Application of Improved Deep Convolutional Neural Network Algorithm in Damaged Information Restoration

Wenya Jia
Department of Instrument Engineering, Shanxi Pharmaceutical Vocational College, Taiyuan, 030031, China

***Abstract*—The repair of damaged documents has practical significance in multiple fields and can help people better analyze data information. This study proposes an improved algorithm model based on deep convolutional neural networks to address the issues of poor restoration performance and insufficient restoration information in the current process of restoring damaged document information. The new model improves the ability of document image classification and recognition data by using deep convolutional neural networks and incorporates grayscale rules to enhance the edge information restoration problem in the document information restoration process. The results indicated that in the repair of document data, the research model could achieve good document repair results. The average accuracy of the research model was 94.2%, which was 4.6% higher than the 89.6% of other models. The average percentage error of the model was around 3.6, which was about 2.2 lower than other models. The algorithm model used had the lowest average root mean square error of only 4.4, which was 1.9 lower than the highest model, and its stability was the best among several models. Therefore, the new model has a good repair effect in document information restoration, which has good guiding significance for the research of damaged information restoration.**

Keywords—Damaged document information; restoration; deep convolutional neural network; grayscale rules

I. Introduction

A. Research Background

With the rapid development of information technology, the application of image and video data in various fields has become increasingly widespread, including medical imaging, satellite remote sensing, security monitoring, and multimedia communication [1]. However, in practical applications, these data are often damaged due to various reasons, such as transmission errors, compression losses, sensor defects, or environmental interference, which seriously affect the quality and availability of the data [2]. Therefore, effective Document Information Restoration (DIR) technology is of great significance for improving data quality and ensuring information integrity. Traditional DIR technology is mainly based on various mathematical models, such as linear filters, statistical models, and partial differential equations. In recent years, with the rise of deep learning technology, Deep Convolutional Neural Network (DCNN) has become a hot topic in the field of information restoration due to its excellent feature extraction ability and ability to learn complex data representations [3]. Compared to traditional methods, DCNN can automatically learn deeper and more abstract data representations, thus more effectively handling complex damage situations [4].

B. Research Questions and Methods

The existing methods for document information restoration, especially those that rely on traditional mathematical models such as linear filters, statistical models, and partial differential equations, often have poor performance in dealing with complex damage situations. These methods often struggle to recover high-quality images when faced with highly complex or widely distributed types of damage, especially in terms of edge information and details. In the process of document information restoration, existing technologies often cannot effectively recover all necessary information. The lack of information not only affects the readability of documents but may also lead to the loss of key data, thereby affecting decision-making and subsequent processing. In addition, DCNN has good adaptability and can adapt to different types and degrees of damage through training. Based on this, this study proposes a new model that combines grayscale rules and DCNN to address the current shortcomings of DIR technology and poor repair effects.

C. Research Content and Innovations

The model utilizes the image segmentation and document image processing capabilities of DCNN to judge paper documents, improving the restoration and image stitching processes for document modifications. At the same time, it uses grayscale rules to enhance the edge information effect of the document, in order to enhance the efficiency of the entire DIR. The study accelerates the data recovery of damaged document information by using DCNN to effectively extract the depth feature information in the fragments of paper-damaged documents, train the depth information of the neural network, and judge and analyze the data information of the damaged documents. At the same time combined with a variety of information technology and so on, in order to realize the data splicing and restoration of damaged document information, and provide more feasible technical methods for related problems.

D. Article Structure Description

This study is divided into six sections. Section II is an explanation of domestic and foreign research. Section III is the modeling of the current research methods. Section IV involves conducting feasibility analysis and performance testing on the current research model through experiments. Discussion and conclusion is given in Section V and Section VI respectively.

II. Related Works

In the past few decades, deep learning techniques, especially DCNN, have made significant progress in the field of information processing. They have demonstrated excellent performance in various aspects such as image recognition, speech processing, and natural language understanding. Chang et al. proposed a hierarchical classification Head-based Convolutional Gated Deep Neural Network (HCGDNN) to improve the performance of Automatic Modulation Classification (AMC). This method utilized outputs from different layers and only used in-phase/orthogonal cues for modulation prediction. Compared to AMC methods using other clues, HCGDNN had lower computational overhead and achieved excellent performance on public benchmarks [5]. Wang et al. proposed a novel Domain Adversarial Transfer CNN, i.e. DATCNN, to solve the insulation defect diagnosis problem of small sample gas insulated switchgear. This network could achieve the diagnosis of insulation defects in small sample gas insulated switchgear equipment through small sample data, and the diagnostic accuracy was high. Compared to other methods, DATCNN had better effectiveness and superiority [6]. Stecula et al. proposed a hit recognition method using AtomNet to search for inhibitors targeting aspartate N-acetyltransferase for the treatment of Carnarvon's disease. Despite the lack of protein structure or high sequence identity homologous templates, this method successfully identified five low micromolar inhibitors with drug like properties [7]. To simplify network representation and solve the core problem of network deformation, Wei et al. proposed a scheme of transforming convolutional layers into any module of neural networks. Abstracting modules into graphs, where blobs were vertices and convolutional layers were edges, the new scheme could effectively verify and solve problems such as network deformation [8].

Research on repairing damaged documents not only involves modifying general paper data information but also enables the recovery of more useful data information. Alkhazraji and others have made the restoration of ancient texts a necessary task for ancient scientific experts and researchers to connect modern humans with ancient civilizations, and inherit cultural, religious, and scientific knowledge. This article reviewed the different ways and methods currently used to restore ancient classics, as well as the achievements of these methods while pointing out the challenges that need to be addressed in the future. Significant progress has been made in using DCNN to repair ancient text datasets [9]. Zhang et al. proposed a method of applying evidence-based medicine theory to virtual restoration practices of disappearing architectural heritage in order to protect and restore it. The digital protection stage of virtual restoration of architectural heritage based on evidence-based design could form a comprehensive knowledge system that was scientific, humanistic, and practical, providing new ideas for the restoration of architectural heritage, and had important practical application value [10]. Elbshbeshi et al. proposed a method of developing a digital document process using laser scanning technology to protect and restore important archaeological sites. By using precise measurement networks and laser scanners, a 3D model with geographic coordinates was successfully created and deformation rates were measured. The established 3D digital model had high accuracy, providing strong support for heritage protection, tourism promotion, and future restoration work [11]. Kim et al. proposed an enhanced CycleGAN model based on enhanced identity loss to address issues such as scratches, ink fading, and handwriting loss caused by weathering damage. This model had higher structural similarity and accuracy than traditional methods, and could achieve automatic repair of early Japanese book pages about 300 years ago [12].

In summary, the current DCNN model is used in image recognition and classification in multiple fields, but in many cases, using only DCNN has many shortcomings in recognition accuracy and classification performance. Therefore, this study proposes a new model based on DCNN and grayscale rules to address the current issues of poor DIR performance. The model improves the classification performance of document image information through DCNN, and then enhances the processing effect of document edges through grayscale rules to achieve better document restoration results. The combination of grayscale rules and DCNN in research is significantly better than traditional methods compared to traditional methods, mainly due to the enhanced ability of the research method to process and recover damaged document images, improving accuracy and efficiency. Traditional document recovery methods often rely on linear filters, statistical models, or partial differential equations, which are often difficult to handle complex types of damage. Moreover, traditional methods are often insufficient to effectively handle abstract representations of corrupted data. DCNN is renowned for its excellent feature extraction ability, excelling in learning complex and abstract data representations, which makes it particularly useful in dealing with complex corruption patterns in documents. By automatically learning deeper and more abstract representations, DCNN provides a more dynamic and adaptable solution for document recovery.

III. Construction of Damaged DIR System

This section mainly analyzes the improvement process of DCNN and elaborates on the use of grayscale rules. A clearer explanation is provided on how to use DCNN and how to build a DIR system during the document repair process.

A. Design of Improved DCNN Algorithm Model

DCNN is a 2D neural network structure for processing mesh data, which is often used in the processing and analysis of mesh data due to its ability to calculate product through the matrix of the neural network structure. In general convolution, the common method is to multiply two integration functions and integrate them simultaneously, as shown in Eq. (1).

$$\int_{-\infty}^{+\infty} f(t)g(x-t)dt \tag{1}$$

In Eq. (1), $f(t), g(x)$ represent the functions that can be integrated in neural CNN. By using this special method of product of functions, the integration value between different functions can be calculated, and a new function value $h(x)$ can be defined. At this point, $h(x)$ can be denoted as shown in Eq. (2) [13].

$$h(x) = (g * f)(x) \tag{2}$$

The product of functions in Eq. (2) can be verified by identity as shown in Eq. (3).

$$(g * f)(x) = (f * g)(x) \tag{3}$$

The current $h(x)$ represents the identity in neural networks. $f(t), g(x)$ are the input function and output function in the neural network model, respectively. When calculating the discrete data of document information through DCNN, when the value of the discrete data is x, the convolution calculation formula at this time is Eq. (4) [14].

$$h(x) = (f * g)(x) = \sum_{t=-\infty}^{\infty} f(t)g(x-t) \tag{4}$$

Due to the fact that DCNN needs to consider the dimension size of the document when inputting information data. Therefore, the data size obtained from the input dataset and output dataset of the kernel function of the model are both dimensional data parameters learned through the kernel function. At the same time, when performing product operations on kernel functions, the calculated values are all 0, which enables the analysis and operation of document data to be achieved through convolution summation and product operations between different data. When the dimension of convolution operation reaches the 2D level, its 2D operation formula is Eq. (5).

$$h(x, y) = (f * g)(x, y) = \sum_{m}\sum_{n} f(m,n)g(x-m, y-n) \tag{5}$$

In Eq. (5), x, y represent the 2D coordinates of DCNN, and m, n are the input and output values of DCNN. Because the operation methods in data parsing and convolution of documents can be replaced with each other, their expressions can also be as shown in Eq. (6) [15].

$$h(x, y) = (g * f)(x, y) = \sum_{m}\sum_{n} g(m,n) f(x-m, y-n) \tag{6}$$

In Eq. (6), the expression of parameters is consistent with the parameter expression in the above formula. Due to the upper and lower limits of image information and grayscale values in the document when repairing images, a new operation needs to be provided in the model for the upper limit size of the model, as shown in Eq. (7) [16].

$$h(x, y) = (g * f)(x, y) = \sum_{m}\sum_{n} g(x+m, y+n) f(m,n) \tag{7}$$

In Eq. (7), the expression of the parameters is consistent with the above parameter expression. Due to the relatively small processing effect of feature data for stable paper edges in DCNN, grayscale matching rules are added to DCNN to perform pixel restoration judgment on the edge paper of the document. Fig. 1 shows the process of edge repair algorithm.

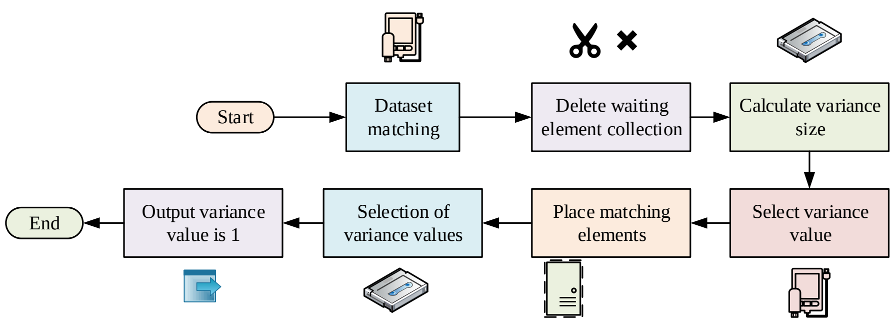


Fig. 1. Edge repair algorithm process.

Firstly, in the grayscale matching rule, the dataset obtained by DCNN classification is matched as empty, and the initial and waiting matching values are also set as empty. The initial value is the classification set of damaged documents obtained through deep neural networks. Afterwards, the set of waiting elements to be matched in the set is deleted from the total set to obtain a new sequence of matching element pixels, and then combined with the set that needs to be matched to calculate the variance size of the left and right document pixel columns. The current minimum variance value is selected as the basis for missing parts of the document to obtain the best matching effect, and then the matching elements are placed in the already matched set. The matching element values are placed into the set that has already been matched, and the process of selecting variance values is repeated to obtain the best matching result. Afterwards, the process of calculating the variance value is repeated until the remaining parameter data of the best matching set is 1. Finally, the obtained matching elements are input into the document order. At this point, the output document sequence element is the edge paper splicing sequence of the damaged document. For grayscale matching rules, the histogram is a method of adjusting grayscale matching. This method can enhance images and standardize them, as shown in Eq. (8).

$$H^{'}(v) = G(H(v)) \tag{8}$$

In Eq. (8), $H(v)$ is the cumulative histogram of the original image, $H^{'}(v)$ represents the cumulative histogram of the original image, and G is the size of the transformation function of the grayscale image. The normalized image data processing process for grayscale values is Eq. (9) [17].

$$NCC = \frac{\sum_{i,j}[I(i,j)-\bar{I}][T(i,j)-\bar{T}]}{\sqrt{\sum_{i,j}[I(i,j)-\bar{I}]^2\sum_{i,j}[T(i,j)-\bar{T}]^2}} \tag{9}$$

In Eq. (9), NCC represents normalization processing. I,T are the image and template that require grayscale processing. $\bar{I},\bar{T}$ represent the grayscale value size of the image and the grayscale value size of the template, respectively. When performing grayscale processing on an image, not only should the grayscale value of the image be considered, but also similarity should be taken into account, as shown in the similarity formula in Eq. (10) [18].

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C)(\sigma_x^2+\sigma_y^2+C_2)} \tag{10}$$

In Eq. (10), $SSIM(x,y)$ represents the similarity size of 2D images. μ_x,μ_y are the average sizes of the image in different directions. σ_x,σ_y are the standard deviation sizes in different directions of the image. σ_{xy} represents the covariance size, and C_1,C_2 represent the constant sizes, respectively. Improving the current DCNN by adding grayscale value matching can enhance the edge recognition and text recognition performance of document images. At the same time, due to the need to follow the best matching effect when calculating different paper damaged documents, the cosine distance formula needs to be used for calculating the best effect of the document, as shown in Eq. (11) [19].

$$x = (x_1, x_2, \cdots, x_n) \tag{11}$$

In Eq. (11), x represents the horizontal coordinate of the document in the n-th dimension. $x_1, x_2, \cdots, x_n$ refer to the horizontal coordinates of different dimensions. The vertical coordinates are shown in Eq. (12) [20].

$$y = (y_1, y_2, \cdots, y_n) \tag{12}$$

In Eq. (12), y is the vertical coordinates of the document in the n-th dimension. $y_1, y_2, \cdots, y_n$ are the vertical coordinates of different dimensions. The cosine distance of the document at this time is Eq. (13) [21].

$$d_{xy} = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2} * \sqrt{\sum_{i=1}^{n} y_i^2}} \tag{13}$$

In Eq. (13), d_{xy} represents the cosine distance, and x_i, y_i are the size of the dimension vector in the horizontal and vertical coordinates, respectively. After calculating the cosine distance of the document, an improved DCNN is used to cluster and analyze the document information, obtaining different fragments of document information. Fig. 2 shows the process of processing fragmented data.

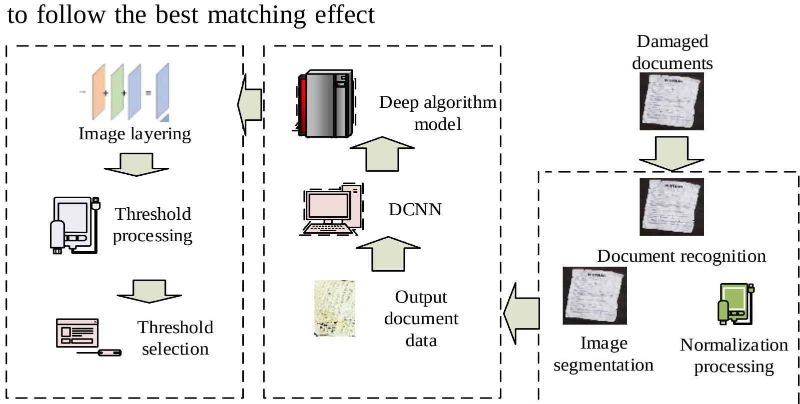


Fig. 2. Fragmented data processing process.

In Fig. 2, when analyzing the fragmented image of a damaged document, the fragmented information of the document is first read and the image information data is converted into damaged document data. Afterwards, the document is normalized to obtain the document image data, and the image data is input into the DCNN algorithm model. The threshold setting and selection of data are achieved through the convolutional layer of DCNN, and the final threshold is used for the next part of selection and data processing.

B. Design of Damaged DIR Model

The most important step in repairing damaged document information is to train the current document data, which is to convert the damaged document information into image data parameters that the computer can recognize. At this point, several conditions need to be met: adjacent paper documents are marked as 1 when splicing, and non-adjacent documents are marked as 0 when splicing. To cut the complete document through a program and train and validate it using an improved DCNN. Fig. 3 shows the process of paper document processing.

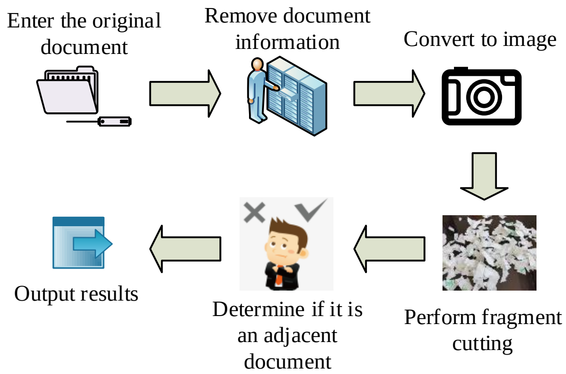


Fig. 3. Paper document processing.

In Fig. 3, the algorithm model can input the current original document into the computer during training. Setting the font and size of the document to be the same, removing redundant data information and parameters from the document. Afterwards, the document is converted into image data and fragmented according to the same image size. Splicing image fragments and determining whether the current document is an adjacent document. Adjacent or non-adjacent documents are set, and the result is output after the setting is completed. The matrix result of damaged documents can be generated by judging whether the documents are adjacent. At the same time, in DIR, some document images may have edge fragments with blank edges. To this end, after clustering analysis of the document, to find the fragmented document at the leftmost edge of the current document, and to perform fragment processing and document search. Fig. 4 shows the process of searching for document fragments.

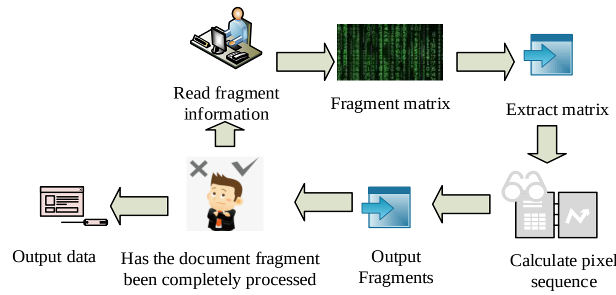


Fig. 4. Document fragment search process.

In Fig. 4, when searching for document fragments, the current fragment data information is first read and processed into a fragment matrix. The pixel matrix on the left of the extraction matrix represents the current feature matrix. Afterwards, to calculate the pixel sequence of the feature matrix, output the minimum left document fragment of the current sequence, and determine whether the document fragment classification has been fully processed. If so, to output the edge document fragment directly. If not, continue reading the document fragment size until the current document fragment has been fully processed. After searching for missing edge information in documents, due to the presence of different feature data in some documents and the same feature data in some identical document information, the following feature processing is required to complete the repair of the entire document information, as shown in Fig. 5.

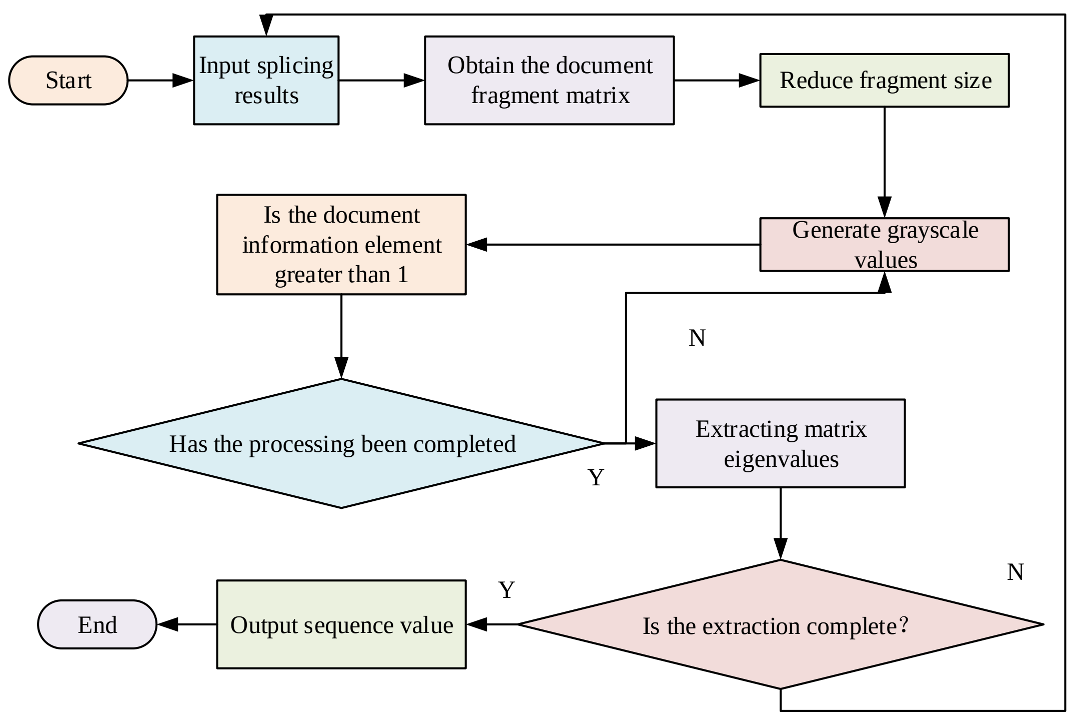


Fig. 5. Document information restoration feature processing process.

In Fig. 5, the results of concatenating different document fragments are input into the algorithm model, and the corresponding document fragment matrix is obtained through model processing. Afterwards, reducing the size of the document fragments to generate a grayscale value document fragment information matrix sequence, and determining whether the document information elements are greater than 1: if greater than 1, set the matrix to 1, and if not greater than 1, process it as 0. Judging whether the processing of the element data has been completed: once the element processing is completed, start extracting matrix feature values. If not, continuing to judge the result of the element processing. Judging whether the extracted document fragments have been completely extracted: If they are complete, to concatenate the matrix and output matching sequence values. If they are not processed, to re-input the document fragment information into the computer. The repair of document information can be basically completed by concatenating the side and overall document information. It also includes the most important step of auxiliary repair system function in the model, which is used to concatenate complete document information. Fig. 6 shows the auxiliary repair system process.

In Fig. 6, in the auxiliary repair of damaged documents, the fragments of the document are first inputted, and the results of the document are processed and feature extracted through an algorithm model. Afterwards, the sequence number on the left side of the current fragment is obtained based on the number of fragments obtained, and an improved DCNN model is used to process document fragments. The sequence of document fragments obtained is concatenated and output to the front-end. The document is manually adjusted to assist in concatenation, and then the concatenated document is output.

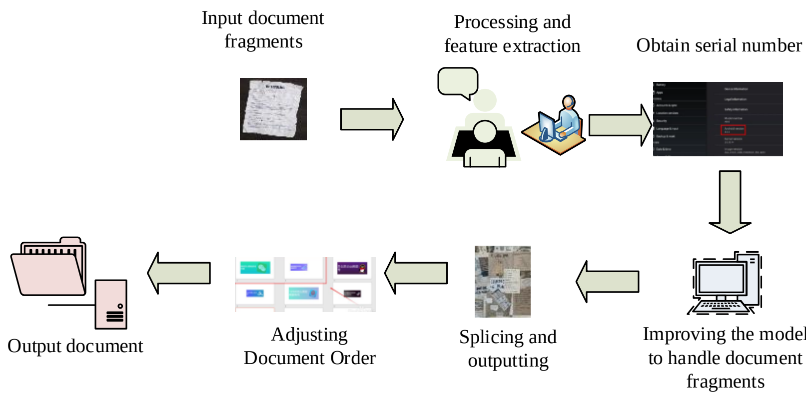


Fig. 6. Auxiliary repair system process.

IV. Analysis of DIR Results for Improving DCNN

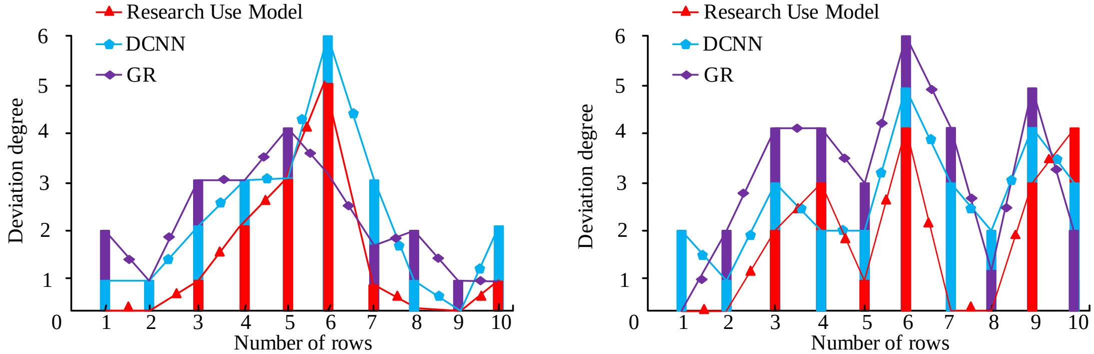
For document repair, it is necessary to verify the serial number of the repaired document, whether it is the final document data information obtained, and whether the repair is still needed. Therefore, this study will repair some of the document data currently used and calculate the degree of damage deviation of the document fragments after clustering analysis using the algorithm model. Deviation is an indicator of the degree of dispersion of data. The greater the deviation, the greater the deviation of the current document repair data. Table I compares the deviation of the concatenated documents in the current model.

TABLE I. Comparison of Deviation Degree in Document Repair of Improved DCNN

Number of document repair lines	1	2	3	4	5	6	7	8	9	10	11	12	Total
Dataset 1	1	2	0	0	1	3	4	0	0	1	2	1	15
Dataset 2	0	0	2	3	1	4	0	0	3	4	0	1	18
Dataset 3	0	0	3	2	4	3	0	0	5	4	1	2	24
Dataset 4	0	0	3	2	4	1	0	5	1	4	0	4	24
Dataset 5	0	0	1	2	3	5	1	0	0	1	2	2	17

In Table I, the row number represents the number of rows in the current document, where 1 represents the first row and 2 represents the second row. In comparing the deviation degrees of different document repairs, dataset 1 has the lowest deviation degree of 15, indicating that the smallest deviation degree can be achieved in the data of this document, and the repair effect of the document is the best. At the same time, in each line of document repair, the deviation is relatively small, indicating that using the improved DCNN model has a good effect on document repair, and the overall repair effect is also within an acceptable range. Comparing the model used with DCNN and Grayscale Rules (GR) to calculate the deviation of damaged documents. Selecting Dataset 1 and Dataset 4 for calculation testing. Dataset 1 has the smallest total deviation, while dataset 2 has a normal deviation range. Fig. 7 shows the comparison results.

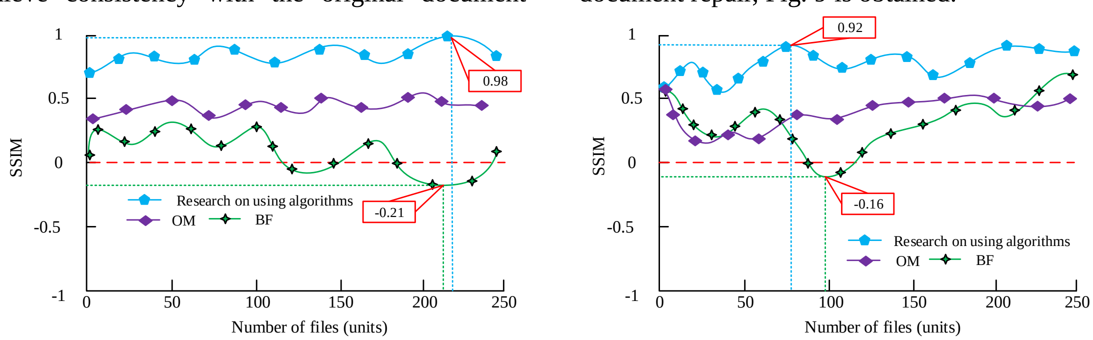
In Fig. 7 (a), when comparing the three algorithm models, the study found that the deviation of the model was smaller in different document line numbers, and the overall repair effect on the document was better. The deviation degree of the research model can reach a maximum difference of 2 compared to the other two algorithms. In Fig. 7 (b), the deviation of the research method is also small, with a maximum deviation value of 2. This indicates that the research model can enhance the document repair ability of a single algorithm model. Comparing the SSIM values of the traditional algorithm models Otsu's Method (OM) and Bilateral Filter (BF) with the research model in the document. Both dataset 1 and dataset 2 are selected, and the larger the SSIM value, the better the overall repair effect of the model, as shown in Fig. 8.



(a) Dataset 1 (b) Dataset 2

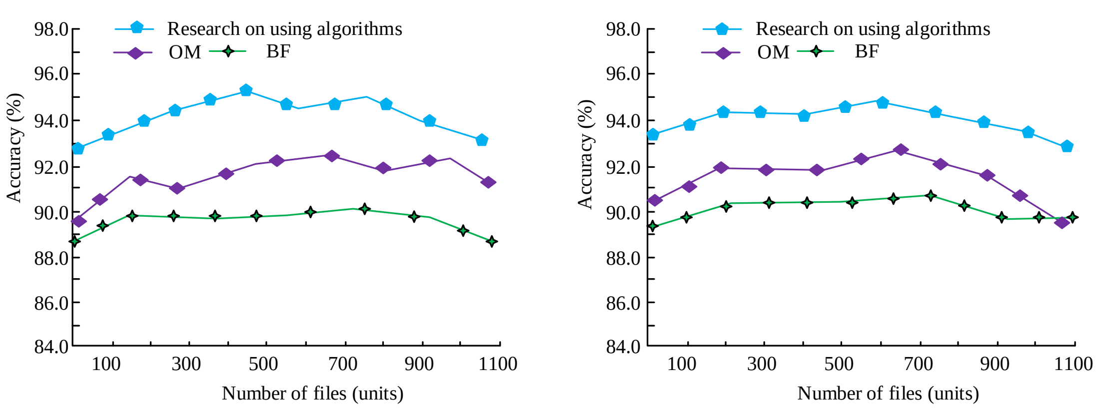
Fig. 7. Comparison test chart of deviation degree of three models.

In Fig. 8 (a), among the three algorithms, the similarity between the document repaired by the research model and the initial document is higher, closer to 1, with the highest value appearing around 220 documents. At this point, the SSIM value is 0.98. The lowest SSIM value appears around 220, with a minimum of -0.21, which is 1.19 lower than the highest value. This indicates that the current research method can basically achieve consistency with the original document when repairing document information, which may be the reason why the method is more superior. In Fig. 8 (b), the SSIM value of the research method is also the highest at 0.92, which is 1.08 higher than the lowest model BF of -0.16. As a result, the research method has a higher similarity in document repair between the two datasets, and the repair effect is better. Comparing the accuracy trends of three current algorithms in document repair, Fig. 9 is obtained.



(a) Dataset 1 (b) Dataset 2

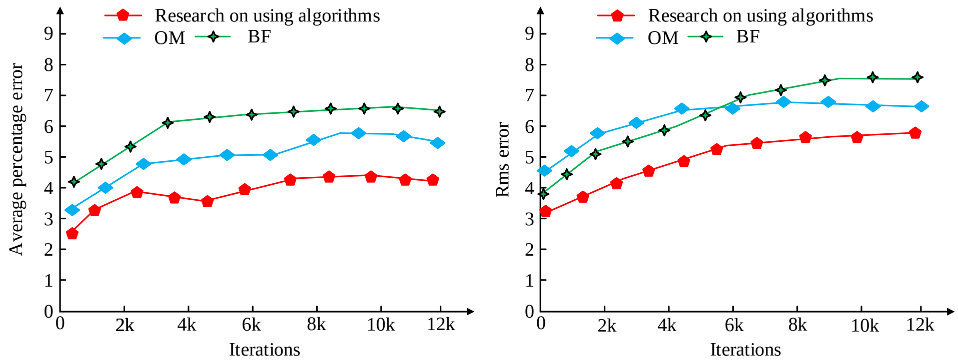
Fig. 8. Comparison of SSIM values among three algorithm models.



(a) Dataset 1 (b) Dataset 2

Fig. 9. Comparison of Accuracy of Three Algorithms on Two Datasets.

In Fig. 9 (a), the accuracy trend of the three algorithm models first increases and then gradually decreases, and the overall trend belongs to an upward and downward fluctuation trend. The accuracy of the research model is relatively high, with an average accuracy of 94.2%, which is 4.6% higher than the average accuracy of the BF model with the lowest accuracy of 89.6%. In Fig. 9 (b), the average accuracy of the research method at 94.1% is at a high level, which is about 5.0% higher than the lowest average accuracy of BF at 89.1%. Therefore, the document repair accuracy of the research model is better, and the processing effect on document fragments is better. Comparing the Average Percentage Error (APE) and Root Mean Square Wrror (RMSE) changes of the current three method models to obtain Fig. 10.



(a) Dataset 1 (b) Dataset 2

Fig. 10. Comparison of errors among three algorithm models.

In Fig. 10 (a), among the three algorithm models, the study model has the smallest APE value, with an average value of around 3.6, which is about 2.2 lower than the highest BF of 5.8. In Fig. 10 (b), the lowest RMSE value of the research model is only 4.4, which is 1.9 different from the highest BF of 6.3. Therefore, the error of the research model's DIR is smaller, and the data model is better, indicating that using this method can improve the effectiveness of document restoration to a certain extent. To test the stability of the current research model, it was compared and tested with the two algorithm models mentioned above, and Fig. 11 was obtained.

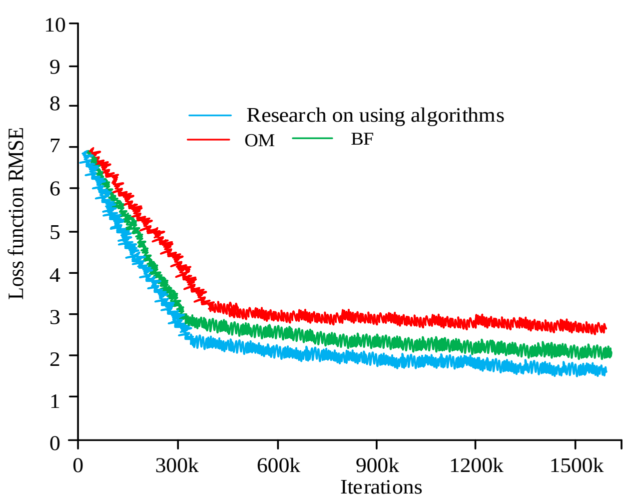


Fig. 11. Changes in loss functions of three algorithm models.

In Fig. 11, in the comparison of the three models, the loss function of the model decreases with the increase of iteration times, and the value of the loss function tends to stabilize when it reaches a certain value. The lowest loss function value appears in the research model, only around 2, with the highest loss function model being OM and a loss value of 3, with a difference of 1 between the two models. Therefore, in model comparison, the loss function value of the research model is lower, and the algorithm model is more stable.

V. Discussion

In today's information age, document and image data play a vital role in a variety of fields, including healthcare, education, law, and business. However, these important data are often at risk of corruption due to transmission errors, storage problems, physical damage, or other technical issues. Damaged documents and images not only affect the availability and readability of information but can also lead to the loss of critical information, which can have a significant impact on related business and decision-making. Therefore, the development of efficient information recovery technologies, especially those that can accurately repair damaged documents and images, has important practical application value and wide market demand.

Therefore, the study repairs broken documents and broken information by using the improved DCNN algorithm, and enhances the effect of information modification by using the grayscale rule. From the comparison of the deviation values, it can be seen that in the process of repairing different information, the deviation of the method used in the study reaches a maximum of 5 and a minimum of 0. This indicates that in the process of document repair, the method used in the study is able to repair the data and information efficiently, and the deviation is within a relatively small range, which may be due to the use of grayscale rules. From the comparison of the deviation of different models, it can be seen that the maximum difference between the deviation of the research model and the comparison of the deviation of the other models is 2. This indicates that the research uses methods that are more effective in modifying the document information, which may be due to the use of the grayscale rule to enhance the model's ability to repair the edge documents. In comparing the SSIM values, the research use model can basically approach the SSIM value of 1.00, which indicates that the research use model has a better document repair effect and its modification ability is closer to the real document information. This may be due to the better performance of the improved DCNN algorithm model.

In the comparison of repair accuracy of the algorithmic models, the average accuracy of the research use model is at 94.2% and 94.1%, which is relatively higher than the traditional method. This may be due to the reason that the research use method can effectively extract the depth feature information of document information. From the error comparison of the algorithm model, it is found that the average root-mean-square error of the algorithm model is only 4.4, which is 1.9 lower than that of the BF model, which can be seen that the research model has a better repair effect in the repair of the deviation value, which may be due to the reason that the research use model is able to judge the data of the damaged document information. To summarize, in the repair of damaged document information, the research using the method in the document repair effect, information repair accuracy and information document repair deviation have better performance, which shows that the research using the model than the traditional method has the ability to repair better, which has a better research value for the future of the document information repair research.

Although the improved model in the document shows high accuracy in handling damaged documents, the model still faces the problem of decreased accuracy when dealing with highly complex or extreme damage situations. The performance of DCNN is highly dependent on the quality and quantity of training data. If the training data is insufficient to cover all possible types of damage, the model may not be able to accurately identify and recover when encountering complex or uncommon types of damage that have not been seen before. Although DCNN performs well in extracting complex features, it may not be sensitive enough to some subtle and difficult to distinguish features, which limits its application in situations that require high-precision recognition. In practical applications, certain types of damages may be more common than others, which may lead to better recognition performance of the model for common types of damages during training, while performing poorly for less common types of damages. DCNN may be limited by the complexity and diversity of the features it captures when making classification decisions. If the depth or structure of the model cannot fully capture the key features that determine classification, its classification performance may not be ideal. Although the model mentioned in the document performs well on specific datasets, its generalization ability may be limited to other broader or different types of damaged documents.

VI. Conclusion

The current document information restoration technology often faces the problem of unsatisfactory restoration results when dealing with damaged documents, especially in the areas of edge information restoration and information integrity. By introducing an improved DCNN model, the data processing capability of document image classification and recognition is enhanced. And add grayscale rules on the basis of DCNN. When processing edge information in documents, use grayscale rules to improve the accuracy of edge repair. And through experimental testing of the feasibility and performance of the new model, analyze the restoration effect that the proposed method can achieve in practical applications. This study first analyzed the current DCNN and grayscale rules, introduced the main process of the current research, described the repair process, built an improved DIR model, and finally tested the feasibility and performance of the research model through experiments. Experiments had shown that in document data restoration, research model could achieve good document restoration results. The similarity of document repair occurred at a maximum quantity of around 220, with a value of 0.98, which was 1.19 higher than the lowest SSIM value. In dataset 2, the SSIM value of the research model was also the highest at 0.92, which was 1.08 higher than the lowest model. The accuracy of the research model was relatively high, with an average accuracy of 94.2%, which was 4.6% higher than the lowest accuracy model of 89.6%. The average APE value of the research model was around 3.6, which was about 2.2 lower than the highest model. The lowest RMSE value of the research model was only 4.4, which was 1.9 lower than the highest model. At the same time, the algorithm stability of the research model was the highest, and the model performance was better. Although the research has achieved a lot of results, there are limitations at present. For example, the research has been optimized and tested mainly for specific types of documents, while it may not be effective for other types of broken documents. The applicability and flexibility of the model may be limited, and the document's word order and sentence coherence may not be sufficiently considered and recovered. Advanced deep convolutional neural networks typically require significant computational resources, which may limit the utility of the model in resource-constrained environments. While grayscale rules assist in the restoration of edge information, their effectiveness in dealing with highly complex or irregular edge damage may be limited. Although the models mentioned in the study perform well on the current dataset, the adaptability and flexibility of the models for different degrees and types of damage have not been fully validated. Therefore, subsequent studies need to increase the diversity of document types, optimize the algorithm's ability to deal with word order and sentence coherence, as well as improve the computational efficiency and adaptability of the model, to enhance the overall performance and practical value of the model.

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References

[1] Sayeed A, Choi Y, Eslami E, Lops Yannic, Roy Anirban.Using a deep convolutional neural network to predict 2017 ozone concentrations, 24 hours in advance. Neural Networks, 2020, 121(5):396-408.

[2] Borjali A, Chen A F, Muratoglu O K. Detecting total hip replacement prosthesis design on plain radiographs using deep convolutional neural network. Journal of Orthopaedic Research, 2020, 38(7):1465-1471.

[3] Feng C, Zhang J. SolarNet: A sky image-based deep convolutional neural network for intra-hour solar forecasting. Solar Energy, 2020,

204(1):71-78.

[4] Missert A D, Yu L, Leng S. Synthesizing images from multiple kernels using a deep convolutional neural network. Medical Physics, 2020, 47(2):422-430.

[5] Chang S, Zhang R, Ji K, Sai Huang, Zhiyong Feng. A Hierarchical Classification Head Based Convolutional Gated Deep Neural Network for Automatic Modulation Classification. IEEE transactions on wireless communications, 2022, 21(10):8713-8728.

[6] Wang Y, Yan J, Jing Q, Zhenkang Qi, Jianhua Wang. A novel adversarial transfer learning in deep convolutional neural network for intelligent diagnosis of gas-insulated switchgear insulation defect. IET generation, transmission & distribution, 2021, 15(23):3229-3241.

[7] Stecula A, Hussain M S, Viola R E. Discovery of Novel Inhibitors of a Critical Brain Enzyme Using a Homology Model and a Deep Convolutional Neural Network. Journal of Medicinal Chemistry, 2020, 63(16):8867-8875.

[8] Wei T, Wang C, Chen C W. Modularized Morphing of Deep Convolutional Neural Networks: A Graph Approach. IEEE Transactions on Computers, 2020, 70(2):305-315.

[9] Alkhazraji AA, Baheeja K, Alzubaidi AM. Ancient Textual Restoration Using Deep Neural Networks: A Literature Review. In2023 Al-Sadiq International Conference on Communication and Information Technology (AICCIT) 2023, 4(7):64-69.

[10] Zhang Z, Zou Y. Exploration of a virtual restoration practice route for architectural heritage based on evidence-based design: a case study of the Bagong House. Heritage Science. 2023, 11(1):35-36.

[11] Elbshbeshi A, Gomaa A, Mohamed A, Othman A, Ibraheem IM, Ghazala H. Applying geomatics techniques for documenting heritage buildings in Aswan region, Egypt: A Case study of the Temple of Abu Simbel. Heritage. 2023, 6(1):742-761.

[12] Kaneko H, Ishibashi R, Meng L. Deteriorated characters restoration for early japanese books using enhanced cyclegan. Heritage. 2023, 6(5):4345-4361.

[13] Sahani M, Dash P K. FPGA Based Deep Convolutional Neural Network of Process Adaptive VMD Data with Online Sequential RVFLN for Power Quality Events Recognition. IEEE Transactions on Power Electronics, 2020, 36(4):4006-4015.

[14] Li Y, Wu W, Chen H, Wen Wu, Chen Houjin. 3D tumor detection in automated breast ultrasound using deep convolutional neural network. Medical Physics, 2020, 47(11):5669-5680.

[15] Du Y, Li F F, Zheng T, Li Jiang. Fast Cascading Outage Screening Based on Deep Convolutional Neural Network and Depth-First Search. IEEE Transactions on Power Systems, 2020, 35(4):2704-2715.

[16] Choi S, Sim J, Kang M, Choi Yeongjae. An Energy-Efficient Deep Convolutional Neural Network Training Accelerator for In Situ Personalization on Smart Devices. IEEE Journal of Solid-State Circuits, 2020, 55(10):2691-2702.

[17] Saqlain M, Abbas Q, Lee J Y. A Deep Convolutional Neural Network for Wafer Defect Identification on an Imbalanced Dataset in Semiconductor Manufacturing Processes. IEEE Transactions on Semiconductor Manufacturing, 2020, 33(3):436-444.

[18] Gao B, Aelterman J, Laforce B, Luc Van Hoorebeke, Laszlo Vincze. Self-Absorption Correction in X-Ray Fluorescence- Computed Tomography With Deep Convolutional Neural Network. IEEE Transactions on Nuclear Science, 2021, 68(6):1194-1206.

[19] Choudhuri S, Adeniye S, Sen A. Distribution Alignment Using Complement Entropy Objective and Adaptive Consensus-Based Label Refinement For Partial Domain Adaptation. Artificial Intelligence and Applications. 2023, 1(1): 43-51.

[20] Ghimire P. Digitizing Cultural Heritage of Nepal: Tools for Conservation and Restoration. Unity Journal. 2023, 4(1):254-279.

[21] Wenjun Z, Benpeng S, Ruiqi F, Shanxiong C. EA-GAN: restoration of text in ancient Chinese books based on an example attention generative adversarial network. Heritage Science. 2023, 11(1):42-43.