Deep Learning-Based CT Imaging in Perioperative Period and Nursing of Esophageal Carcinoma Patients

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1. Introduction

Esophageal carcinoma is one of the common malignant tumors originating in the digestive tract. It mainly develops in the glands or mucosal epithelium of the esophagus and is one of the top ten malignant tumors with high incidence. The esophageal carcinoma is highly prevalent in China, and both of its morbidity and mortality rates rank first worldwide. An estimated 200,000 population are diagnosed with esophageal carcinoma each year, and approximately 15.32–20.78/100,000 people die of esophageal carcinoma each year [1]. The current treatment of esophageal cancer is surgical resection, but long-term effects of surgical resection are not good, with only about 30% survival rate within 5 years [2]. An abundance of research results reveals that lymph node metastasis is one of the most important factors affecting the prognosis of esophageal carcinoma patients, and the number of lymph node metastases is a key factor for the prognosis of esophageal carcinoma patients [3]. Therefore, to accurately identify the lymph node metastasis number and the metastatic area is of great significance to the surgical treatment and prognosis of esophageal carcinoma.

In recent years, a number of diagnostic methods such as CT, Magnetic Resonance Imaging (MRI), endoesophageal
ultrasound, and esophageal endoscopy have been used in
diagnosis of esophageal carcinoma as a result of the rapid
progression of medical imaging technology. Among them,
CT is characteristic of non-invasiveness and high accuracy,
and it is superior to other methods in the diagnosis of
esophageal carcinoma, the identification of foci, and the
judgment of lymph node metastasis [4]. Clinical data have
found that conventional CT scanning images rely on pro-
fessional knowledge of physicians to extract and label lymph
nodes, which is subjective to a certain extent, and the
detection rate is quite different from that of the pathological
diagnosis of lymph nodes at different locations [5]. Thanks
to the development of deep learning, many researchers have
applied various deep learning algorithms in the diagnosis of
CT images. At present, the organ segmentation algorithms
mainly include region growing method, clustering method,
Mean Shift segmentation method, and CNN segmentation
method [6]. Among them, CNN demonstrates superb ca-
pabilities in retaining spatial information of the image,
which lays a solid foundation for the segmentation of organs
in the focal area. Although CNN has found broad appli-
cations in the segmentation of medical images, most re-
search focuses on the MRI-based human brain image
segmentation. There is little research on CT image seg-
mentation, let alone esophageal CT image segmentation.

In summary, the esophageal carcinoma lymph node
metastasis number and the metastasis area have important
implications for surgical methods and prognosis. CT, as one
of the important methods for the diagnosis of esophageal
carcinoma, still has certain limitations in the diagnosis of
lymph node metastasis. In the study, CNN was used to
optimize the lymph node recognition model, which was
applied to the diagnosis and prognosis analysis of esophageal
cancer. Patients with esophageal cancer were selected as the
research subjects, and they were grouped based on different
nursing methods. The primary objective of the study was to
investigate the role of CNN-based CT imaging technology in
diagnosis of esophageal cancer, and the secondary aim was
to explore the effects of different nursing methods.

2. Materials and Methods

2.1. Research Subjects and Grouping. 158 patients with
esophageal carcinoma who underwent radical resection in
hospital from September 2017 to April 2020 were selected as
the research subjects. Among them, there were 102 males
and 56 females, aged between 23 and 79 years old, and the
average age was \(60.84 \pm 8.33\). They were randomly divided
into the control group and intervention group according to
different nursing methods, with 79 in each. The inclusion
criteria of this study were as follows: (i) patients with
esophageal cancer undergoing radical resection; (ii) patients
with no history of malignant tumors; (iii) patients having
chest and abdomen CT examinations before and after
surgery; and (iv) patients not receiving radiotherapy and
chemotherapy before or after surgery. The exclusion criteria
were as follows: (i) those with severe disease involving
important organs; (ii) those who have received radiotherapy
or chemotherapy before surgery; (iii) those who refused
surgical treatment; and (iv) those who had incomplete pa-
tient examination and surgical data. The experimental
procedure has been approved by the ethics committee of
hospital, and all subjects included in the study had signed an
informed consent form.

2.2. The Image Segmentation Algorithm Based on CNN.
CNN is an end-to-end fully convolutional image segmen-
tation neural network based on deep learning [7]. For \(n\)
sample points in the \(d\)-dimensional space \(x_i, i = 1, 2, \ldots, n\),
the calculation method for the dimensional numerical vector
\(M_k\) at any point \(x\) is as follows:

\[
M_k = \frac{1}{k} \sum_{x \in S_k} (x_i - x),
\]

where \(S_k\) represents a \(d\)-dimensional spherical area with
a radius of \(r\), \(k\) is the number of sample points that fall into the
spherical area, and \((x_i - x)\) represents the relative offset
between the sample points \(x_i\) and the reference point \(x\). The
set of all sample points in this spherical area is then
expressed as follows:

\[
S_k(x) = \{ y: (y - x)^T(y - x) < r^2 \}.
\]

For a two-dimensional matrix \(A\), the matrix coordinate
point \((x, y)\) is subjected to convolution operation, as shown
in equation (3), where \(K\) is the convolution kernel; \(S\) is
the convolution result; \(m\) is the number of neurons in the input
layer; and \(n\) is the number of neurons in the output layer.

\[
S(x, y) = (K * A)(x, y) = \sum_m \sum_n A(x - m, j - n)K(m, n).
\]

After compressing the CT image and extracting its
features, the effective features of the compressed image can be
expressed as follows:

\[
W_2 = \frac{(W_1 - W_F + 2P)}{B + 1}, \quad H_2 = \frac{(H_1 - H_F + 2P)}{B + 1},
\]

where \(W_2\) is the width of the output feature map; \(H_2\) is the
height of the output feature map; \(W_1\) and \(H_1\) are the width
and height of the input feature map and \(W_F\) and \(H_F\) are the
width and height of the convolution kernel, respectively; \(P\) is
the number of pixel values filled on the input feature image;
and \(B\) is the step size of the convolution kernel.

Assuming that the input item of a certain segment of
neural network is \(x\), the expected complex latent mapping is
represented by \(H(x)\), and the shortcut connection is used to
directly pass the input \(x\) to the output, which can be
expressed as follows:

\[
H(x) = f(x) + x.
\]
to express nonlinear relationships [8]. In the study, ReLU is used as the basic activation function. The expression of ReLU nonlinear activation function is as follows:

$$f(x) = \max(0, x)$$

(6)

Compared with the traditional Sigmoid and tanh activation functions, ReLU can accelerate the training of the model [9]. After optimization, it is expressed as follows:

$$f(x_i) = \begin{cases} x_i, & x_i > 0, \\ a_i x_i, & x_i \leq 0, \end{cases}$$

(7)

where $a_i$ is a learnable parameter and $i$ is the channel number. $a_i$ can learn using the backpropagation algorithm, and the propagation learning method can be expressed as follows:

$$\frac{\partial \eta}{\partial a_i} = \sum_i \frac{\partial \eta}{\partial f(x_i)} \frac{\partial f(x_i)}{\partial a_i},$$

(8)

where $\eta$ is the learning rate, and $\frac{\partial f(x_i)}{\partial a_i}$ needs to meet the conditions $\frac{\partial f(x_i)}{\partial a_i} = \begin{cases} 0, & x_i > 0, \\ x_i, & x_i \leq 0. \end{cases}$

In the training phase, the Softmax loss function is used to update the weight of the loss of the sample. Softmax can update and optimize the weight parameters without interruption, and the normalization operation in the Softmax classifier makes the value more stable [10]. The optimized CNN algorithm is named U-Net algorithm. The Softmax loss function can be expressed as follows:

$$p(y = k|x_i; \theta) = \frac{e^{\theta_k^T x_i}}{\sum_{j=1}^k e^{\theta_j^T x_i}},$$

(9)

where $k = 4$, $(x_i, y_i)$ is the data training set, $y_i \in \{1, 2, \ldots, k\}$, and $p$ represents the probability of each category.

In the study, the commonly used image segmentation evaluation index mPA and IOU are used to quantitatively analyze the organ segmentation effects [11]. They are calculated as follows:

$$mPA = 1 - \frac{A \text{ xor} B}{m \times n},$$

(10)

$$\text{IOU} = \frac{Y_i \cap X_i}{Y_i \cup X_i},$$

where $A$ and $B$ are the label image and segmentation results, respectively; xor represents the exclusive OR operation between image $A$ and image $B$; $m$ and $n$ represent the length and width of the image, respectively; and $Y_i$ and $X_i$ represent the area occupied by an organ and the corresponding area occupied by the segmented organ.

2.3. Lymph Node Recognition Process of Esophageal Carcinoma Based on CNN Algorithm. In this study, an esophageal cancer lymph node recognition model was established based on the CNN image segmentation algorithm. The specific process is shown in Figure 1. The initial CT image was preprocessed by removing the examination bed and subcutaneous tissue, and then the U-Net CT was used to extract the esophagus region, followed by further extraction of the region of interest. Finally, the topological relationship between the suspected lymph node and the surrounding tissue was identified, and the suspected lymph node was extracted.

2.4. CT Scan Conditions and Diagnostic Criteria. Before the CT scanning, the patient was instructed to lie supine. The scan range mainly included the lower neck, supraclavicular, chest, and upper abdomen. During the scan, the patient needed to inhale deeply and hold the breath. CT scan parameters were as follows: 120 kv, 90 mA, collimation of 2.5–5.0 cm, screw pitch of 25 mm, bed speed of 50 mm/s, layer thickness of 3.0–6.0 mm, and layer spacing of 3.0–6.0 mm. Non-ionic iohexol injection was used as a contrast agent for enhanced scanning. The injection dose was calculated at 1.5 mL/2 mL/kg, the injection rate was 2.0–3.0 mL/s, and the scan started 30 seconds after injection. The CT images of all patients were transferred to the three-dimensional treatment planning system to obtain the required indexes.

The diagnostic criteria for esophageal lesions are as follows: the thickness of the esophageal wall more than 5 mm and the diameter of the airless esophagus greater than 10 mm; the diagnostic criteria for lymph node metastasis referred to the diagnostic criteria in the study of Kashima et al. [12].

2.5. Perioperative Nursing Methods and Observation Indexes for Esophageal Carcinoma. The patients in the control group were treated with routine care after esophageal carcinoma surgery. The intervention group patients accepted rapid rehabilitation referring to research of Borrett [13] on the basis of routine nursing, during which a series of measures such as intraoperative heat preservation and postoperative analgesia were adopted.

A number of indexes were observed for the postoperative time to get out of bed, hospital stay, and indwelling chest tube duration to evaluate the pain degree at different time periods after the operation. The pain evaluation referred to the method of Wang et al. [14] and used the Visual Analogue Scale (VAS) to evaluate.

2.6. Statistics. Experimental data were processed using SPSS19.0. Measurement data were calculated as mean± standard deviation (±s), and count data were expressed in percentage (%). The $\chi^2$ test was applied. $P < 0.05$ was set as the threshold for significance.

3. Results

3.1. Analysis of Organ Segmentation Ability. The improved and optimized U-Net network was compared with Mean Shift and Fuzzy C-means (FCM) organ segmentation algorithms for the loss function (loss) curve. As shown in
Figure 2, the loss function of U-Net was superior to that of the Mean Shift and FCM methods in terms of convergence speed, and the loss of the FCM method was stable around 0.1. When the epoch was 50, the loss of the Mean Shift method was stable around 0.05, while the loss of the optimized U-Net was stable around 0 under the same conditions.

The IOU curves were compared and analyzed between different algorithms. As shown in Figure 3, the IOU value of the U-Net algorithm was notably higher versus the Mean Shift and FCM methods.

The comparison of the mPA of CT images of different algorithms showed that the U-Net algorithm exhibited higher mPA value versus the Mean Shift, FCM, and Fully Convolutional Network (FCN) methods, as shown in Figure 4.

3.2. Analysis of Suspected Lymph Node Detection Results. The suspected lymph node detection method based on the U-Net algorithm was applied. As shown in Figure 5, the CT diagnosis revealed that 95 cases (60.13%) with esophageal cancer did not show lymph node metastasis (the metastasis number was 0), 54 cases (34.17%) had 1-2 lymph node metastases, and 9 cases (5.70%) showed lymph node metastases greater than 3. The pathological diagnosis results illustrated that there are 108 cases (68.35%) with esophageal cancer exhibiting no lymph node metastasis, 36 patients (22.78%) had lymph node metastases of 1-2, and 14 (8.86%) patients had lymph node metastases greater than 3. There were notable differences in diagnosis for 1-2 lymph node metastases between CT and postoperative pathology diagnosis ($P < 0.05$).

CT images were used to diagnose suspicious lymph nodes in patients with esophageal cancer. As shown in Figure 6, CT images can significantly identify the tracheal carina and the right trachea paraesophageal groove lymph nodes.
3.3. Analysis of the Efficacy of CT Imaging in the Diagnosis of Suspected Lymph Nodes in Esophageal Cancer. The suspected lymph node metastasis area identified by CT imaging and the pathological diagnosis was as shown in Figure 7. The pathological diagnosis results revealed that there were 33 patients (20.89%) with lymph node metastasis in 1 area, and 17 patients (10.76%) exhibited lymph node metastasis with more than 2 areas involved. CT imaging showed that 40 patients (25.32%) had lymph node metastasis in one area, and 23 patients (14.56%) had lymph node metastasis in more than two areas. The difference between CT and postoperative pathology in the diagnosis of lymph node metastasis area was not notable ($P > 0.05$).

Based on the gold standard of pathological diagnosis, the effectiveness of CT imaging in diagnosing suspicious lymph nodes in esophageal cancer was analyzed. As shown in Figure 8, the accuracy, sensitivity, specificity, positive predictive value, and negative predictive value of CT imaging in diagnosing suspicious lymph nodes in esophageal cancer were 84.37%, 80.74%, 88.65%, 85.02%, and 87.16%, respectively.

3.4. Comparison of Pain Degree after Different Nursing Methods. After different nursing methods were adopted, the pain degree at different time periods was compared. As shown in Figure 9, both groups of patients had the highest VAS scores at 6th hour after surgery. As time went by, the VAS scores of the two groups showed a downward trend, and during the entire observation period, the VAS scores of the intervention group were lower versus the control group ($P < 0.01$).

3.5. Comparison of Postoperative Recovery Time between the Two Groups. The time needed to get out of bed after the surgery was analyzed. As shown in Figure 10, in the intervention group, the time to get out of bed was shorter ($28.76 \pm 1.96$ versus $52.92 \pm 4.13$) ($P < 0.01$).

The postoperative chest tube duration and bowel movement recovery time of the two groups were analyzed. As shown in Figure 11, the postoperative chest tube duration and bowel movement recovery time of the intervention group were shorter ($P < 0.01$).

The postoperative hospital stay of the two groups was analyzed. As shown in Figure 12, the postoperative hospital stay of the intervention group was shorter ($8.03 \pm 0.63$ versus $9.45 \pm 0.74$) ($P < 0.01$).

4. Discussion

Mean pixel accuracy (mPA) is an index defined as the ratio of correctly classified pixels to the total number of pixels and is one of the commonly used evaluation indexes for image segmentation [15]. The IOU is an important index to measure the accuracy of image segmentation [16]. In the study, the improved and optimized U-Net was compared with Mean Shift and FCM segmentation algorithms. It was found that the IOU value of U-Net algorithm was notably
higher than that of Mean Shift and FCM, and it showed a higher mPA value versus Mean Shift, FCM, and FCN. Taken together, these results suggested that the optimized U-Net algorithm demonstrated better organ segmentation effects.

The lymphatic network of the esophageal lymphatic system is relatively rich. The diagnosis results of ordinary CT for the esophageal carcinoma lymph node metastasis are quite different from the pathological results [17]. In this study, the diagnosis results of the lymph node metastasis based on the U-Net segmentation algorithm found that there were notable differences in diagnosis for 1-2 lymph node metastases between CT diagnosis and postoperative pathological diagnosis ($P < 0.05$). The CT diagnosis and postoperative pathology diagnosis showed no notable differences in the diagnosis of lymph node metastasis area ($P > 0.05$). It was evident that CT imaging exhibited a higher number of false-negative lymph nodes in the diagnosis of suspicious lymph node metastases.
esophageal carcinoma lymph nodes, which was consistent with the results of Wu et al. [18]. It may be because of the different standards for CT diagnosis of lymph nodes, which contributes to the deviations from the pathological results. The accuracy, sensitivity, specificity, positive predictive value, and negative predictive value of CT imaging in the diagnosis of suspicious esophageal carcinoma lymph nodes were 84.37%, 80.74%, 88.65%, 85.02%, and 87.16%, respectively, while these indexes of ordinary CT in diagnosing suspicious esophageal carcinoma lymph nodes were 71.81%, 54.87%, 84.93%, 73.81%, and 70.86%, respectively [19]. Notably, the optimized algorithm in this study has improved the diagnostic efficiency of suspicious lymph nodes in esophageal carcinoma.

Based on the CT diagnosis results, different nursing methods were adopted to care for patients with esophageal carcinoma. It was found that the intervention group had lower postoperative VAS score, time of getting out of bed, indwelling chest tube duration, bowel movement recovery time, and postoperative hospital stay versus the control group \((P < 0.01)\). It illustrated that rapid rehabilitation nursing intervention can significantly alleviate postoperative pain and speed up postoperative recovery, which was in line with the results of Wang et al. [20].

### 5. Conclusion

Aiming to explore the role of CT imaging based on deep learning in the perioperative period and nursing of esophageal carcinoma patients, an optimized U-Net segmentation algorithm was used to establish a lymph node recognition model, which was applied during the perioperative period of esophageal carcinoma patients. Based on the CT diagnosis results, different nursing methods were given and their effects on the rehabilitation were investigated. It was found that the U-Net algorithm demonstrated better organ segmentation effects, and the diagnostic efficiency was notably heightened. Rapid rehabilitation nursing was found to greatly alleviate the postoperative pain and speed up postoperative recovery. However, some shortcomings should be noted in this study. It only evaluates the diagnostic efficiency of CT images for lymph nodes and does not analyze the prognostic value. In future work, the prognostic value of CT imaging will be further analyzed, which is expected to provide reference for the prognosis of esophageal carcinoma surgery.

### Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

### Conflicts of Interest

The authors declare that they have no conflicts of interest.

### References


