

Research on Aided Reading System of Digital Library Based on Text Image Features and Edge Computing

Vaishnavi Suresh Deshmane¹, Prof. Suyog Medhe², Dr. H. B. Jadhav³

Student, Department of Computer Engineering¹

Guide, Department of Computer Engineering²

HOD, Department of Computer Engineering³

Adsul Technical Campus, Chas, India

Abstract: With the rapid development of library informatization, traditional text information retrieval service methods have been unable to meet the needs of users. Therefore, personalized assisted reading technology has attracted wider attention, as it can discover hidden associations by mining user information, book information, and user operation logs, and recommend the acquired knowledge to users. In order to improve the service quality and experiences of users, this paper presents a digital library assisted reading system that combines text image features and edge computing. Firstly, the digital library reading assistance system framework is proposed based on edge computing technology, which will improve the service quality and information transmission level of the digital library. The auxiliary reading model of the digital library is presented based on text image features and an RBF neural network. Detailed simulation results verify the applicability and efficiency of the proposed scheme.

Keywords: Digital library, edge computing, assisted reading, text image features, RBF neural network.

I. INTRODUCTION

Since the 1990s, computer, network, and communication technologies have developed rapidly [1]. This is to meet the requirements of processing massive digital information resources, improve the orderly release, organization, processing, and delivery of network information resources, and improve the efficiency of user retrieval and acquisition of required information resources [2]. The theory and technology of digital libraries came into being and became the development direction of traditional libraries. The United States is the first country in the world to start research, development, and construction of digital libraries, and it is also the country with the highest level of digital library construction and the widest range of applications in the world [3], [4].

The construction of digital libraries in the United States first began in the late 1980s. At that time, some scientific research institutions, academic libraries, and urban public libraries began to research and explore the construction of digital libraries. In September 1993, the National Science Foundation, the National Aeronautics and Space Administration, and the Advanced Research Projects Agency of the United States Department of Defense jointly issued the "Digital Library Initiative", which kicked off the comprehensive construction of digital libraries in the United States [5].

As a provider of network information services, libraries have undergone profound changes in the information needs of users under the network environment, so the library's information services have also undergone profound changes. Among them, the main obstacle for users to obtain information in the network environment has changed from a spatial obstacle to a selective obstacle [6], [7]. The development of the network requires that libraries strengthen cooperation,



break through the limitations of time and region, and realize resource sharing. Users require libraries to provide accurate and personalized information services, etc. These factors have affected the information services of university libraries, shifting from traditional common services to personalized services.

Recommendation systems based on various library-assisted reading recommendation algorithms, although they have been used in some applications, still have problems [9], [10]. Some of them also hinder the healthy development of recommendation services. In past research on auxiliary reading, there are many problems such as resource description characteristics, sparse matrix problems, and scalability [11].

II. RELATED WORK

A. TEXT IMAGE FEATURES

As a special image with textual meaning, text images have become more and more popular on the Internet with the rapid development of their storage and acquisition technology [14], [15]. Such as e-contracts, e-documents, e-files, advertising pictures of shopping malls or streets, images of bus stations, etc which are ubiquitous on the Internet [16], [17]. This kind of information digitization has brought great convenience advantages to society.

However, for massive text image data, how to find the image or images that users are interested in is a very difficult task. HOG feature is a description operator used to express the local structural features of an image [18], [19]. The general idea of this feature extraction is to divide the image into regions of the same size and regularly distributed, calculate the gradient histogram of each region, and finally connect the gradient histograms of all regions on the entire image according to certain rules to form the HOG feature vector.

People's visual interest in document images is concentrated on the text and images, and the background and noise will not and should not be overly prominent. In fact, the sharper the text strokes and patterns in the document image, the weaker the background and noise interference, and the more prominent the text in the document [20], [21]. The overall effect of the document image is better.

B. EDGE COMPUTING

Edge computing is a new computing model, which refers to the migration of some computing tasks from the original cloud computing center to the vicinity of the data source to reduce the pressure on cloud computing [22]. Many existing resource allocation algorithms for mobile edge computing focus on minimizing delay or energy consumption.

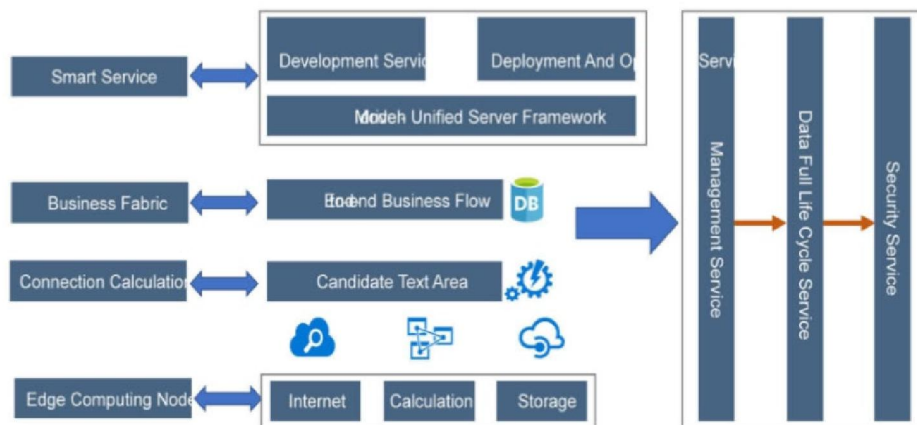


Fig. 1. Reference example framework of edge computing



The service model of cloud computing cannot satisfy real-time feedback. In this mode, after the data source obtains the data, the data needs to be uploaded to the cloud. Data transmission takes a certain amount of time and costs. Therefore, cloud computing is suitable for processing long-term data and depends on different application scenarios.

On the other hand, edge computing plays an irreplaceable role in scenarios such as real-time, short-period data, and local decision-making. Compared with cloud computing, edge computing is not a replacement, but a supplement and extension to cloud computing, providing a better computing platform for mobile computing.

III. THE PROPOSED SCHEME

Local binary mode has the characteristics of gray invariance, simple and efficient calculation, and is widely used in artificial intelligence fields such as pattern recognition and machine vision. In the image, the pixel is selected as a 3×3 neighborhood; the center pixel is defined as the threshold, and the other eight pixels in the neighborhood are binarized. Starting from the upper-left pixel, in a clockwise direction, the size is compared with the center pixel in turn. If it is greater than or equal to the threshold, it is marked as 1; otherwise, it is marked as 0. Arrange the marked numbers from high order to low order in the order of comparison to form an eight-bit binary number. Converted into a decimal number, this is the local binary mode operator of this central pixel.

As an artificially extracted feature, LBP has been widely used in face recognition and pedestrian detection, and the calculation of LBP features is simple; it is mainly used to describe the local texture features of the image, and the effect is good. This paper mainly analyzes text images, so the LBP feature operator is used. The calculation principle of LBP is to select any pixel in the image as the center point, take the gray value of the center point pixel as the threshold value, and compare the gray values of its eight neighboring pixels one by one. After the comparison, the point greater than the threshold is set to 1, and vice versa, to obtain a set of 8-bit binary numbers.

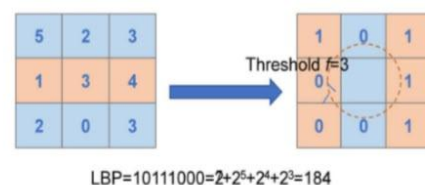


FIGURE 3. Local binary mode transformation process.

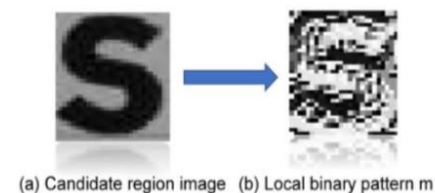


FIGURE 4. Candidate text area image and local binary pattern map.

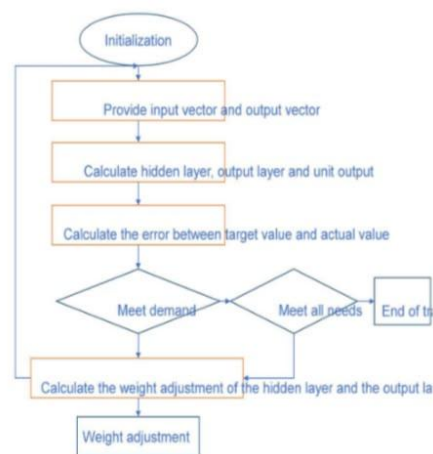


FIGURE 5. RBF neural network learning flowchart.

Fig. 2. Local binary mode transformation process.

RBF NEURAL NETWORK

The RBF neural network learning process is shown in Figure 5. RBF neural network can reflect the different division of sample data in space. Choosing an inappropriate center point position will have a great impact on the mapping result. The width of the hidden layer of the RBF neural network is also an important factor affecting its classification and prediction ability.



RBF NEURAL NETWORK LEARNING PROCESS

$$u_j = \sum_{i=1}^n w_{ij} x_i - \theta_j$$

$$h_j = f(u_j) = 1 / (1 - \exp(-u_j))$$

$$l_t = \sum_j v_{jt} h_j - \gamma_t$$

$$y_t = 1 / (1 + \exp(l_t))$$

$$\varepsilon_j = (c_t - y_t) y_t (1 - y_t)$$

$$w_{jt}(N+1) = w_{jt}(N) + \partial \varepsilon_j x_i$$

$$\theta_j(N+1) = \theta_j(N) + \beta \varepsilon_j$$

Calculate the error between the output value and the expected value. If it meets the set accuracy requirements, learning is completed; otherwise, the process continues. [29]

IV. PERFORMANCE TEST

A. TEST ENVIRONMENT ASSISTED READING SYSTEM ARCHITECTURE BASED ON EDGE COMPUTING

The edge node layer is mainly composed of a large number of distributed networks that exist in the physical environment and edge servers that serve cameras. Because the traditional camera does not have computing power, it is mainly responsible for collecting text and image data. The edge server is mainly responsible for storing and processing data from the camera and running video image processing tasks.

The data processing module consists of two parts: data cache and data extraction algorithm. The data cache part caches the original data from the camera. Therefore, how to map the recognized text feature data to each specific page in a distributed camera network has become a major challenge for the system. Due to the high number of original video data frames and resolutions generated by some high-definition cameras, this will cause the efficiency of the extraction algorithm to decrease, and the system cannot guarantee real-time performance.

B. EXPERIMENTAL CONDITION SETTING

Test the classification performance of candidate regions, and use the control variable method to test feature performance and classifier performance respectively. For testing feature performance, keep the classifier unchanged, and test the performance of each feature on the classifier separately.

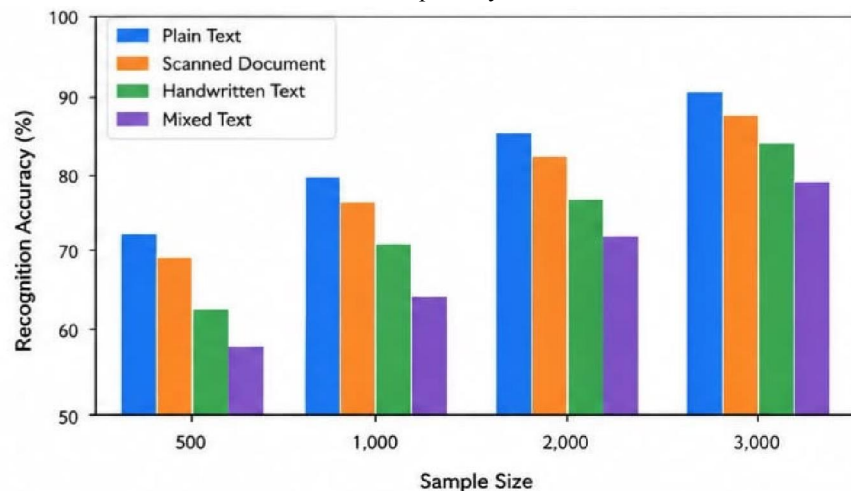


Fig. 3. Load capacity test of auxiliary reading terminal in different environments



Select 3000 positive samples and 3000 negative samples as the training set, and 4000 positive samples and 4000 negative samples as the test set. The Gabor feature, LRF feature, and HOG feature of the sample are extracted, and each feature is combined with the number of boundary corner points and the stroke area ratio to evaluate classification performance.

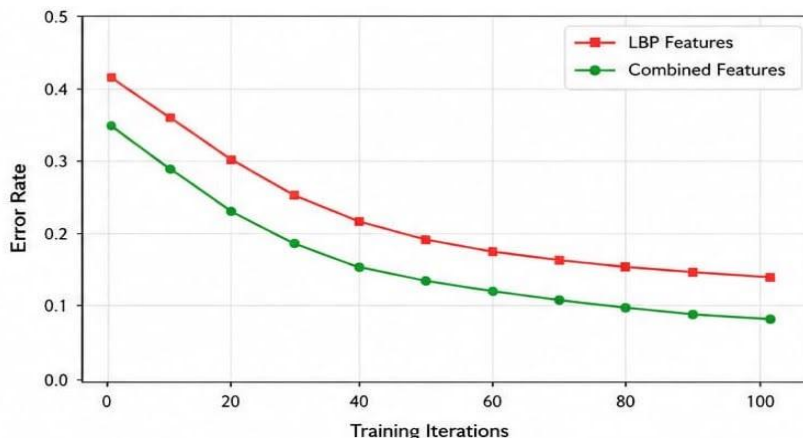


Fig. 4. Auxiliary reading terminal carrying capacity test under different methods in the same environment.

C. AUXILIARY READING MODEL PERFORMANCE TEST RESULTS

It can be seen that when the number of positive samples is 3000 and the number of negative samples is 3000, the AUC area is the largest; that is, the classifier has the best performance.

More or fewer negative samples than positive samples will cause the performance of the RBF neural network to decrease. The ROC curve shows that the performance of the classifier is difficult to distinguish with the naked eye. The performance is usually expressed by the value of AUC. The higher the value of AUC, the better the classification ability of the classifier, and its range is usually 0.5–1.0.

Therefore, this paper selects 3000 positive samples and 3000 negative samples, uses the combination of LRBF features, HOG features, border corner points, and stroke area ratio to train the RBF neural network, and uses the trained model to classify.

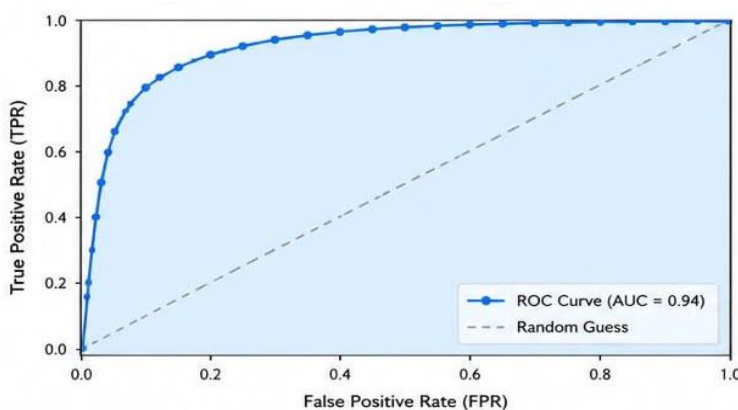


Fig.5 ROC curve of the classifier when the positive and negative samples are different



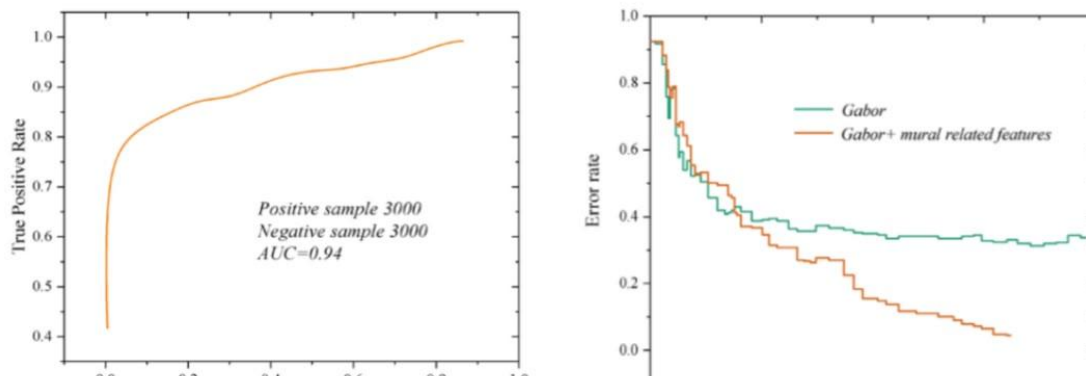


Fig. 6 ROC curve of the classifier when the positive and negative samples are equal.

D. FEATURE COMPARISON AND CLASSIFICATION RESULTS

By using the classifier and combining the underlying feature combination of the text image, the model of the text image training sample set can be obtained. Using the test sample set of text images to test the RBF neural network generated by the training sample set, the results can predict the document image very well.

The classification results of text images are evaluated by recall and precision. Experiments show that the text image classification method proposed in this chapter is feasible, and the document images have 100% precision and recall.

E. COMPARATIVE SIMULATION RESULTS

In the above-mentioned test of text image recognition in digital libraries, we found that the auxiliary reading system based on text images and edge computing established in this paper has obtained relatively good test results. In order to horizontally compare the advantages of the model established in this paper with previous studies, we conducted a series of comparative simulation test procedures.

In the comparison, we mainly compared the text recognition accuracy rate of digital libraries under different categories and the amount of text recognition under the same category of digital library.

According to the comparison, the assisted reading technology established in this paper has obtained better results than other methods. The traditional concepts of classification and cataloging can still be applied to electronic and network information resources, but some methods need to be modified to adapt to the network environment and the characteristics of network information resources.

V. CONCLUSION

Personalized assisted reading can dig deeply dig hidden information in digital libraries and obtain results that users cannot obtain through information retrieval. Due to the intelligence and humanization of personalized service, its application fields are becoming wider and wider, and the recommendation technology adopted is becoming more reasonable and complicated.

When comparing several recommendation algorithms that are currently widely used and considering the application environment of the library, they have problems such as sparse scoring data and poor scalability. How to allow users to obtain the recommendation information of similar types of books and periodicals, to obtain recommendations for new books, and to obtain recommendation information of books and periodicals with higher recommendation value has become a research hotspot of digital library recommendation services.

This paper discusses a digital library assisted reading system that combines text image features and edge computing. After the above model and architecture are established, simulation tests and system trial results verify the applicability



and efficiency of the model. Through this improved algorithm, the recommendation system can obtain information that users are more interested in from a large amount of data, which not only further improves the quality of recommended information, but also improves the overall utilization of library resources.

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