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The Design and Implementation of a Rural Medical Mutual Assistance Platform for Predictive Health Analysis Based on Big Data

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ABSTRACT : *This paper designs and implements a rural medical mutual aid platform based on big data analysis, aiming to improve the efficiency and quality of rural medical services. The project solves the problems of uneven distribution of medical resources in rural areas, fragmentation of the medical insurance system, and weak health awareness of farmers through the Internet and technological means. The platform applies deep learning techniques for form recognition and data processing to optimize the coordination and distribution of medical resources and improve the efficiency of rural doctors. Experimental results show that the model performs well in form detection and recognition tasks, but there is still room for improvement in complex scenarios. Ultimately, the goal of the platform is to improve the overall medical level in rural areas and realize the rational allocation of resources and efficient services.*
KEYWORDS *Rural Medical Care,Mutual Aid Platform,Big Data Analytics,Deep Learning,Form Recognition.*

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I. INTRODUCTION

The strategy of rural revitalization, a key decision by the 19th National Congress of the CPC, stems from analyses of national policies and future plans. It is a significant historical mission for the successful building of a modern socialist country in every respect. This strategy serves as the overarching approach to addressing the "Three Rural Issues" in the new era. Optimizing and upgrading the level of medical services is an important measure to ensure that the rural revitalization strategy can be fully implemented. Recently, the General Offices of the CPC Central Committee and the State Council released opinions aimed at further deepening reforms and promoting the healthy development of rural medical and healthcare systems. These opinions set a goal to achieve notable progress in the reform and development of these systems by 2025. The operation mechanism of the rural medical and healthcare system will be further improved. The input mechanism will become more robust. A hierarchical diagnosis and treatment pattern will begin to take shape. This pattern includes primary diagnosis, two-way referral, emergency and slow diagnosis, and coordinated efforts between different levels of care. At the same time, the response to the "Opinions" outlines four working principles. First, it emphasizes maintaining and strengthening the party's overall leadership of rural healthcare work. Second, it focuses on enhancing medical and health resources at the county level. Third, it prioritizes building human resources. Fourth, it aims to further deepen the reform of the system and mechanism. In addition, the "Opinions" also set target tasks for 2025. These include a more balanced and reasonable functional layout of rural medical and health institutions, as well as a significant improvement in infrastructure conditions. There is a focus on the development and growth of rural medical and healthcare personnel, with an emphasis on improving the quality and structure of the workforce. The operation mechanism of the rural healthcare system will be further improved, and significant progress will be made in the reform and development of the rural medical and healthcare system.

Based on the analysis of the survey results from industry stakeholders, the current challenges in rural medical development are mainly reflected in three aspects. The first aspect is the unequal allocation of medical resources. There is a clear gap between urban and rural services, with urban residents having access to higher quality medical equipment and specialized treatments. Rural areas lack sufficient medical personnel and have a shortage of backup staff, leading to the issues of "not being able to go down" (difficulty in attracting talent) and "not being able to stay" (difficulty in retaining talent). The second aspect is the serious fragmentation of the medical insurance system. There are varying levels of coordination, and the system lacks integration. The two-track system operates under different implementation guidelines, creating inconsistencies. The third aspect is the low health awareness among farmers and their weak willingness to participate in the insurance system. Rural residents generally have lower income levels. Facing the pressures of medical expenses and daily living costs, they tend to overlook health issues and habitually cut back on health expenditures, often refusing to join the insurance system. Additionally, transferring medical insurance is complicated, and the procedures for seeking medical treatment in other locations are cumbersome.Relieving the work pressure of township doctors is a crucial driving force for the development of rural healthcare. Technology can improve lives, and technological assistance is an indispensable support for the advancement of modern medical fields. Currently, rural healthcare development faces challenges such as insufficient funding, a shortage of high-level, highly skilled medical professionals working on the front lines, heavy reliance on manual labor leading to significant work pressure, and a scarcity of technological support platforms. According to the 48th Statistical Report on China's Internet Development released by the China Internet Network Information Center, the number of Internet users in China has reached 1.011 billion, with an Internet penetration rate of 71.6%.

The project team aims to leverage the widespread availability of the Internet and its low information dissemination costs to connect healthcare industry professionals with accurate resources and plans. By applying big data analysis technology, the goal is to reduce the workload of rural healthcare workers, providing more convenient operations and tailored services. The team seeks to develop an app that alleviates the work pressure of rural healthcare personnel and enhances the overall medical standards in rural areas. This app would promote the progress and development of rural healthcare, facilitate reasonable two-way referrals, improve coordination between different healthcare levels, and achieve effective allocation of healthcare resources.

Whether it is layout analysis or table recognition, the existing methods can be roughly divided into the traditional methods based on image processing shown in Figure 1 and the methods based on deep learning shown in Figure 2:

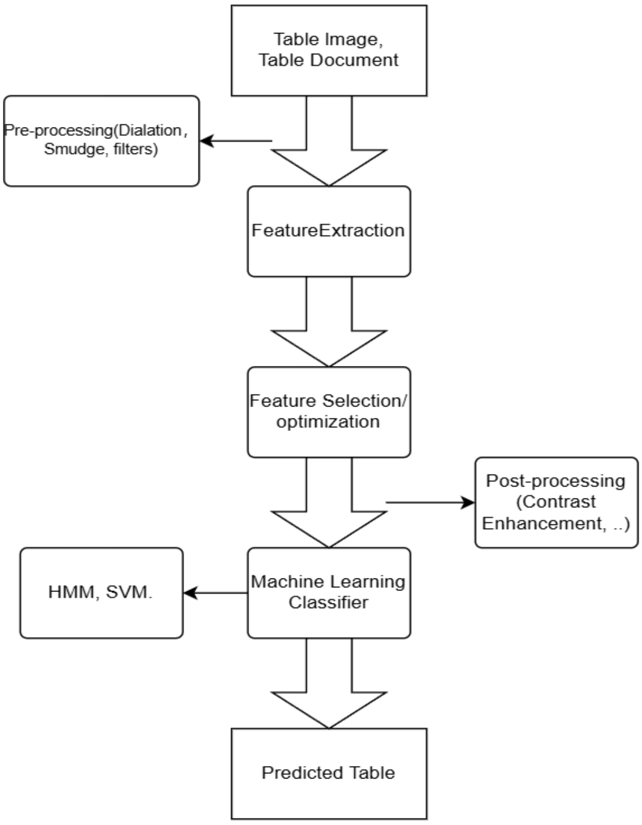

Figure 1 Traditional table detection approache

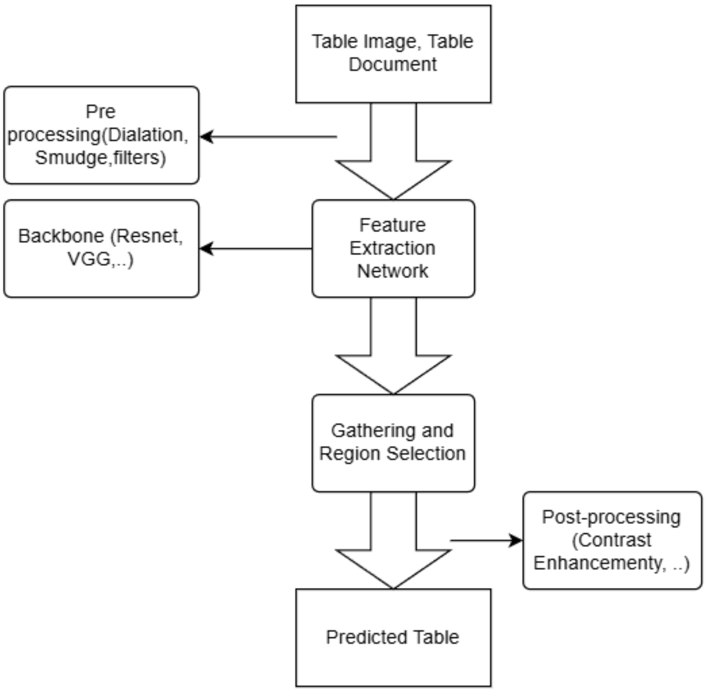

Figure 2 Deep learning approaches for table detection

In traditional methods, the Docstrum algorithm, published by O'Gorman in TPAMI in 1993, is widely used for layout analysis. This approach follows a bottom-up process, dividing the connected black-and-white regions in an image into characters, text lines, and text blocks to obtain layout information.

For table recognition, traditional methods extract table lines and divide rows and columns through operations like erosion and dilation, reconstructing table objects by combining cell structure and textual content. However, traditional algorithms face a major issue: they rely heavily on various thresholds and parameter settings for layout analysis and table structure extraction. This makes it difficult for these methods to generalize well to document images in different scenarios.

In contrast, deep learning-based methods not only directly use detection models to classify layout content but also integrate advanced techniques such as detection, segmentation, graph neural networks, and attention mechanisms. One of the key advantages of deep neural networks is their ability to be carefully designed without relying on threshold and parameter selection, resulting in much better generalization across various document scenarios[1].

In the following sections, the principles and implementation steps of deep learning-based table recognition will be introduced in detail. This will include the design and implementation of experiments, as well as an analysis of the performance and stability of the proposed table recognition algorithm based on the experimental results.

II. SOLAR PLANTS MONITORING SYSTEM COLLABORATIVE FILTERING BASED ON TABLE RECOGNITION BASED ON DEEP LEARNING GORITHM

Table Recognition Technology Based on Deep Learning primarily relies on neural networks, especially models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). These models automatically learn and extract high-level features from images to achieve table recognition. The technical principles mainly include the following aspects[2]:

1. Image Preprocessing: The input document or image undergoes preprocessing steps such as denoising, binarization, and normalization to improve the efficiency and accuracy of subsequent processes.
2. Table Detection: Deep learning models (e.g., Faster R-CNN, YOLO series for object detection, or FCN, U-Net for semantic segmentation) are used to detect table regions in the preprocessed image. These algorithms identify the table boundaries and output them as detection results.
3. Table Structure Recognition: After detecting the table region, deep learning models (e.g., RNN, LSTM) are employed to recognize the structure of the table. These models learn the structural features of the table, such as rows, columns, and cells, and use them to construct the logical structure of the table.
4. Content Recognition: Based on the identified table structure, Optical Character Recognition (OCR)

technology is used to recognize the textual content within the table. OCR converts the text from the image into an editable text format, enabling digitization of the table contents.
Information Integration: The recognized table structure and content information are integrated to generate a complete table dataset. This process may involve formatting, correction, and structured storage of the table content.

III. EXPERIMENTAL RESULTS AND ANALYSIS

3.1 Experimental Cluster Environment

In constructing the distributed computing environment, we chose MXNet as the computational platform, integrated with the Hadoop distributed system, and used CentOS 6.5 as the operating system. The deployment employs a Spark HA (High Availability) cluster based on Zookeeper. Both the primary and standby nodes are configured with hardware environments running on quad-core CPUs and 4GB of memory. The specific experimental environment is shown in Table 1:

Table 1 Experimental cluster environment

Software and hardware environment	releases
Virtual machine	15.x
Operating system	CentOS 6.5
Hadoop	3.0.0
JDK	1.8.0
ZooKeeper	3.5
Master node	Quad-core CPU,4GB RAM,Qty 1
Slave node	Quad-core CPU,4GB RAM,Qty 3

3.2 Experimental Dataset

In this section, we will demonstrate the implementation and effectiveness of deep learning models in the table recognition task through experiments. The dataset used in this experiment is TableBank, an image-based table detection and recognition dataset that contains high-quality labeled tables extracted from various documents. The TableBank dataset covers multiple domains, including business documents, official reports, and research papers, providing rich training samples for table recognition tasks[3].

The TableBank dataset used in the experiment includes table images and their corresponding structured information, such as table bounding boxes and cell content. Each table image is accompanied by detailed annotation information, allowing the model to learn how to extract table structures from the images.

During the experiment, the data was divided into three parts:

60% of the data was used to train the deep learning model, enabling the model to learn to recognize table structures from images.

20% of the data was used for validation, adjusting the model's parameters and hyperparameters during training, ensuring that the model performs well on unseen data.

The remaining 20% of the data was used to test the model's final performance, providing an objective evaluation of the model in real-world application scenarios.

3.3 Experimental Evaluation Metrics

The table detector's performance is measured using several metrics, including Frames Per Second (FPS), precision, and recall. However, the most commonly used evaluation metric is the mean Average Precision (mAP). Precision is derived from the Intersection over Union (IoU), which is the ratio of the overlap area to the union area between the ground truth and predicted bounding boxes. A threshold is set to determine whether a detection is correct: if the IoU is above the threshold, it is classified as a true positive; if the IoU is below the threshold, it is considered a false positive. Additionally, if the model fails to detect an object present in the ground truth, it is categorized as a false negative.

These metrics provide a comprehensive evaluation of the model's performance in detecting and recognizing tables.

$$Average\ Precision(AP) = \frac{Ture\ Positive\ (TP)}{(Ture\ Positive(TP) + False\ Positive(FP))} = \frac{TurePositive}{Allbservative}$$

$$Average\ Recall(AR) = \frac{Ture\ Positive\ (TP)}{(Ture\ Positive(TP) + False\ Nagative(FN))} = \frac{TurePositive}{AllGroundTruth}$$

$$F1 - score = \frac{2 * (AP * AR)}{(AP + AR)}$$

Based on the above formula, the average precision (AP) for each class is calculated. To compare the performance between detectors, the mAP is used as the single evaluation metric, which is the average of the AP across all classes.

IoU is a metric used to measure the difference between the ground truth annotations and the predicted bounding boxes[4]. The metric is used in most state-of-the-art object detection algorithms. In object detection, the model predicts multiple bounding boxes for each object and removes unwanted boxes based on the confidence score of each bounding box according to its threshold value. We need to declare the threshold value as per our requirement.

$$IOU = \frac{Area\ of\ union}{area\ of\ intersection}$$

3.4 Experimental Procedure

Dataset preprocessing: the TableBank dataset is preprocessed, including image enhancement, normalization and other operations to improve the robustness of the model.

Dataset division: the TableBank dataset is divided into three parts: 60% of the data is used to train the deep learning model so that the model can learn the ability to recognize the structure of a table from an image; 20% of the data is used for validation, which is used to adjust the parameters and hyperparameters of the model during the training process to ensure that the model can perform well on unseen data; the remaining 20% of the data is used to test the final performance of the model to objectively assess the model's performance in real application scenarios.

Model Optimization: Use the preprocessed training set data to train the deep learning model until the model's performance on the validation set is stable. Testing: Evaluate the trained model using the test set data to calculate the accuracy, recall, F1 score, and other metrics to measure the performance of the model. The experimental process is shown in Figure 3:

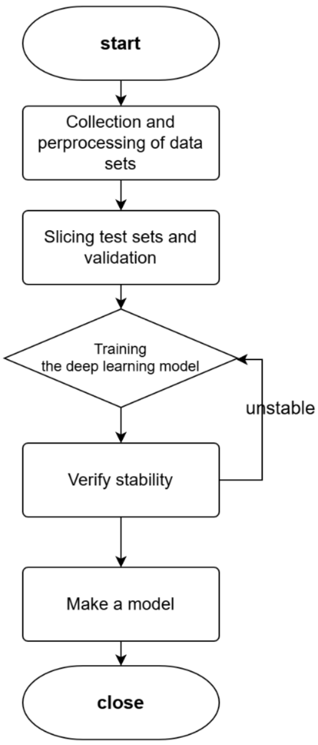

Figure 3 Table detection flow chart based on deep learning

3.5 Experimental results

The form recognition technology mainly uses RARE, a picture description model based on attention mechanism. The overall process of form recognition for the form area is shown in the Figure 4:

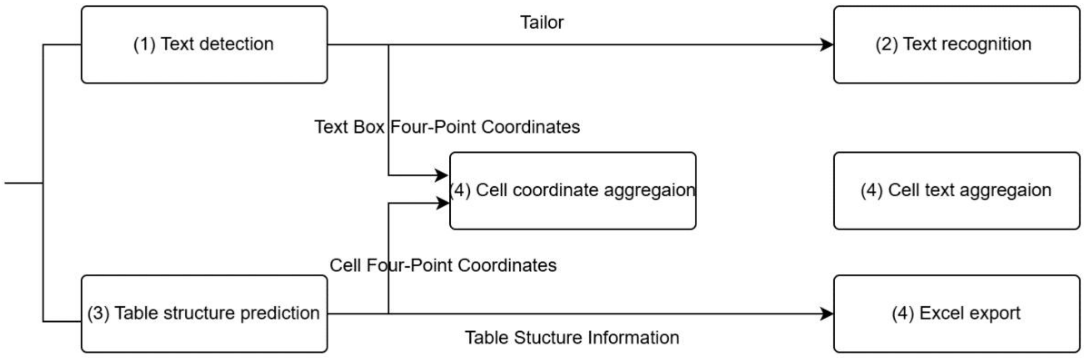

Figure 4 Table recognition model flow chart

Figure 4 shows the following steps:

Input an image and output a text describing the image through a network with an attention mechanism.

The image description network for table images inputs an image of a table that has been analyzed by layout analysis and outputs a string of HTML characters (as shown below). The structure of the form is represented by the structural markup of HTML, where the content is what is in the form text. Through further HTML parsing, the cell four-point coordinates and table structure information can be obtained for each text.

The IOU and vertex distance between the text box coordinates obtained by the text detection algorithm and the Cell coordinates obtained by the table structure prediction module (are computed to perform single to multi-row aggregation. The IOU is used to determine which text box coordinates belong to the same Cell coordinate, and the vertex distance and IOU are used to determine the order of the text boxes.

According to the existing order of text box coordinates, in accordance with the order from top to bottom from left to right using (4) Cell coordinate aggregation module results will be (2) text recognition results and splicing, so that the cell contents of the multi-line text can be spliced into a string.

(3) Table structure prediction results html results combined with (5) Cell text aggregation module text results, and finally exported to Excel output.

The output Excel table shows that the TableBank dataset achieves significant performance gains on the table detection task. The model is able to accurately locate the position of the table in the document and define it by the border. The model also showed good performance on the table structure recognition task. It is able to recognize the row and column layout of a table and represent the table structure as a sequence of HTML tags.The TableBank dataset provides rich training resources for deep learning models in table recognition and detection tasks, which helps to improve the performance of the models. The deep learning model performs well in table detection and recognition tasks, but there are some limitations in performance on complex layout tables and blurred images. Subsequent practical development should further improve the performance of the model in complex situations, such as introducing more contextual information and using more complex network structures.

IV. CONCLUDING

This project aims to develop a rural medical mutual assistance platform based on big data analysis technology to alleviate the workload of township doctors and improve the efficiency and quality of rural healthcare services. By utilizing digital tools and the widespread availability of the internet, the project seeks to build a convenient medical technology support platform to address issues such as uneven distribution of rural medical resources and the lack of technological support. Ultimately, the goal is to enhance the overall level of rural healthcare.

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