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Intelligent Imaging Technology in Diagnosis of Colorectal Cancer Using Deep Learning

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ABSTRACT In order to explore the application of deep learning based intelligent imaging technology in the diagnosis of colorectal cancer, Tangdu Hospital patients are selected as the research object in this study. By scanning the cancer sites, then distinguishing and extracting the features of the tumors, the collected data are input into the designed in-depth learning intelligent assistant diagnosis system for comparison. The results show that in the analysis of image prediction accuracy, the best prediction accuracy of T1-weighted image method is matrix GLCM (gray level co-occurrence matrix) algorithm, the best prediction accuracy of adding T1-weighted image method is matrix MGLSZM (multi-gray area size matrix) algorithm, and the best prediction accuracy of T2-weighted image method is ALL combination of all texture features, and the best prediction accuracy of three imaging sequences is not more than 0.8. In the AUC analysis of the area under the curve of different texture features, it is found that T2-weighted imaging method has obvious advantages in differentiating colorectal cancer from other methods. Therefore, through this study, it is found that in the use of deep learning intelligent assistant diagnosis system for the diagnosis of colorectal cancer, it can provide useful information for the clinical diagnosis of colorectal cancer to a certain extent. Although there are some deficiencies in the research process, it still provides experimental basis for the diagnosis and treatment of colorectal cancer in later clinical stage.

INDEX TERMS Deep learning, colorectal cancer, weighted images, accuracy, texture features.

I. INTRODUCTION

With the rapid progress of science and technology, information technology is constantly developing. With the rising of people's living standards, health has become the focus of people's primary concern. Rectal cancer is a common malignant tumour of the intestine and stomach in the body, and its incidence is increasing, which has a great impact on people's lives and property [1]. With the rapid development of science and technology, the level of medical treatment is also constantly improving. As an important imaging examination technology in medical treatment, its clarity and intellectualization are constantly improving, such as CT, MRI and other applications in medical imaging, which are very common [2], [3]. However, in the current trend of rapid development of science and technology, how to make diagnosis more intelligent has attracted the attention of researchers.

As a new trend in this era, the Internet of Things mainly relies on intelligent sensing technology, remote sensing technology, intelligent data processing technology, etc. It is constructed on the basis of the Internet, thus forming an intelligent network connected by objects, which provides a seamless connection for medical diagnosis results [4], [5]. With the rapid development of computer-aided technology and medical imaging technology, deep learning algorithm has gradually emerged. Because of its self-learning ability, its application in medical imaging diagnosis has become more and more important because of people's attention [6]. Rectal cancer is a cancer of the digestive system of the body. Its diagnosis and treatment are of great significance.

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Medical imaging, as one of the methods of visual detection of diseases, can directly understand the structural changes and physiological changes of the lesion sites of patients through its imaging technology, and judge the similarity and difference of suspicious tumors, thus providing a direct basis for the clinical diagnosis of the lesion sites observed [7]–[9].

In conclusion, intelligent assistant diagnosis based on deep learning is not widely used in cancer diagnosis. Therefore, in this study, patients with colorectal cancer in the Tangdu Hospital are selected as the research object. Through scanning, tumor differentiation and feature extraction, the collected data are input into the designed deep learning intelligent aided diagnosis system for comparison, in order to provide experimental basis for the diagnosis and treatment of colon cancer in later clinical stage.

II. LITERATURE REVIEW

A. EXPLORATION OF INTERNET OFTHINGS IN MEDICA FIELD

The Internet of Things is a scientific field which has been developing gradually in recent years. Its related applications involved in medicine make many researchers explore. Dimiter V. Dimitrov et al. reviewed the integration of medical Internet of things with telemedicine and telehealth in 2016. They found that there was a great improvement in people's cognitive function, mental health and lifestyle, and its role became more and more obvious with the aging of the population [10]. In 2017, Arum Park et al. applied the Internet of Things technology to the whole channel of hospital patient care in order to improve the quality of medical services and maximize the benefits. Finally, it is found that the accuracy of medical treatment level has increased, and through the introduction of service model, patients can provide better medical services, which significantly improves the efficiency and benefits of the hospital [11]. Yang He et al. proposed a portable lung function parameter detection device in 2018. Through experiments, it is found that the error rate is less than 5%, and because of its various performances, it has great significance for clinical application and family detection [12]. Raja Jayaraman et al. in 2019, by combining with the Internet, provided a peer-to-peer distributed, secure and shared ledger tracking and product tracking superior way through block chain network. Its recent challenges are overcome and rationally applied [13].

B. DEVELOPMENT OF DEEP LEARNING ALGORITHMS

The concept of deep learning originates from the study of artificial neural networks. As a new technological science, the research and development of the theory and technology for simulating, extending and expanding human intelligence have great challenges in various fields, especially in the medical field, the importance of which cannot be ignored.

Benjamin Q. Huynh et al. learned and trained features from image data through neural convolution network in 2016, and analyzed the extracted features. It is found that using CNN (Convolutional Neural Network) method to classify medical graphics according to their features can obviously promote their classification and feature extraction, which will make human-related problems very easy to solve and improve the medical level [14]. Bradley J. Erickson et al. discovered in 2017 that the advantage of deep learning algorithm is that it does not need to recognize and calculate image features first, and that features are identified as part of the learning process [15].

Gregory R. Hart et al. predicted the risk of lung cancer in 2018 using artificial neural network (ANN) based on personal health information, which has high sensitivity and specificity. Experiments show that this algorithm provides a low-cost, non-invasive clinical tool for cost-based prediction and risk stratification [16].

Chunyan Qiu et al. constructed artificial neural network (ANN) and logistic regression (LR) models in 2019 and compared them to find out the important factors related to the occurrence of new metastasis of invasive breast cancer. Finally, it is found that the artificial neural network model is superior to the traditional LR model in the recognition of breast cancer neonatal metastasis [17].

C. EXPLORATION OF IMAGE DIAGNOSIS TECHNOLOGY

For many diseases of the body, the diagnostic results do not represent 100% of the diagnosis, and its accuracy can continue to improve. Medical imaging is a kind of diagnostic and therapeutic method which can observe the lesion directly, and it is widely used in medical treatment. Florian Wiesinger et al. studied the morphological description and segmentation of skull structure by proton density (PD) - weighted zero TE (ZT) imaging in 2016. It is found that this method can not only make structural bone imaging, but also be used for positron emission tomography (PET)/MR attenuation correction and MR-based radiotherapy planning [18]. In 2017, Bradley J. Erickson et al. studied the application of in-depth learning technology in medical images, and its application degree is very wide, which has achieved good results in image recognition and calculation. Daniel S. W. Ting et al. could classify retinal images from optical coherence tomography (OCT) in 2018 by using in-depth learning artificial intelligence, which has the potential to be applied to other image-based medical diagnoses [19]. Dong Wook Kim et al. applied artificial intelligence algorithms to medical diagnostic analysis performance in 2019. The results show that the feasibility of the technology is studied in medical images of performance evaluation and diagnosis analysis of artificial intelligence algorithm, but clinical experiments are needed to verify its function [20].

In summary, through the exploration of Internet of Things, deep learning and medical imaging technology by many scholars, the application of this technology in cancer, such as rectal cancer, is discussed in this study, and the results are analyzed.

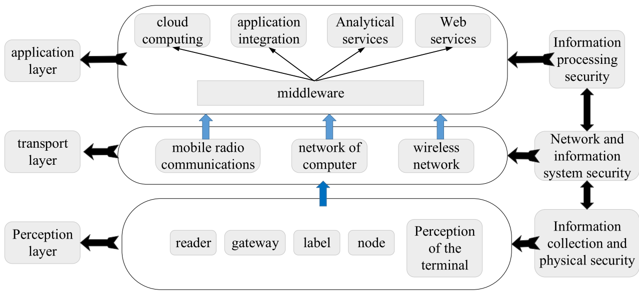

FIGURE 1. The architecture of internet of things technology.

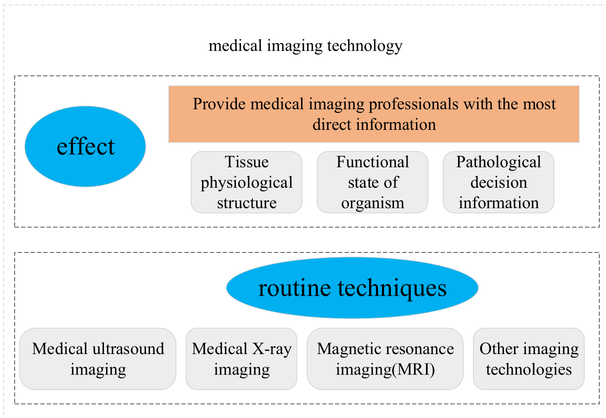

FIGURE 2. The role and classification of medical imaging technology.

III. METHODS

A. INTERNET OF THINGS TECHNOLOGY

Today, with the development of science and technology, information acquisition and Internet of Things technology are inseparable. Intelligent Internet of Things is the basic link of information aggregation. Intelligent products in its environment have keen perception ability, intelligent processing ability and natural interaction mode. They can receive, process and classify external information automatically. It participates in human life with a machine entity with part of human intelligence to do more complex work, and constructs an intelligent feedback network [21]. The architecture of Internet of Things technology is shown in Figure 1.

B. MEDICALIMAGING TECHNOLOGY

With the progress of science, medical imaging technology has become more and more important in clinical diagnosis of various diseases. For doctors, it can make doctors have a more intuitive perspective of observation, a more detailed understanding of the disease, and more accurate suggestions for patients. For patients, it can enable patients to understand their own health more clearly, and more confident in life. There are many kinds of medical imaging techniques, including medical ultrasound imaging, medical X-ray imaging, magnetic resonance imaging and other imaging techniques, as shown in Figure 2 [7].

Medical ultrasound imaging is often used in human tissue imaging, and its probe mainly acts on the skin surface. According to its performance, it can be divided into diagnostic ultrasound and therapeutic ultrasound. Generally, the comprehensive information of the detected tissue can be judged by this technology, and the plane or section of the internal organs and tissues can be constructed by using the probe through the skin [22]. Medical X-ray imaging exists as electromagnetic radiation and can penetrate most substances, but the attenuation coefficients of different substances are different. Medical X-ray imaging equipment can reconstruct the corresponding images of human tissues and organs by receiving residual ray information after penetrating the human body. Using X-ray source of a certain thickness, computed tomography scanner scans the human body with a circular trajectory and processes the collected attenuation information on the detector on the opposite side. Three-dimensional mammography is the most common technique. Magnetic resonance imaging is also a kind of medical imaging. In the body, the hydrogen protons in each molecule have been in disordered motion, thus achieving the diagnostic effect [23]. However, in a stable magnetic field, some hydrogen atoms are activated and emit radio frequency signals by emitting pulses of a specific frequency. In the process of magnetic resonance imaging, people are placed in the magnetic resonance imaging scanner, and there is a strong near uniform magnetic field around the part to be scanned. This technique can image different tissues on arbitrary sections with multi-parameters. Its contrast and resolution are very high, and the effect is good [24]. Other imaging techniques, such as microwave mammography, fluorescence imaging, thermoacoustic imaging and molecular imaging, have been applied in medicine, but they are seldom used.

C. INTELLIGENT DIAGNOSIS TECHNOLOGY BASED ON DEEP LEARNING ALGORITHMS

In medical diagnosis, patients are often diagnosed according to the information they get. Intelligent diagnosis technology based on deep learning algorithms is to discuss medical image data under the trend of rapid development of science and technology.

Generally, there are many deep learning algorithms, and their application scenarios are also very extensive. With the support of physical network technology, deep learning can search the parameters of data and corresponding known labels on the whole network, so as to obtain the label prediction system of the same kind of unknown data with the best performance [25]. Its core part mainly includes feature extraction, feature dimension reduction and machine learning, as shown in Figure 3.

Feature extraction is to transform the input samples (such as medical images) into a series of valuable digital information by computational method. It is a reconstruction of samples and an important part of image recognition process. Among them, dimensionality reduction is an inevitable way, which mainly adopts two ways: feature compression and feature selection. In this process, no new features are generated and the original features need not be modified, so it has better explanability in the intelligent aided diagnosis

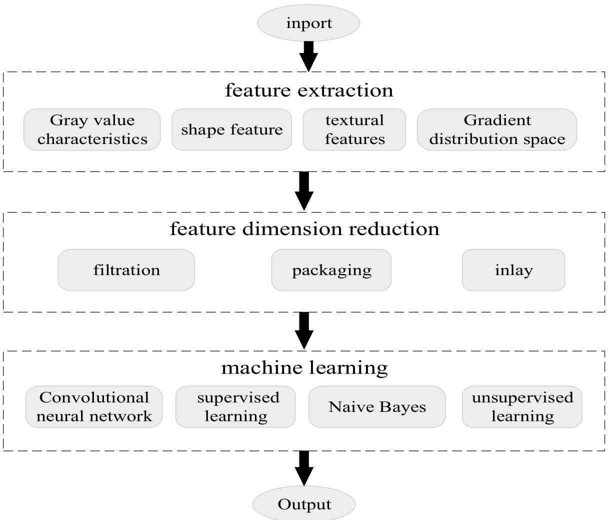

FIGURE 3. Intelligent diagnostic assistant flow chart based on deep learning algorithms.

system based on deep learning algorithms. Feature screening methods mainly include filtering method, packaging method and embedding method. Ultimately, the construction of the auxiliary system needs to update the image data continuously to maintain the leading position of the system [26]. Machine learning is to teach the machine to learn or solidify some knowledge and patterns to help improve the decision-making performance of users. It can be divided into supervised learning, enhanced learning and unsupervised learning. The commonly used supervised learning models include artificial neural network, support vector machine, decision tree and random forest, naive Bayesian and K-nearest neighbor. To sum up, in this study, the effect of intelligent image aided diagnosis technology based on deep learning algorithms is used to explore and analyze the cancer, especially rectal cancer, so as to observe the effect of this technology.

IV. EXPERIMENTS

A. RESEARCH SUBJECTS

In this study, 259 colorectal patients are collected from June 2017 to December 2018 in the Tangdu Hospital. Among them, patients who have not undergone surgery are excluded, and 241 patients are confirmed as colorectal cancer after clinical diagnosis, including 129 males and 112 females. The age ranges from 25 to 69 years, with an average age of 57.62 $\pm$ 5.17 years. The main clinical manifestations are intermittent blood stool, mucous stool, change of stool habits, abdominal pain, intestinal obstruction, weight loss, anemia and palpation mass. Through CT diagnosis, 64 cases of rectum, 47 cases of sigmoid colon, 52 cases of descending colon, 8 cases of splenic flexure of colon, 17 cases of transverse colon, 5 cases of colon liver region, 39 cases of ascending colon and 9 cases of ileocecal region are found. In this study, all subjects and their immediate family members sign the informed consent. This experiment is approved by the Ethics Committee of the Tangdu Hospital (Shaanxi, China).

Inclusion criteria: subjects have no other diseases. Subjects have no history of radiotherapy/chemotherapy. Subjects and their immediate family members sign informed consent. Exclusion criteria: Subjects have other complications.

B. SCANNING METTHOD

241 subjects are scanned with Siemens 3.0 Tesla magnetic resonance imaging equipment. Two days before the examination, patients should be advised to take liquid food. The night before the examination, the patient takes laxatives, or oral Mannitol 250mL, and drink a lot of water. One day before the examination, the patient undergoes clean enema. About 10 minutes before the scan, the patient is injected with Anisodamine 20mg intramuscularly, and then 800-1000mL of water is injected through the anus. Scanning range is from diaphragm top to ischial tubercle level with 5.0mm interval, 5.0mm thickness and 1.0 pitch. The original data is reconstructed by standard algorithm, the thickness of reconstructed layer is 1mm and the interval is 1mm. The image is uploaded and processed by two-dimensional and three-dimensional reconstruction techniques. Preoperative TNM staging, angiography and perioperative and postoperative re-examination of colorectal cancer are performed using axial images, two-dimensional and three-dimensional post-processing images.

C. IMAGE DATA COLLECTION

Firstly, the images obtained from the above subjects are collected by T1 weighting. Then, in three-dimensional magnetic resonance imaging data, professional radiologists with more than four years of experience first select the largest transverse section containing the tumor area in the whole volume data, and then calibrate multiple coordinate points in the tumor area, so that the colorectal cancer area is completely contained in the polygon composed of coordinate points. Then, the free curve fitting method, Hermite cubic curve interpolation, is used to automatically separate regions of interest. Finally, in order to reduce the errors of regions of interest caused by these artificial sketches, the results of the separated brain cancer regions are verified by two additional doctors. If there is a wrong sketch, the section image will be re-sketched.

Different patients have different image features, and texture features take full account of the spatial distribution of images, gray statistics of pixels and local structure information. In this study, texture features are mainly extracted from gray level co-occurrence matrix GLCM, gray level run-length matrix GLRLM, gray area size matrix GLSZM and multi-gray area size matrix MGLSZM. The adjustable parameters and feature dimensions are shown in Table 1.

In this study, the texture features used belong to high-order texture statistics. Among them, the gray level co-occurrence matrix and GLCM fully consider the spatial information and gray level information between any two pixels. These parameters include orientation σ of matrix statistics, distance d between two pixels and gray scale n after quantization.

TABLE 1. Texture features and dimension statistics table.

	Adjustable parameters	Characteristic Dimension
GLCM	σ=0, d=1. n=32	21
GLRLM	σ=0, n=32	11
GLSZM	n=32	11
MGLSZM	n=32	11

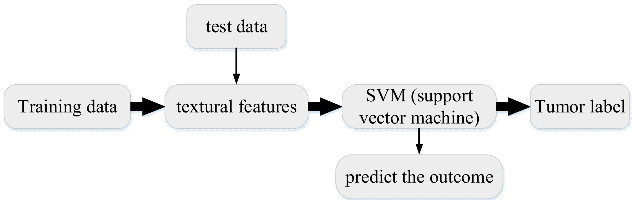

FIGURE 4. Design flow chart of intelligent image aided diagnosis system based on deep learning algorithms.

Gray run-length matrix is the statistics of two-dimensional matrix. In addition, GLSZM takes into account the eight-connection of the pixels, that is, how many pixels are a separate connected block under a given gray scale. The multi-gray area size matrix MGLSZM is the complexity of the gray area size matrix GLSZM, which quantifies the gray scale of the region of interest in a multi-range.

D. DESIGN OF INTELLIGENT IMAGE AIDED DIAGNOSIS SYSTEM BASED ON DEEP LEARNING ALGORITHMS

In this study, the intelligent assistant system based on deep learning algorithms designed combines texture features and support vector machines, and its structure is shown in Figure 4. The case number of the experimental patient is used as the unique identifier of the study object. Based on the randomly generated sequence number, the first 100 patient cases are selected as the training set, the next 20 cases as the verification set, and all the remaining cases as the test set. In this way, it can be ensured that the same patient can only appear in one data set, and that the images from different perspectives of the same patient will not appear in different data sets. The first is the training process of the system (when no data is input). Then, when the training reaches the required state in this study, the data is input into the intelligent assistant system for deep learning to evaluate the system. Nonlinear support vector machine is adopted, and radial basis function is used as the kernel function of support vector machine to map the obtained features to high-dimensional space.

In the deep learning intelligent image assistant system studied in this study, all codes are on Ubuntu 14.04 system and equipped with Nvidia K80 GPU graphics card. Medical image preprocessing is realized by off-line MATLAB 2012b.

E. STATISTICAL METHODS

In the intelligent assistant system based on deep learning algorithms, the main evaluation parameters are specificity, sensitivity, accuracy and area under curve. If the gold standard of colorectal cancer is positive for a + c cases and negative for b + d cases, it means that the positive predicted in the intelligent system based on deep learning algorithm is a + b cases, and the biopsy of b cases is negative. The predicted negative rate is c + d, of which c is positive by biopsy. Therefore, the true positive (TP) of the system is predicted to be equation 1:

$$TP = \frac{a}{a+c} \tag{1}$$

True negative (TN) is the equation 2:

$$TN = \frac{d}{b+d} \tag{2}$$

False positive (FP) is the equation 3:

$$FP = \frac{b}{a+b} \tag{3}$$

False negative (FN) is the equation 4:

$$FN = \frac{c}{c+d} \tag{4}$$

The corresponding specificity is as equation 5:

$$SP = \frac{TP}{TN+FP} \tag{5}$$

Sensitivity is the equation 6:

$$SEN = \frac{TP}{TP+FN} \tag{6}$$

Accuracy is the following equation 7:

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

The area under the curve refers to the area under the working characteristic curve of the subjects. The value of this area is between [0, 1]. The larger the area under the curve is, the better the prediction result is. In the intelligent system based on deep learning algorithm, when different features are used to assist diagnosis for each MR medical image, contingency can be excluded by repeated experiments, so as to obtain the final mean value of measurement, and to fully express the comprehensive performance of the intelligent system based on deep learning algorithm.

In the intelligent image aided diagnosis system constructed in this research, all the codes are running on Windows 8 system, and the image processing is realized by offline MATLAB 2012b. In the system, the support vector machine and convolution neural network are realized by Caffe software. The specific operation environment is shown in Table 2.

V. RESULTS AND DISCUSSION

A. ANALYSIS OF TYPICAL RECTAL CANCER IMAGING CASES

As shown in Figure 5, there are three typical medical images of colon cancer. From Figure 5A, it can be seen that in the cases of rectal cancer with liver metastasis, the lesion shows

TABLE 2. Development and running environment of intelligent image aided diagnosis system based on deep learning.

Software	Operating system	Linux 64bit
	Integrated development environment	Pycharm2018.11
Hardware	Memory	Kingston ddr4 2400MHz 16G
	CPU	Intel core i7-7700@4. 0GHz 8 core
	GPU	Nvidia GeForce 1060 8G

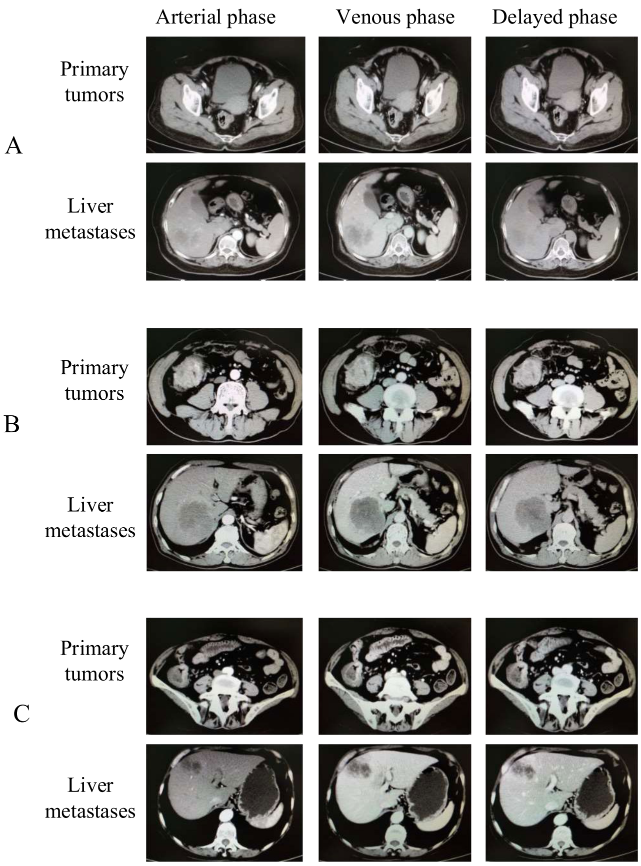

FIGURE 5. Typical medical images of colon cancer (A. rectal cancer with liver metastasis; B. Recurrence of ascending colon cancer with liver metastasis after operation; C. ascending colon cancer with liver metastasis.

mild marginal enhancement in arterial phase, but no enhancement in internal phase. In portal vein phase, the enhancement of the edge of the lesion is more obvious than that of the anterior lesion, and the enhancement of small nodules appears in the interior of the lesion. The enhancement of delayed

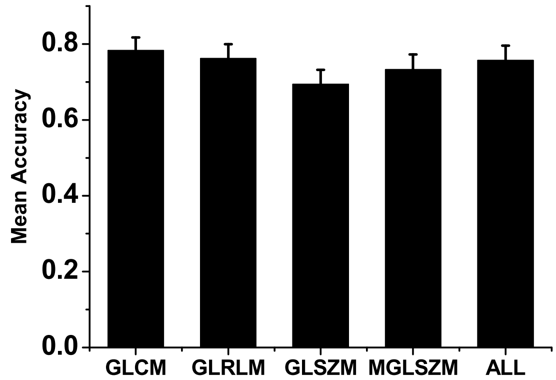

FIGURE 6. Subtype differentiation of colorectal cancer based on T1 weighted imaging.

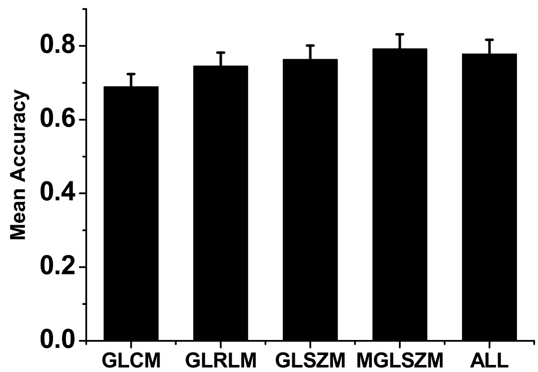

FIGURE 7. Subtype differentiation of colorectal cancer based on increased T1 weighted imaging.

lesions is slightly decreased and the internal enhancement is more obvious than before. From Figure 5B, it can be seen that in the cases of recurrence and liver metastasis after operation of colon cancer, the intrahepatic lesions in arterial phase are enhanced annularly and the capsular depression is more obvious. In portal vein stage, the lesions still show circular enhancement, and the capsular depression is further evident. In delayed phase, the enhancement of the lesion decreases, but the capsule depression is still visible. From Figure 5C, it can be seen that in ascending colon cancer with liver metastasis, the edge of the left lobe lesion in arterial phase is enhanced, but there is no enhancement in the interior, and the right lobe lesion appears to be enhanced, showing unclear. In portal vein phase, the edge of the left and right lobes of the liver is slightly enhanced, but there is no enhancement in the interior, and the edge is clearly displayed. In delayed phase, the lesions in the left and right lobes of the liver show mild circular enhancement and nodular enhancement, and the lesions in the right lobe of the liver show less clearly than before.

B. T1 WEIGHTED IMAGE ANALYSIS

Figure 6 shows that after statistical analysis of the collected data, the average prediction accuracy and variance of different algorithms can be obtained. It can be seen from the figure that the best prediction accuracy algorithm is GLCM,

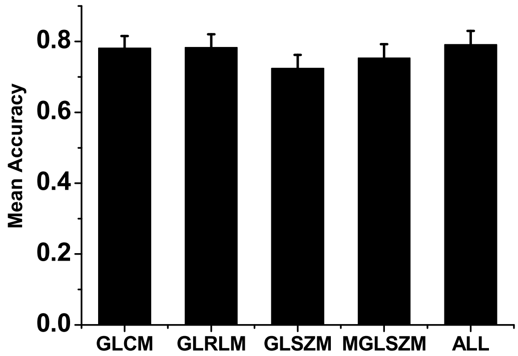

FIGURE 8. Subtype differentiation of colorectal cancer based on T2-weighted imaging.

whose accuracy is about 0.78, while the accuracy of GLSZM is the smallest and less than 0.7. The other matrix algorithms GLRLM, MGLSZM and texture feature combination ALL are in the middle of the prediction accuracy, and are significantly higher than the accuracy of GLSZM algorithm. Therefore, in T1 weighted image analysis, the matrix GLCM algorithm can be selected to obtain the best accuracy.

C. INCREASED T1-WEIGHTED IMAGE ANALYSIS

Figure 7 shows the average prediction accuracy and variance of different algorithms after statistical analysis of the collected data. As can be seen from the figure, the best precision algorithm is MGLSZM, and its accuracy is slightly lower than 0.8, while the accuracy of GLCM is the smallest and less than 0.7. The other matrix algorithms GLRLM, GLSZM and texture feature combination ALL are in the middle of the prediction accuracy. Therefore, in increased T1 weighted image analysis, the matrix MGLSZM algorithm can be selected to obtain the best accuracy.

D. T2-WEIGHTED IMAGE ANALYSIS

From Figure 8, it can be seen that after statistical analysis of the collected data, the average prediction accuracy and variance of different algorithms for T2 weighted images can be obtained. It can be seen from the figure that the best precision algorithm is ALL, which is composed of all texture features. Its accuracy is about 0.79, while the accuracy of GLSZM is the smallest. The other matrix algorithms GLRLM, MGLSZM and GLCM are in the middle of the accuracy prediction, and are significantly higher than the accuracy of GLSZM. Therefore, in T2 weighted image analysis, ALL, a combination of all texture features, can be selected to obtain the best accuracy.

E. A COMPARATIVE ANALYSIS OF THE RESULTS OF SUBTYPE DIFFERENTIATION OF COLON CANCER

From Figure 9, it can be seen that by comparing T1 weighted images, increased T1 weighted images and T2 weighted images, the best prediction accuracy and the worst prediction accuracy and feature algorithm are found, as shown in Table 3. Among the three weighted image algorithms,

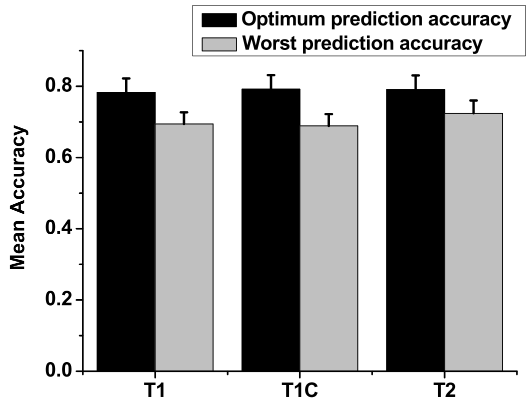

FIGURE 9. Cylindrical chart for comparison of ACC result in differentiation of tumor subtypes.

TABLE 3. Comparison of ACC results in differentiation of tumor subtypes.

Imaging sequenc e	Optimum prediction accuracy	Correspondin g feature algorithm	Worst prediction accuracy	Correspondin g feature algorithm
T1	0.783±0.03 5	GLCM	0.694±0.03 3	GLSZM
T1C	0.792±0.03 9	MGLSZM	0.689±0.03 3	GLCM
T2	0.791±0.03 8	ALL	0.724±0.03 6	GLSZM

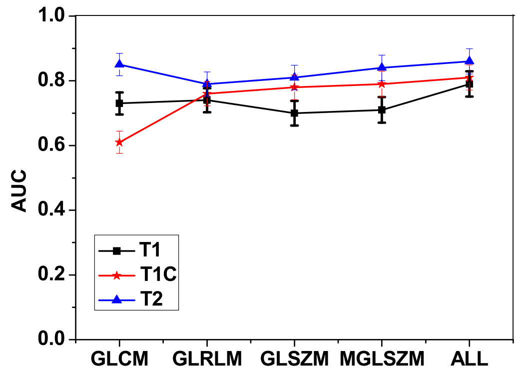

FIGURE 10. Cylindrical maps for comparing AUC results in subtype differentiation of tumors.

the best and worst result feature algorithms are different. Through the analysis, it can be found that no matter which weighting method is adopted, the accuracy of any texture feature algorithm is less than 0.8, that is, the help of texture analysis in subtype discrimination of colon cancer is very limited.

From Figure 10, the AUC comparative analysis of the area under the curve of three different texture feature algorithms of T1-weighted image, increased T1-weighted image and T2-weighted image can be seen. From the overall effect of three imaging sequences, it is found that the prediction accuracy of any feature description has a deviation of about 15%, which indicates that there is room for improvement of the intelligent aided diagnosis system based on deep learning algorithms. At the same time, among the three algorithms, T2-weighted image has some advantages compared with other imaging sequences.

VI. CONCLUSION

In this study, in order to explore the application of in-depth learning based intelligent imaging technology in the diagnosis of colorectal cancer, patients with colorectal cancer in Tangdu Hospital are selected as the research object. The cancer site is scanned, then the tumor differentiation and feature extraction are performed, and the collected data are input into the designed Intelligent aided diagnosis system based on deep learning algorithms for comparison. The results show that in the analysis of image prediction accuracy, the best prediction accuracy of T1-weighted image method is matrix GLCM algorithm, the best prediction accuracy of increased T1-weighted image method is matrix MGLSZM algorithm, the best prediction accuracy of T2-weighted image method is ALL combination of all texture features, and the best prediction accuracy of three imaging sequences is all less than 0.8. In the AUC analysis of the area under the curve of different texture features, it is found that T2-weighted imaging method has obvious advantages in differentiating colorectal cancer from other methods.

In conclusion, through this study, it is found that the use of deep learning intelligent aided diagnosis system in the diagnosis of colorectal cancer can provide useful information for the clinical diagnosis of colorectal cancer to a certain extent, and provide new ideas for the diagnosis and treatment of colorectal cancer in the later clinical stage. There are also some shortcomings in the research process, such as too small sample size, which will be further increased in the follow-up study process, so that the accuracy of classification can be further improved.

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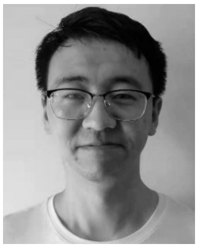

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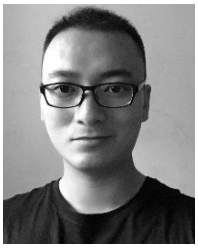

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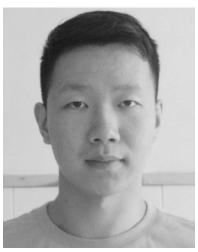

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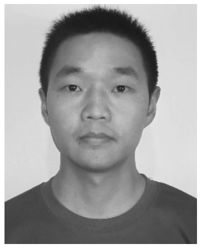

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