150. https://doi.org/10.1016/j.labeco.2016.12.008

[5] Brown, G.T.L.; Hanna, E.: Swedish student perceptions of achievement practices, The role of intelligence, Intelligence, 69(3), 2018, 94-103. https://doi.org/10.1016/j.intell.2018.05.006

[6] Chen, Z.; Yuan, X.; Tian, H.: et al. Improved gravitational search algorithm for parameter identification of water turbine regulation system, Energy Conversion and Management, 78(5), 2014, 306-315. https://doi.org/10.1016/j.enconman.2013.10.060

[7] Gissel, S. T.: Scaffolding Students' Independent Decoding of Unfamiliar Text with a Prototype of an eBook-feature, Journal of Information Technology Education Research, 14(2015), 2015, 439-470. https://doi.org/10.28945/2317

[8] Gotmare, A.; Patidar, R.; George, N. V.: Nonlinear system identification using a cuckoo search optimized adaptive Hammerstein model, Expert Systems with Applications, 42(5), 2015, 2538-2546. https://doi.org/10.1016/j.eswa.2014.10.040

[9] Kamble, R. R.; Kodavade, D. V.: Relevance Feature Search for Text Mining using FClustering Algorithm, International Journal of Computer Sciences & Engineering, 6(7), 2018, 223-227. https://doi.org/10.1016/j.eswa.2014.10.040

[10] Kelly, B. S.; Rainford, L. A.; Darcy, S. P.: et al. The development of expertise in radiology: in chest radiograph interpretation,expert search pattern may predate expert levels of diagnostic accuracy for pneumothorax identification, Radiology, 280(1), 2016, 252-260. https://doi.org/10.1016/j.eswa.2014.10.040

[11] Klusmann, U.; Richter, D.; Lüdtke.; Oliver.: Teachers' emotional exhaustion is negatively related to students' achievement: Evidence from a large-scale assessment study, Journal of Educational Psychology,108(8), 2016, 1193-1203. https://doi.org/10.1037/edu0000125

[12] Marsh, H. W.; Abduljabbar, A. S.; Parker, P. D.: et al. The Internal/External Frame of Reference Model of Self-Concept and Achievement Relations: Age-Cohort and Cross-Cultural Differences, American Educational Research Journal, 52(1), 2015, 168-202. https://doi.org/10.3102/0002831214549453

[13] Maruthu,P.; Vimala Devi, K.R.: Efficient Feature Extraction for Text Mining, Advances in Natural & Applied Sciences, 10(4), 2016, 64-73.

[14] Mcgill, R. J.; Spurgin, A. R.; Assessing The Incremental Value Of Kabc-Ii Luria Model Scores In Predicting Achievement: What Do They Tell Us Beyond The Mpi?, Psychology in the Schools, 53(7), 2016, 677-689. https://doi.org/10.1002/pits.21940

[15] Mohammad, M.; HosseinEbrahimpour,k.; Seyedjalaleddin,M.: A Hybrid Feature Selection Approach in Text Categorization, International Journal of Intelligent Systems Technologies & Applications, 8(3), 2016, 42-47. https://doi.org/10.5815/ijisa.2016.03.05

[16] Mohoric, T.; Taksic, V.: Emotional understanding as a predictor of socio-emotional functioning and school achievement in adolescence, Psihologija, 49(4), 2016, 357-374. https://doi.org/10.2298/PSI1604357M

[17] Patwardhan, A. P.; Patidar, R; George, N. V.: On a cuckoo search optimization approach towards feedback system identification, Digital Signal Processing, 32(2), 2014, 156-163. https://doi.org/10.1016/j.dsp.2014.05.008

[18] Pinxten, M.; Soom, C. V.; Peeters, C. M.: et al. At-risk at the gate: prediction of study success of first-year science and engineering students in an open-admission university in Flandersany incremental validity of study strategies, European Journal of Psychology of Education, 34(5), 2019, 45-66. https://doi.org/10.1007/s10212-017-0361-x

[19] Rabiner, D. L.; Godwin, J.; Dodge, K. A.: Predicting Academic Achievement and Attainment: The Contribution of Early Academic Skills, Attention Difficulties, and Social Competence, School Psychology Review, 45(2), 2016, 250-267. https://doi.org/10.17105/SPR45-2.250-267

[20] Soleymanpour, M.; Marvi, H.: Text-independent speaker identification based on selection of the most similar feature vectors, International Journal of Speech Technology, 20(1), 2016, 1-10. https://doi.org/10.1007/s10772-016-9385-x

[21] Takuro, O.: Scene Text Localization Using Object Detection Based on Filtered Feature Channels and Crosswise Region Merging, Growth & Change, 21(3), 2015, 61-76.

[22] Tehseen, Z.; Muhammad, P.A.; Qaiser A.: Comparative Study of Feature Selection Approaches for Urdu Text Categorization, Malaysian Journal of Computer Science, 28(2), 2015, 93-109.

[23] Wu, G.; Zhao, M.; Han, L.: A Fingerprint Feature Extraction Algorithm based on Optimal Decision for Text Copy Detection, International Journal of Security & Its Applications, 10(11), 2016, 67-78. https://doi.org/10.14257/ijsia.2016.10.11.06

[24] Zhao, H.; Liu, Z.; Yao, X.; Yang, Q.: A machine learning-based sentiment analysis of online product reviews with a novel term weighting and feature selection approach, Information Processing & Management, 58(5), 2021, 102656. https://doi.org/10.1016/j.ipm.2021.102656