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The use of artificial intelligence in MRI diagnostics of rectal cancer

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ABSTRACT AIM: to work out decision-making support systems for MRI diagnostics of rectal cancer: site and segmentation of the primary tumor.

PATIENTS AND METHODS: the study included 450 MRI studies of patients with rectal cancer and 450 MRI studies of patients without. All patients with tumors of rectum had histological verification. Data were collected in T2Wcoronal and axial projections (MRI Philips Achieva 1.5 T). Object marking was carried out only for T2W projections, where the area of interest was segmented — rectum, sigmoid colon and tumor. The ITK-Snap program was used to label MRI images. The validated studies and labeling were used to create a machine learning model that demonstrates the capability of the dataset to build medical decision support systems. SegResNet, Trans Unet, 3D Unet neural networks were used to create a basic artificial intelligence model.

RESULTS: dice similarity coefficient (DSC) of various neural networks were: TransUnet — 0.33, SegResNet — 0.50, 3D Unet — 0.42. The diagnostic efficiency of the SegResNet neural network in detecting rectal tumors with the addition of negative examples and post-processing was accuracy 77.0%; sensitivity 98.1%; specificity 45.1%; positive predictive value 72.9%; negative predictive value of 94.1%. At this stage, AI has a high sensitivity and accuracy, which indicates a high diagnostic efficiency in terms of visualizing the primary tumor and determining localization in the rectum. However, the specificity of the method is still at an unsatisfactory level (45.1%), which indicates a high percentage of false positive results in healthy patients and does not allow the model to be used as a screening method at this stage of development.

CONCLUSION: the collected dataset of MRI and their markup made it possible to obtain an AI model that allows solving the problem of segmenting a rectal tumor and determining its site. The next stage in the development of AI is to improve its specificity, expand the analyzed parameters, such as the depth of tumor invasion, visualization of metastatic lymph nodes and the status of the resection margin. To further develop the model metric and improve its diagnostic capabilities, we should experiment with training parameters and increase the dataset.

KEYWORDS: MRI, magnetic resonance imaging, artificial intelligence, neural network, rectal cancer.

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INTRODUCTION

Colorectal cancer (CRC) occupies a leading position in terms of morbidity and mortality among oncological diseases both in the Russia and around the world. In our country, colorectal cancer ranks second in both prevalence and mortality among all malignant diseases. Approximately half of all cases of malignant neoplasms of the colon are due to rectal cancer (RC) [1–3].

An integrated approach to the treatment of patients with RC using surgery, radiotherapy and chemotherapy has significantly increased disease-free survival and improved their quality of life. Accurate preoperative check-up plays an important role in the selection and determination of treatment options for patients with malignant rectal neoplasms [4]. Diagnostic errors lead to a discrepancy between preoperative and postoperative treatment plans, which can negatively affect the prognosis in patients who have already undergone surgery [5]. At the moment, the leading method of diagnosis and preoperative staging of RC is magnetic resonance imaging (MRI) of the pelvis, which allows to determine the site, extent, depth of invasion, and to assess regional lymph nodes [6,7].

Thanks to the continuous improvement of imaging technologies and the experience of radiologists, the accuracy of preoperative diagnostics has significantly increased. However, the high prevalence of RC, the lack of the necessary experience of radiologists in general hospitals for the diagnosis of CRC, large volumes of MRI data that require detailed analysis, in some cases lead to an erroneous diagnosis. Thus, one of the main tasks is to reduce the number of errors in preoperative diagnosis [8]. The use of artificial intelligence for processing and preliminary analysis of medical imaging data, including MRI, is becoming one of the recent trends [9–11]. Artificial intelligence (AI) provides stable diagnostic efficiency, high computational speed and accuracy in data processing. Due to the use of deep learning methods, AI can provide high diagnostic accuracy comparable to that of radiologists specializing in the diagnosis of CRC.

Recently, AI technology for image analysis has already found application in clinical practice [12,13].

The use of artificial intelligence for image interpretation can help in the work of radiologists who do not have sufficient experience in the diagnosis of RC, increase the speed of image analysis, reduce the number of errors caused by the human factor, and improve the diagnosis accuracy [8]. Due to the complexity of the task, at the first stage of the development of an AI model for the analysis of pelvic MRI, it is necessary to focus on determining the site and segmentation of the primary tumor, which in the future will significantly reduce the time of analysis and interpretation of MR images for radiologists who do not have much clinical experience in the diagnosis of RC. In the future, the most important parameters for the evaluation of MRI studies using AI will be the determination of the depth of tumor invasion, visualization of lymph nodes metastases, and assessment of the resection lateral margins.

AIM

The aim of the study was to work out decision-making support systems for MRI diagnostics of rectal cancer (site and segmentation of the primary tumor).

PATIENTS AND METHODS

To enable the AI model to learn to visualize RC on MRI images, 450 patients with rectal tumors aged 26 to 82 years, with histological verification of “adenocarcinoma”, were included in the prospective cohort study. Patients without histological verification of a malignant tumor were not included. All the patients with rectal tumors included in the study underwent preoperative pelvic MRI using high-resolution of T2-WI (FOV = 180x180 mm; Voxel = 0.7 × 0.7 mm; Matrix = 256x256 mm). Further, all the patients underwent curative surgery, followed by a pathomorphological examination of removed specimens. The characteristics of the sample

Table 1. *Characteristics of patients with rectal cancer*

	Gender		T stage				Chemo radiotherapy	
	Male	Female	T1	T2	T3	T4	Yes	No
Patients with rectal tumor	214 (47.6%)	236 (52.4%)	33 (7.3%)	96 (21.4%)	279 (62.1%)	42 (9.2%)	209 (46.4%)	241 (53.6%)

of patients with tumors are presented below (Table 1). All MRIs were performed using the Philips Achieva high-field magnetic resonance

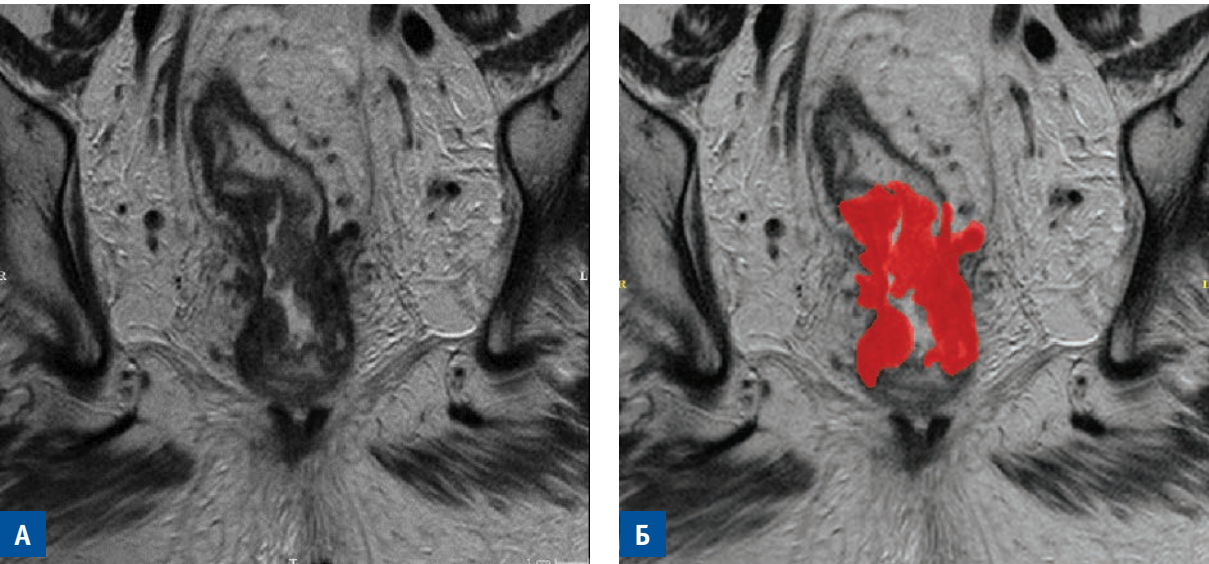


Figure 1. *MRI of the pelvis, T2-WI coronal view. A — tumor of the rectum without marking. Б — tumor of the rectum with markings*

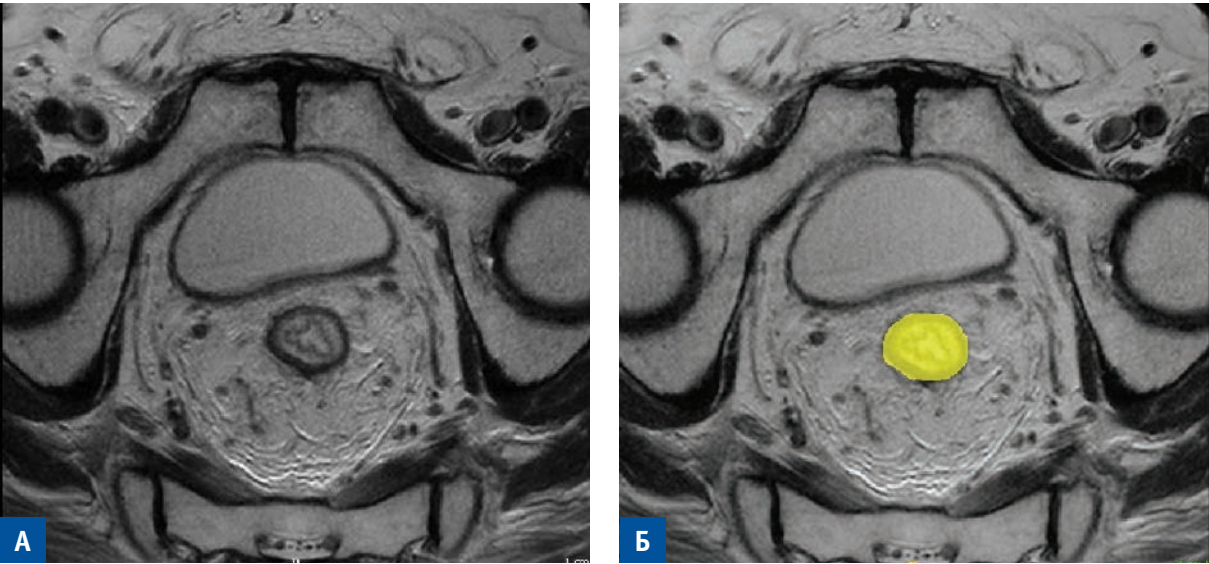


Figure 2. *MRI of the pelvis, T2-WI axial view. A — rectum without markings. Б — rectum with radiologist markings*

system (the Netherlands) with a magnetic field strength of 1.5 T. The marking was performed by radiologists. Each study was marked by one specialist; however, with an ambiguous MR image and difficulties in marking, a second specialist was involved. The final segmentation of the tumor in such cases was carried out on the basis of consensus. To label the MRI images, the ITK-Snap program was used, with the help of which the corresponding segmentation mask of the primary tumor was placed in all 450 patients [14]. Machine learning was carried out using the marking of the primary tumor on high-resolution T2-WI in axial and coronal projections (Fig.1).

Also, the volume of data for artificial intelligence learning for rectal segmentation included 450 patients without rectal tumor lesions, who underwent pelvic MRI using high-resolution protocols without additional marking. Anatomical rectal areas were marked for 120 patients in the group with tumors and for 48 patients without rectal neoplasms (Fig.2).

In total, the volume of data contained 1,761 volumes of T2-WI. The balance of marking classes by volume and slices is shown in Figure 3.

The volume data set was randomly divided into learning, validation and test samples in the ratio of 60%, 20%, 20% (Fig.4).

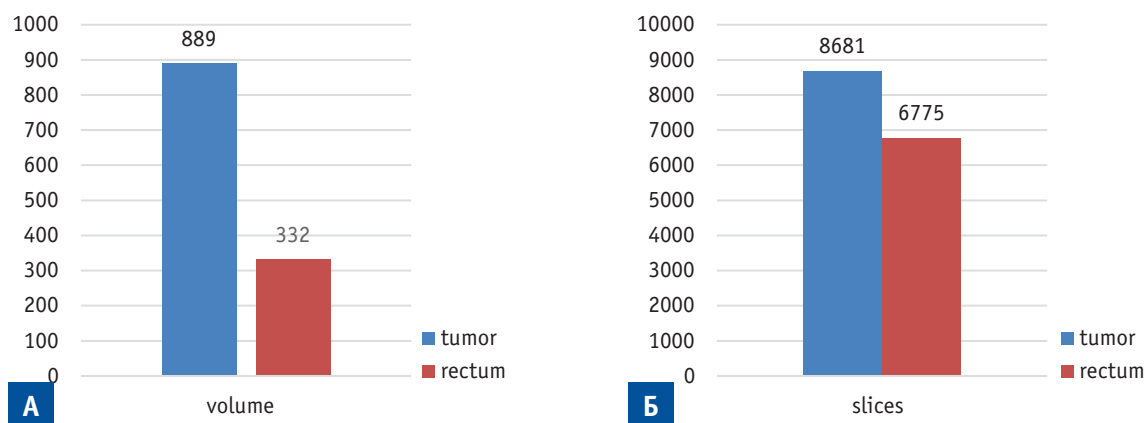


Figure 3. Balance of markup classes by volumes (A) and slices (B)

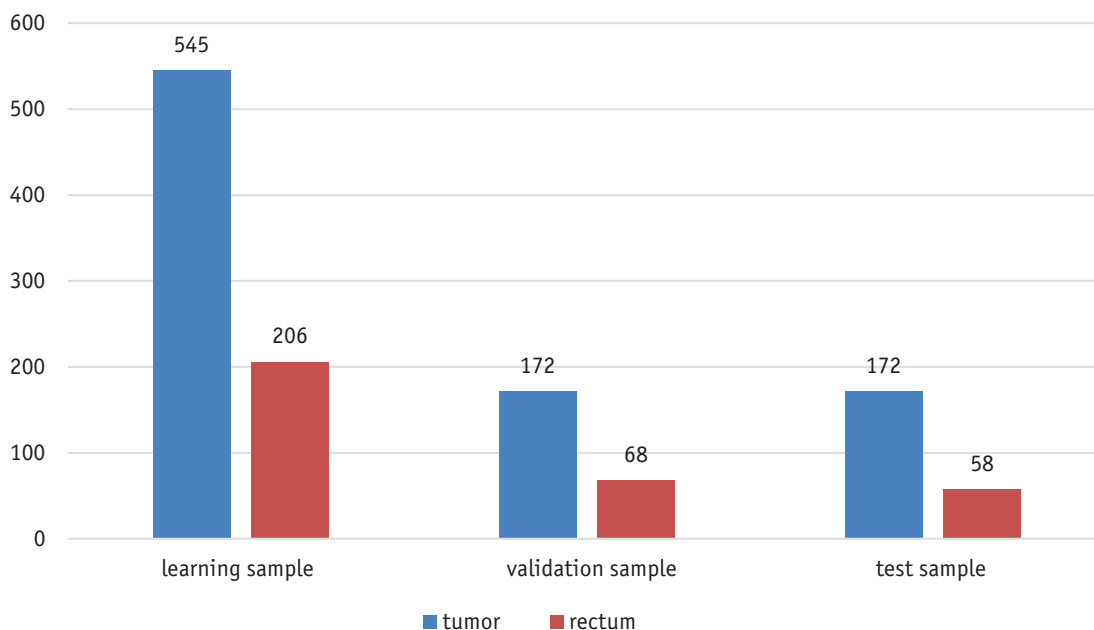


Figure 4. Volume of training, validation and test sets

The collected data set was balanced in terms of the number of patients with and without tumors.

A modified SegResNet neural network with data preprocessing and postprocessing algorithms was used as a basic model to demonstrate the suitability of a data set for solving the tasks set (Fig.5) [15].

The SegResNet neural network is a three-dimensional U-net-like architecture in which the input set of slices is processed as a set of three-dimensional patches on the principle of a sliding window. Such architectures have proven themselves well in the processing of medical images, since they make it possible to effectively use the three-dimensional context when segmenting objects [16]. When learning this model, the patch size is $256 \times 256 \times 16$ with an overlap of 0.5. Since the dimension of the processed volumes in the original implementation of the neural network was smaller, an additional convolutional layer in the encoder branch and an additional verification layer in the decoder branch were added to the neural network for more complete extraction of features. The additional branch — autoencoder, introduced in the SegResNet architecture for regularization, was not used. The

general scheme of the basic model is shown in Figure 6.

Preprocessing consists of normalizing the intensities of the input volume, as well as dividing the input array into three-dimensional overlapping patches of dimension $256 \times 256 \times 16$. In this case, the operation of subtracting the arithmetic mean of non-zero values in the array and dividing by the standard deviation of non-zero elements in the array was assumed (Fig.7). During the collection of the data set, several experiments were conducted to compare the quality of work of various neural networks to solve the task. In addition to the chosen SegResNet architecture, 3d Unet and TransUnet neural networks were learning [17], which also proved themselves well in medical image processing. The TransUnet neural network is two-dimensional, unlike 3d Unet and SegResNet, and was chosen to assess the importance of using a three-dimensional image in the analysis of pelvic MRI. In the experiments conducted, all neural networks were learning on the same subsets of the data set; and the following augmentations were used: random framing, random horizontal reflection, random vertical reflection, random intensity shift, random scaling.

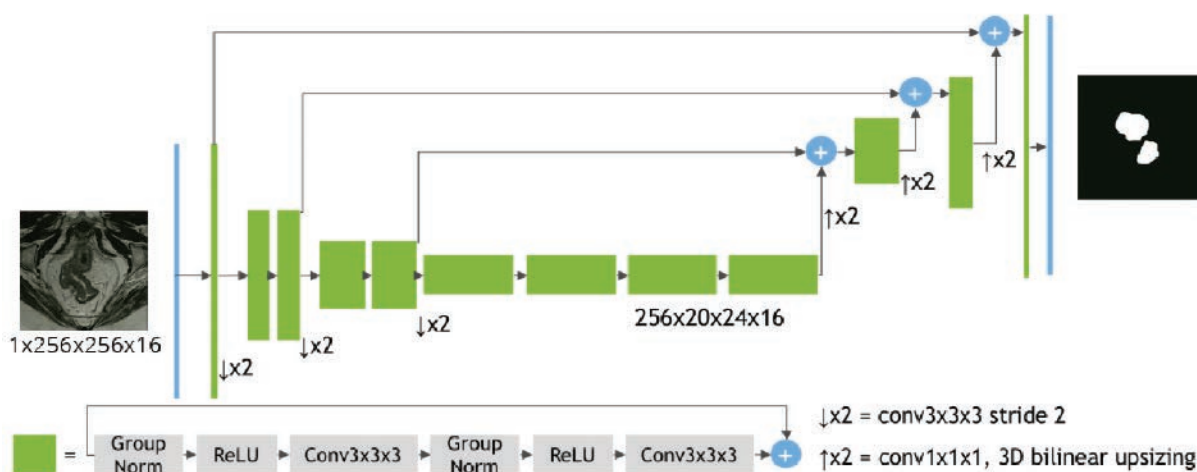


Figure 5. Architecture of SegResNet neural network



Figure 6. General scheme of the basic model

Table 2. Outcomes of learning on the sample without negative cases

Architecture	Number of parameters, 10 ⁶	Dice similarity coefficient (DSC)	
		Tumor	Rectum
TransUnet	105	0.33	–
SegResNet	18	0.53	0.71
3D Unet	44	0.66	–

Table 3. Outcomes of learning on an expanded sample with the addition of negative examples

Architecture	Number of parameters, 10 ⁶	Dice similarity coefficient (DSC)	
		Tumor	Rectum
TransUnet	105	0.33	–
SegResNet	18	0.50	0.71
3D Unet	44	0.42	–

RESULTS

The first experiment was conducted before adding cases without rectal tumors to the dataset and contained 66 volumes with tumors in the learning sample and 30 volumes in the test sample. The proximity coefficients obtained as a result of learning (dice similarity coefficient (DSC)) are presented in Table 2.

The table shows that 3d Unet and SegResNet neural networks with a three-dimensional

architecture have a higher proximity coefficient (DSC).

After expanding the data set and adding cancer-free cases, an analysis was carried out with the inclusion of 520 volumes in the learning sample and 178 volumes in the test sample, after which the proximity coefficients (DSC) were calculated (Table 3).

Analyzing the data from Tables 2 and 3, it can be seen that with the addition of patients without rectal tumors to the sample, the proximity

$$\hat{X}_i(x, y, d) = \frac{x_i(x, y, d) - \mu}{\sqrt{\sigma^2}},$$

$\hat{X}_i(x, y, d)$ - normalized value

$x_i(x, y, d)$ - value of an array element with coordinates x, y, d

$\mu = \frac{1}{k} \sum_{i=1}^k x_i(x, y, d); x_i \neq 0$ - mathematical expectation of non-zero elements in the array

$\sigma^2 = \frac{1}{k} \sum_{i=1}^k (x_i(x, y, d) - \mu_B(x, y, d))^2; x_i \neq 0$ - standart deviation of non-zero elements in the array

Figure 7. The formula for calculating the normalization of the intensities of the input volume

coefficient (DSC) decreases. However, the addition of negative examples to the learning data set allowed the neural network to learn to divide a sample of patients into a group with rectal tumors and a group without pathological changes. Figure 8 shows the error matrix of the SegResNet neural network that learned on a sample without negative examples. Figure 9 shows the error matrix for the SegResNet neural network that learned on a sample with the addition of negative examples and the addition of post-processing predictions.

It can be assumed that the proximity coefficient (DSC) in a mixed sample of patients decreases, due to false positive results in patients without RC.

The diagnostic effectiveness of the SegResNet neural network in detecting rectal tumors with the addition of negative examples and post-processing was: accuracy — 77.0%; sensitivity — 98.1%; specificity — 45.1%; positive prognostic value — 72.9%; negative prognostic value — 94.1%.

Thus, it is shown that the addition of patients without tumors to the learning sample is necessary, despite the fact that in cases with RC there are a large number of slices of a healthy rectum. The obtained classification accuracy demonstrates that it is possible for a neural network to learn from the added data to divide the total sample into two groups of patients.

Visual analysis of the tumor marking showed that the DSC coefficient for the tumor also decreases due to imperfect preliminary contouring. However, the visual marking of the tumor by the neural network has good convergence with the preliminary annotation carried out by radiologists with extensive clinical experience (Fig.10).

DISCUSSION

Timely and accurate diagnosis of rectal tumors allows to use organ-preserving treatment, reduce the extent of curative operation, improve

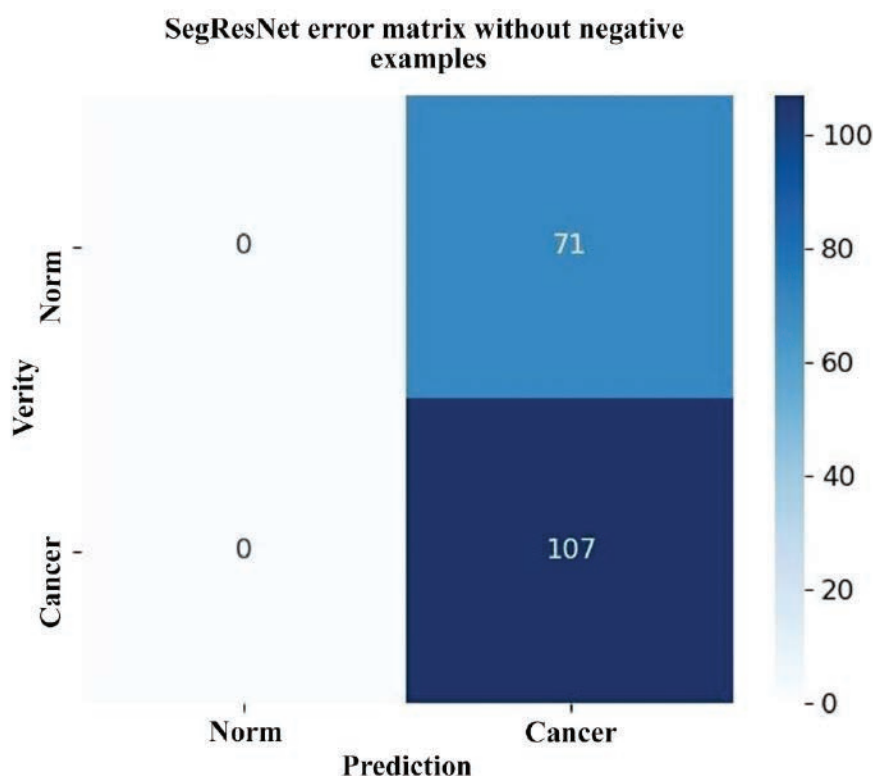


Рисунок 8. Матрица ошибок SegResNet обученной без отрицательных примеров
Figure 8. Error matrix of SegResNet trained without negative examples

the prognosis of the patient's life and improve its quality. Magnetic resonance imaging is a highly informative method of diagnosing and staging rectal cancer [6,7,18]. The information obtained during MRI makes it possible to determine the treatment options for patients with RC [19]. Radiologists, when analyzing MRI, need to evaluate a large amount of information, visualize the primary tumor and assess its extent. Insufficient experience of radiologists in general hospitals in interpreting MR for rectal cancer can lead to errors in diagnosis, significant time spent on analyzing the obtained MR images and subjectivity in assessing the extent of the tumor process.

Recently, with the rapid development of advanced technologies, artificial intelligence is being used in many fields. Artificial intelligence based on neural networks is increasingly used in medicine to collect and analyze large amounts of information that contribute to more effective work [20]. The use of automation of image processing using AI in the analysis of

pelvic MRI in patients with rectal cancer is designed to reduce the time of description and in the future — to increase the diagnostic accuracy of the method and level the subjectivity of the radiologist. The use of AI in the diagnosis of RC is just beginning to be studied, single trials have been done with a small sample of patients [21,22].

Here, we used artificial intelligence technology based on neural networks to automatically search for and segment rectal tumors.

At the beginning, proximity coefficients (DSC) were determined for various types of neural networks in studies with a primary tumor: TransUnet — 0.33, SegResNet — 0.53, 3D Unet — 0.66. 3D Unet and SegResNet neural networks with a three-dimensional architecture have a higher proximity coefficient. MRI allows to visualize a tumor in three-dimensional space in any selected projection, which explains the feasibility of using 3D neural networks.

After increasing the sample and adding patients without rectal tumors, the proximity coefficients

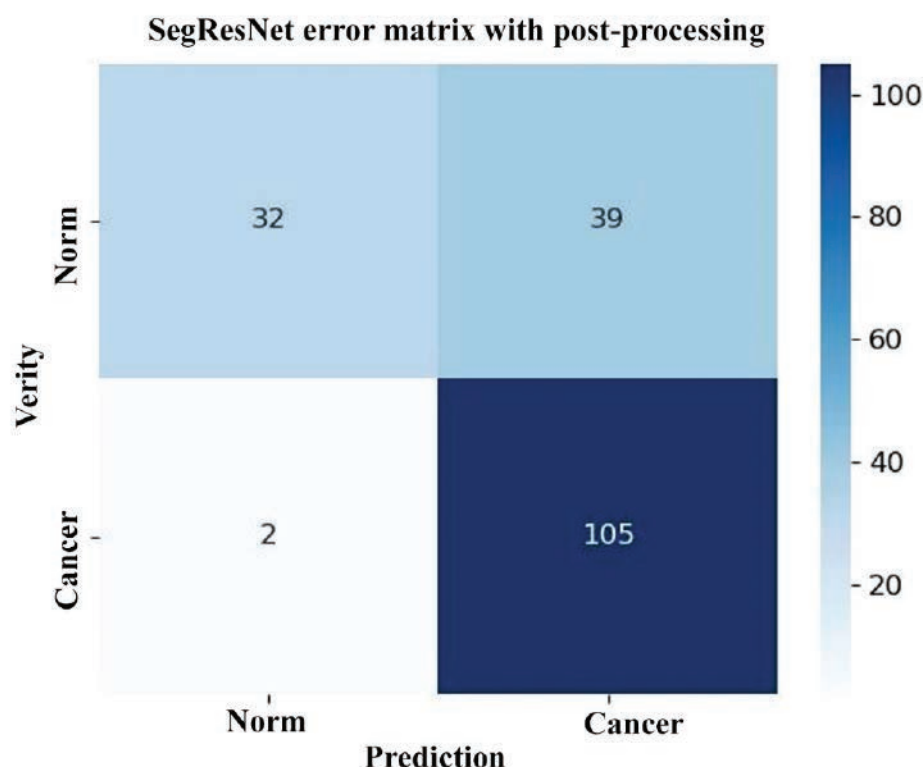


Рисунок 9. Матрица ошибок SegResNet с добавлением отрицательных примеров и постобработкой

Figure 9. Error Matrix of SegResNet with Added Negative Examples and Post-Processing

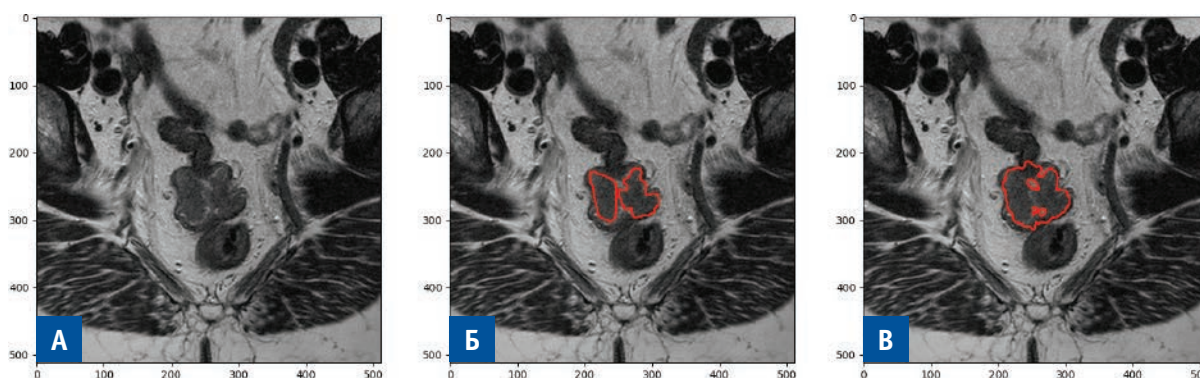


Figure 10. MRI of the pelvis, T2-WI coronal view. A — tumor of the rectum without marking. B — a tumor of the rectum with the markings of a radiologist. B — tumor of the rectum with the markings of SegResNet neural network

(DSC) were re-determined: TransUnet — 0.33, SegResNet — 0.50, 3D Unet — 0.42. The proximity coefficient (DSC) in the mixed sample of patients is lower than in the group with tumors only, due to false positive results in patients without cancer. However, the addition of healthy patients to the comparison group is necessary to enable the neural network to learn to differentiate the tumor and the unaffected rectal wall.

The diagnostic effectiveness of the SegResNet neural network in detecting rectal tumors with the addition of negative examples and post-processing was as follows: accuracy — 77.0%; sensitivity—98.1%; specificity— 45.1%; positive prognostic value —72.9%; negative prognostic value— 94.1%. At this stage, AI has a fairly high sensitivity, which indicates a high diagnostic efficiency for visualization of the primary tumor. However, the specificity of the method in 45.1% is still at an unsatisfactory level, which indicates a high percentage of false positive results in healthy patients.

The developed basic AI model has satisfactory indicators of diagnostic effectiveness for such a complex clinical task and in the future can be used as an aid to a radiologist to increase the speed of searching for a primary rectal tumor and to reduce errors in determining its site. However, the model cannot be used as a screening method at this stage, due to the large number of false positive cases among healthy patients. The results obtained are the starting point of our research and with the development of neural networks for the task being solved, a significant increase in the diagnostic

effectiveness of the method is possible. The next stage of AI development will be to improve its specificity, expand the analyzed parameters, such as the depth of tumor invasion, visualization of metastatic lymph nodes and determination of the status of the resection edge.

CONCLUSION

The collected dataset of MRI studies and their marking allowed to obtain an AI model that allows to solve the problem of segmenting a rectal tumor and determining its site. The SegResNet neural network has an acceptable proximity coefficient (DSC = 0.55), and visual analysis confirmed the high convergence of tumor segmentation by a radiologist and an AI model. Diagnostic effectiveness of the SegResNet neural network in detecting rectal tumors was as follows: accuracy— 77.0%; sensitivity —98.1%; specificity— 45.1%; positive prognostic value —72.9%; negative predictive value— 94.1%.

To further develop the model metric and improve its diagnostic capabilities, it is necessary to experiment with learning parameters and increase the data set.

AUTHORS CONTRIBUTION

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