Research Article

Characteristics of Computed Tomography Images for Patients with Acute Liver Injury Caused by Sepsis under Deep Learning Algorithm

Huijun Wang,1 Qianqian Bao,2 Donghang Cao,1 Shujing Dong,1 and Lili Wu 1

1Department of Anesthesiology, Taizhou Hospital of Zhejiang Province Affiliated to Wenzhou Medical University, No. 150 Linhai West Street, Taizhou 317000, Zhejiang, China
2Department of Operation, Taizhou Hospital of Zhejiang Province Affiliated to Wenzhou Medical University, No. 150 Linhai West Street, Taizhou 317000, Zhejiang, China

 Correspondence should be addressed to Lili Wu; 201801010522@stu.hnie.edu.cn

Received 31 December 2021; Revised 18 February 2022; Accepted 21 February 2022; Published 19 March 2022

1.Introduction

Sepsis is one of the main causes of death in intensive care unit (ICU) patients. According to statistics, there are approximately 18 million new cases each year, with a mortality rate of 2%–40% [1]. As the target organ of sepsis, the liver plays an important role in the occurrence and development of sepsis [2]. Acute liver injury is one of the common acute and critical illnesses caused by sepsis, with a high fatality rate and poor prognosis [3]. However, there are few studies on the clinical characteristics of patients with sepsis complicated by acute liver injury. At present, the diagnosis of sepsis liver injury mainly uses a number of serological indicators to indirectly assess the severity of liver injury [4]. In imaging...
examination methods, CT examination has significant advantages in evaluating liver trauma or intra-abdominal blood volume. Compared with serological test indicators, CT can reflect the extent of liver parenchymal destruction and accurately determine the degree of liver damage [5]. However, there are abundant organs and blood vessels around the liver, and the boundary between normal tissue and the diseased area is blurred. Manually segmenting the diseased area with CT images is time-consuming and prone to segmentation errors [6].

As a new field of machine learning, deep learning can be established to imitate the human brain for data analysis and learning and has powerful feature learning and model representation capabilities. Convolutional neural network (CNN) has strong representation learning capabilities and has been widely used in speech recognition, language processing, and image processing [7]. CNN has been used in the detection of breast cancer, cell carcinoma and brain lesions, knee cartilage segmentation, brain tumor segmentation, and liver tumor segmentation in medical image processing [8]. However, CNN has the disadvantage of losing the spatial information of the original image in image segmentation [9]. Jiang et al. (2021) [10] pointed out that the fully convolutional neural network (FCN) based on CNN can overcome the shortcomings of CNN in the liver segmentation process of CT images and avoid the repeated storage and calculation convolution caused using pixel blocks. However, the image results obtained by the upsampling of the FCN algorithm are smooth and blurred, which is not sensitive to the processing of details in the image [11]. At the same time, some studies pointed out that the relationship between pixels is not fully considered in the image processing process, and the spatial regularization step used in the usual pixel classification-based segmentation methods is ignored, which lacks spatial consistency [12]. Therefore, it needs to be further optimized to overcome the problems of inaccurate segmentation results and lack of spatial consistency of the FCN algorithm.

To sum up, CT shows significant advantages in acute liver injury. The FCN algorithm still has certain limitations in CT image liver segmentation, which needs to be optimized. Moreover, there are few studies on the analysis of CT imaging characteristics of patients with acute liver injury in sepsis. Therefore, the FCN algorithm was optimized to increase its image segmentation performance. It was then applied to liver segmentation of CT images in patients with acute sepsis liver injury, and the clinical characteristics and CT imaging characteristics of patients with acute liver injury in sepsis were discussed, aiming to provide reference basis for the diagnosis of patients with acute liver injury caused by sepsis.

### 2. Materials and Methods

#### 2.1. Research Objects and Grouping

In this study, 92 patients with sepsis in hospital from December 2018 to March 2021 were selected as research objects, and all patients underwent CT examination. There were 51 males and 41 females. The age range of patients was 19–86 years, and the average age was 59.94 ± 10.18 years. The inclusion criteria of this study were defined as follows: patients who had performed with CT examination; and patients who were in line with the inclusion criteria of abnormal liver function [13]. Exclusion criteria were defined as follows: patients with past chronic liver damage; patients after liver tumor or partial liver resection; patients with obstructive jaundice and biliary tract disease; and patients with liver damage caused by nonseptic reasons such as drugs. According to whether they had acute liver injury, they were divided into nonacute liver injury group (50 cases) and acute liver injury group (42 cases). This study had been approved by the ethics committee of hospital, and all subjects included in the study had signed the informed consent forms.

#### 2.2. CT Examination Method

All patients were instructed to fast for 4–6 hours before examination, and the clinical data such as blood pressure and pulse were measured about 20 minutes before scanning. Plain scan and enhanced examination were performed with CT machine. The patient was placed in supine position and scanned in transverse axial position, with both arms raised and head held, from the xiphoid process to the lower margin of the liver. To reduce the motion artifacts in the image, patients must hold the air with inhalation during scanning or hold the air with calm breathing. Scanning parameter setting was tube voltage of 100 kV, tube current of 100 mA, pitch of 1.0, layer spacing of 7.5 mm, layer thickness of 7 mm, window position of 45–75 HU, and window width of 150–250 HU. According to Becker classification [14], liver injury CT images were classified.

#### 2.3. Liver Segmentation Framework Based on FCN

FCN has greatly improved image segmentation accuracy and segmentation speed from traditional CNN [15]. Based on the imprecise segmentation results in the FCN algorithm, the optimization was realized through the CT window and algorithm optimization, and a liver segmentation framework was established, as shown in Figure 1. The initially obtained CT image data set was randomly cropped and then subjected to FCN algorithm for segmentation, and finally the segmented liver CT image was output.

#### 2.4. CT Image Preprocessing for Liver Segmentation

Image preprocessing can reduce the interference of a certain tissue or organ from unrelated tissues or organs. The CT value of different tissues and organs in the human body is different, and the CT value of liver tissue is between 50 and 70 HU [16]. For the initial CT image of the liver, it was inputted to the convolutional layer with a convolution kernel size of 1 × 1 for preprocessing, the Sigmoid function was used to activate it, and the preprocessed CT image was finally output. It was assumed that the upper limit of the serial port function of CT image processing was A, and the liver CT image preprocessing module can be expressed as follows:

\[
G(x) = \frac{A}{1 + e^{-(c(x+d))}}
\]  

(1)
In the equation above, \( C \) and \( b \) were convolutional layer parameters, and \( x \) was the CT value of the original CT image. In order to increase the efficiency of network training, the convolutional layer parameters \( C \) and \( b \) were optimized in the study. The specific algorithm was as follows:

\[
C = \frac{2}{CC} \log \left( \frac{A}{\alpha} - 1 \right),
\]

\[
b = -\frac{2CL}{CC} \log \left( \frac{A}{\alpha} - 1 \right).
\]

In the equations above, \( CC \) was the window width, \( CL \) was the window level, and \( \alpha \) was the difference between the upper bound of the function and the right end of the window, which is related to the slope of the Sigmoid function.

2.5. Design of Liver CT Image Segmentation Network Based on FCN. The encoder-decoder structure can not only improve the feature expression ability in the image segmentation process, but also avoid the problem of gradient disappearance that may occur during the training process of the deep network [17]. DenseNet can avoid the training error caused by deep network training through the short-circuit connection in the residual module [18]. \( l \) was assumed to be the current number of layers, and the output of layer \( l \) can be expressed as follows:

\[
x_l = B_l \{ x_0, x_1, \ldots, x_{l-1} \}.
\]

In (3), \( B_l \{ \} \) represented a combination of operations, and \( x_0, x_1, \ldots, x_{l-1} \) was the splicing of the output of all layers before the layer \( l \).

After the input image passed through the encoder, a low-resolution feature representation was produced, and the decoder network structure was related to the final image segmentation result [19]. In this study, the Dense connection among decoder modules was introduced, and the Skip connection in semantic segmentation was introduced to reduce the potential errors caused by the decoder’s mesoscale modules, thereby improving the accuracy of segmentation. The structure of the liver CT image processing encoder optimized in this study is shown in Figure 2.

2.6. Design of Loss Function of Liver CT Image Segmentation Network Based on FCN. The segmentation evaluation index performance combining cross entropy and Lovász-Softmax’s loss function was significantly higher than that of alone [20]. The calculation method of the cross entropy loss function was given as follows:

\[
D(y, y') = -\frac{1}{N} \sum_{i=1}^{N} \sum_{h=1}^{H} y_i^h \log y_i^h.
\]

In (4), \( y_i^h \) referred to the binary label of pixel \( i \) to category \( h \), \( y_i^h \) represented the probability value that pixel \( i \) belongs to category \( h \), \( N \) was the sum of the number of pixels in a batch in the training process, and \( H \) was the total number of categories.

In liver CT image segmentation, a weighted cross entropy loss function is often used to solve the problem of category imbalance. The calculation method of weighted cross entropy loss function is shown in the following formula, where \( \omega_i^h \) represented the weight of the category:

\[
D(y, y') = -\frac{1}{N} \sum_{i=1}^{N} \sum_{h=1}^{H} \omega_i^h y_i^h \log y_i^h.
\]

During the operation of the cross entropy loss function, there was still rough segmentation of the edge area of the image. The Dice coefficient was a commonly used evaluation index for segmented images. The calculation method was given as follows:

\[
\text{Dice}(A, B) = \frac{2|A \cap B|}{|A| + |B|}.
\]

In the above equation, \( A \) was the number of pixels in the prediction area, and \( B \) was the number of pixels in the labeling area. The optimized Dice coefficient can be used as a loss function to improve the rough edge of the segmented image. The Dice loss function can be expressed as

\[
\text{Dice} = \frac{2 \sum_{i=1}^{N} P_i Q_i}{\sum_{i=1}^{N} P_i^2 + \sum_{i=1}^{N} Q_i^2}.
\]

In (7), \( P \) represented the predicted probability value of pixel \( i \), \( Q_i \) was the binary label value of pixel \( i \), and \( N \) referred to the total number of pixels in a batch. The partial derivative of the predicted probability of the Dice coefficient to the \( j \)-th pixel and the optimized loss function (sDice) are, respectively, expressed as
In order to optimize the discrete Jaccard loss in continuous space, it needs to be expanded smoothly. It was assumed that the set of misclassified pixels was $E_{\omega}$, which could be expressed as

\[ E_{\omega} = \{ y = c, y' \neq c \} \cup \{ y \neq c, y' = c \}. \]  

(12)

Jaccard loss could be expressed as

\[ \Delta J_c: E_{\omega} \in [0, 1] P \rightarrow \frac{|E_{\omega}|}{|\{ y = c \} \cup E_{\omega}|}. \]  

(13)

In the equation above, $E_{\omega}$ referred to the Lovász expanded item of $\Delta J_c$, and $m$ was the vector number.

2.7. Test Data and Image Evaluation Indicators. In this study, the liver CT images were from 86 patients with liver disease collected. The original liver CT tomographic slice parameters were 1.25 mm * 1.25 mm, and the slice spacing was 2 mm. All CT images were randomly divided into a training set (60 cases) and a test set (26 cases). The test environment was defined as follows: computer operating system Ubuntu 16.04 LTS 64 bit system, central processing unit (CPU): Intel Core i7-2600 3.4G HZ, memory: DDR 34 GB, hard disk 1 TB. The Python 3 was selected as a tool for implementing the DBN model code, and the deep learning framework was PyTorch.

The focus detection mainly used the focus detection precision and recall rate for evaluation, and the calculation methods were as follows:

\[ \text{precision} = \frac{TP}{TP + FP} \times 100\%, \]  

(16)

\[ \text{recall} = \frac{TP}{TP + FN} \times 100\%. \]  

(17)

In (16) and (17), $TP$ represented the number of correctly detected lesions; $FN$ represented the number of missed lesions; and $FP$ represented the number of wrongly detected lesions.

Image segmentation evaluation indicators mainly used volume overlap error (VOE) and relative volume difference (RVD) for evaluation, and the calculation methods were as follows:

\[ \text{VOE}(C, D) = 1 - \frac{|C \cap D|}{|C \cup D|}, \]  

(18)

\[ \text{RVD}(C, D) = \frac{|D| - |C|}{|C|}. \]

In the equation above, $C$ referred to the pixel set of the automatically segmented image, and $D$ was the pixel set of the manually drawn image.
The root mean square error (RMSE) can be used to evaluate the burden of liver lesions. The calculation method of RMSE was given as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (C_i - D_i)^2}.$$  \hspace{1cm} (19)

2.8. Statistical Analysis. The test data processing was performed using SPSS19.0 statistical software, the measurement data were expressed as mean ± standard deviation ($\bar{x} \pm s$), and count data were expressed as percentage (%), using the $\chi^2$ test. $P < 0.05$ indicated that the difference was statistically significant.

3. Results and Analysis

3.1. Analysis of CT Image Preprocessing Results. The segmented images without pretreatment (no pretreatment), traditional CT window pretreatment (tradition window), and optimized window pretreatment (optimized window) were compared and analyzed. The results were shown in Figure 3. The Dice value of the CT image preprocessed by the optimized window was $(0.704 \pm 0.06)$, and the Dice values of the CT image preprocessed by the no pretreatment and tradition window were $(0.517 \pm 0.05)$ and $(0.583 \pm 0.05)$, respectively. The Dice value of CT image preprocessed by optimized window was significantly higher than the other two methods ($P < 0.05$).

The output CT values of CT images under different preprocessing methods were compared further, and the results are illustrated in Figure 4. With the continuous increase of the initial CT value, the output CT values of no pretreatment and tradition window both show an obvious linear upward trend; and the output CT value of the optimized window shows an “S” curve with the continuous increase of the initial CT value. When the input CT value was greater than 200 HU, the output CT value no longer changed, showing a stable trend.

3.2. Analysis of CT Image Segmentation Effect. The Loss values of the FCN algorithm before optimization and the optimized-FCN algorithm in this study were analyzed and compared on the training set (Figure 5). As the Epoch value continued to increase, the Loss values of the two algorithms showed a tendency to first decrease and then stabilize. Under the same Epoch value, the Loss value of the Optimized-FCN algorithm was lower than that of the FCN algorithm.

A comparative analysis of the results of segmentation of CT images by the FCN algorithm before optimization and the Optimized-FCN algorithm is shown in Figure 6. It illustrated that, compared with the FCN algorithm, the Optimized-FCN algorithm had a higher degree of fit between the liver CT image lesion segmentation results and the manual segmentation results.

The Dice value of CT image segmentation between the FCN algorithm before optimization and the Optimized-
3.3. Comparative Analysis with Other Segmentation Methods. The results of Optimized-FCN algorithm segmentation of CT images with UNet, ResNet, DenseUNet, and the whole nested edge detection (HED) algorithm were compared (Figure 8). The detection precision, recall, VOE, RVD, and RMSE values of the optimized-FCN algorithm were $(0.91 \pm 0.08), (0.88 \pm 0.09), (21.19 \pm 1.97), (10.45 \pm 1.02)$, and $(0.25 \pm 0.02)$, respectively. The detection precision and recall rate of Optimized-FCN algorithm were greatly higher than other algorithms ($P < 0.05$), and the values of VOE, RVD, and RMSE were significantly lower than other algorithms ($P < 0.05$).

3.4. Comparison of Basic Data. The basic data of the two groups of patients, such as age, gender, smoking history, drinking history, history of hypertension, history of diabetes, and history of low blood pressure, were compared and analyzed (Table 1). There was no significant difference between the two groups of patients in age, gender, the proportion of patients with smoking history, the proportion of hypertension history, and the proportion of diabetes history ($P > 0.05$). The proportion of patients with a history of drinking in the nonacute liver injury group was lower than that in the acute liver injury group ($P < 0.05$), and the proportion of patients with a history of low blood pressure in the acute liver injury group was significantly higher than that in the nonacute liver injury group ($P < 0.01$).

3.5. CT Imaging Results of Acute Liver Injury Caused by Sepsis. The CT imaging manifestations of patients with acute liver injury under different grades were analyzed, and the results are illustrated in Figure 9. Crescent-shaped high-density hematomas under the liver capsule can be observed in CT imaging of patients with grade I; the left liver lobe of grade II patients had a slightly low-density small hematoma; the right hepatic lobe of grade III patients was irregular and the boundary is blurred; and in the grade IV CT image, the right lobe of the liver can be seen with a patchy high-low density hematoma. The liver parenchyma showed a large mixed high-density hematoma under the grade V CT image, and the liver parenchymal lesions involved the right portal vein.

3.6. Clinical Characteristics of Patients with Acute Liver Injury Caused by Sepsis. The clinical characteristics of the two groups of patients were compared, and the results are revealed in Figure 10. There was no significant difference in the proportion of patients with different infection sites between the two groups ($P > 0.05$). The number of organ failures and length of stay in ICU in the acute liver injury group were much higher than that of the nonacute liver injury group ($P < 0.05$).

4. Discussion

Xu et al. (2019) [22] optimized it based on traditional window settings, and the results showed that image segmentation parameters have been improved. This study further optimized it based on the current research results to improve the segmentation performance. The results in the study showed that the Dice value of the CT image preprocessed by the optimized window was obviously higher than the other two methods ($P < 0.05$). It showed that the optimized CT window preprocessing method in this study can improve the performance of liver CT image segmentation. The Loss value of the Optimized-FCN algorithm was lower than that of the FCN algorithm, and the Dice value was higher than that of the FCN algorithm ($P < 0.05$). It showed that, under the same conditions, the loss function value of the optimized-FCN algorithm was lower, which may be related to the selection of weighted cross entropy loss function used in this study. The weighted cross entropy loss function can enable the segmented image to complete the
rough segmentation and refined segmentation of the target object in different periods of training [23], improving the segmentation effect and reducing the Loss value. The detection precision and recall rate of the Optimized-FCN algorithm were significantly higher than other algorithms ($P < 0.05$), and the VOE, RVD, and RMSE values were significantly lower than other algorithms ($P < 0.05$). These results showed that the Optimized-FCN algorithm significantly improved the segmentation performance of liver CT images. Alirr (2020) [24] segmented the liver based on a machine learning algorithm and found that the Dice of the segmented CT image was 0.726. Weston et al. (2020) [25] established a liver segmentation method based on the CNN algorithm, and the results showed that the Dice value of this method for segmenting liver CT images was 0.79. Chen et al. (2021) [26] optimized the model based on the FCN algorithm and applied it to liver segmentation. The results showed that the Dice value of this method for segmenting liver CT images was 0.742. In this study, the Dice value of the Optimized-FCN algorithm for segmenting liver CT images was 0.79.

Figure 8: Comparison on image segmentation indexes of different algorithms. (a–e) showed the comparison on precision, recall, VOE, RVD, and RMSE, respectively. * means the difference was statistically obvious compared with the Optimized-FCN algorithm ($P < 0.05$).
Table 1: Comparison of basic data of the two groups of patients.

| Group                          | Nonacute liver injury group | Acute liver injury group | t value or χ² value | P value |
|-------------------------------|-----------------------------|--------------------------|---------------------|---------|
| Age (years old)               | 60.02 ± 5.78                | 59.96 ± 7.64             | 1.924               | 0.227   |
| Males (cases, (%))            | 28 (56.00)                  | 23 (54.76)               | 2.427               | 0.258   |
| History of smoking (cases, (%)) | 14 (28.00)                  | 12 (28.57)               | 2.337               | 0.265   |
| History of drinking (cases, (%)) | 7 (14.00)                   | 19 (45.24)               | 4.731               | 0.018*  |
| History of hypertension (cases, (%)) | 16 (32.00)                | 14 (33.33)               | 2.019               | 0.198   |
| History of low blood pressure (cases, (%)) | 24 (12.00)                | 38 (90.48)               | 5.213               | 0.008** |
| History of diabetes (cases, (%)) | 10 (20.00)                  | 8 (19.05)                | 2.922               | 0.173   |

* indicated a statistical difference, \( P < 0.05 \); ** indicated a highly significant difference, \( P < 0.01 \).

Figure 9: CT imaging results of acute liver injury caused by sepsis. (a–f) The CT images of patients with normal liver, grade I, grade II, grade III, grade IV, and grade V, respectively.

Figure 10: Comparison on infection site, number of organ failures, and length of stay in ICU between the two groups. (a) Comparison on the infection sites; (b) comparison on number of organ failures and length of stay in ICU. * suggests that the difference was statistically visible in contrast to the nonacute liver injury group \( P < 0.05 \).
was 0.825, which was significantly better than these algorithms.

The typical CT appearance of liver injury is a well-defined low-density change on plain scan, which corresponds to the irradiation field and has nothing to do with liver anatomy [27]. The incidence of acute liver dysfunction in sepsis was about 25%. The results of this study showed that the proportion of patients with a history of drinking and low blood pressure in the nonacute liver injury group was lower than that in the acute liver injury group ($P < 0.05$). The reason was that long-term drinking can cause liver dysfunction, fatty degeneration, and liver compensatory ability to be significantly reduced. When the body develops sepsis, it is accompanied by liver function damage [28]. Insufficient tissue perfusion in patients with severe sepsis leads to hypoxia of feeding cells and ischemia of hepatocytes and ultimately leads to liver damage [29]. The number of organ failures and length of stay in ICU in the acute liver injury group were significantly higher than those in the nonacute liver injury group ($P < 0.05$). The more severe the liver damage, the longer the mechanical ventilation time [30]. Current research results showed that whether there is liver damage in the case of severe infection will affect the level of inflammatory response in the lungs. The incidence of acute lung injury is significantly increased if liver injury is present in sepsis patients, mainly due to the increased inflammatory response in the lung upon liver injury [31]. The results of this study were similar to that.

5. Conclusion

In this study, a liver CT image segmentation method based on FCN was established, and the clinical characteristics of acute liver injury caused by sepsis were analyzed. It was found that the optimized-FCN algorithm significantly improved the CT image segmentation performance. Long-term drinking, low blood pressure, number of organ failures, and length of stay in ICU were all related to acute liver injury caused by sepsis. However, there were some shortcomings in this study. It preliminarily analyzed the clinical characteristics of acute liver injury caused by sepsis. In addition, it was a retrospective study, lacking biochemical indicators and other data analysis. In the future work, the clinical features of acute liver injury caused by sepsis would be further analyzed. In conclusion, this work established an effective vertical liver CT image segmentation method based on the FCN algorithm and obtained the relevant influencing factors of sepsis acute liver injury, which provided a reference for the diagnosis and prognosis of sepsis acute liver injury.

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 no conflicts of interest.

Authors’ Contributions

Huijun Wang and Qianqian Bao contributed equally to this work.

Acknowledgments

This work was supported by Taizhou Science and Technology Bureau Project (no. 20ywa15).

References

[1] M. Huang, S. Cai, and J. Su, “The pathogenesis of sepsis and potential therapeutic targets,” *International Journal of Molecular Sciences*, vol. 20, no. 21, p. 5376, 2019, PMID: 31671729; PMCID: PMC6862039.
[2] J. Sun, J. Zhang, X. Wang et al., “Gut-liver crosstalk in sepsis-induced liver injury,” *Critical Care*, vol. 24, no. 1, p. 614, 2020, PMID: 33076940; PMCID: PMC7574296.
[3] P. Strnad, F. Tacke, A. Koch, and C. Trautwein, “Liver guardian, modifier and target of sepsis,” *Nature Reviews Gastroenterology & Hepatology*, vol. 14, no. 1, pp. 55–66, 2017, Epub 2016, Dec 7. PMID: 27924081.
[4] M.-K. Hong, L.-L. Hu, Y.-X. Zhang et al., “6-Gingerol ameliorates sepsis-induced liver injury through the Nrf2 pathway,” *International Immunopharmacology*, vol. 80, 2020, Epub 2020, Jun 21. PMID: 31978803, Article ID 101696.
[5] B. G. J. Surewaard, A. Thanabalasuriar, Z. Zeng et al., “α-Toxin induces platelet aggregation and liver injury during *Staphylococcus aureus* sepsis,” *Cell Host & Microbe*, vol. 24, no. 2, pp. 271–284, 2018, Epub 2018, Jul 19. PMID: 30333122; PMCID: PMC6295203.
[6] E. Triantafyllou, K. J. Woollard, M. J. W. McPhail, C. G. Antoniades, and L. A. Possamai, “The role of monocytes and macrophages in acute and acute-on-chronic liver failure,” *Frontiers in Immunology*, vol. 9, p. 2948, 2018, PMID: 30619308; PMCID: PMC6302023.
[7] M. Hu, Y. Zhong, S. Xie, H. Lv, and Z. Lv, “Fuzzy system based medical image processing for brain disease prediction,” *Frontiers in Neuroscience*, vol. 15, 2021, PMID: 34393718; PMCID: PMC8361453, Article ID 714318.
[8] F. Schwendtke, T. Golla, M. Dreher, and J. Krois, “Convolutional neural networks for dental image diagnostics: a scoping review,” *Journal of Dentistry*, vol. 91, Article ID 103226, 2019.
[9] R. D. MacDougall, Y. Zhang, M. J. Callahan et al., “Improving low-dose pediatric abdominal CT by using convolutional neural networks,” *Radiology: Artificial Intelligence*, vol. 1, no. 6, PMID: 32090205; PMCID: PMC6884028, Article ID e180087, 2019.
[10] J. Jiang, Y. Luo, F. Wang, Y. Fu, H. Yu, and Y. He, “Evaluation on auto-segmentation of the clinical target volume (CTV) for graves' ophthalmopathy (GO) with a fully convolutional network (FCN) on CT images,” *Current Medical Imaging Formerly Current Medical Imaging Reviews*, vol. 17, no. 3, pp. 404–409, 2021, PMID: 32914716.
[11] X. Zhou, “Automatic segmentation of multiple organs on 3D CT images by using deep learning approaches,” *Advances in Experimental Medicine & Biology*, vol. 1213, pp. 135–147, 2020, PMID: 3203668.
[12] D. Abdelhafiz, J. Bi, R. Ammar, C. Yang, and S. Nabavi, “Convolutional neural network for automated mass segmentation in mammography,” *BMC Bioinformatics*, vol. 21, no. S1, p. 192, 2020.
[13] C. L. Chowdhary, M. Mittal, K. Kumerasan, P. A. Pattanaik, and Z. Marszałek, "An efficient segmentation and classification system in medical images using intuitionist possibilistic fuzzy C-mean clustering and fuzzy SVM algorithm," Sensors, vol. 20, no. 14, p. 3903, 2020, PMID: 32668793; PMCID: PMC7411903.

[14] F. Tang, S. Liang, T. Zhong et al., “Postoperative glioma segmentation in CT image using deep feature fusion model guided by multi-sequence MRIs,” European Radiology, vol. 30, no. 2, pp. 823–832, 2020, Epub 2019, Oct 24. PMID: 31650265.

[15] G. H. B. Miranda and J. C. Felipe, “Computer-aided diagnosis system based on fuzzy logic for breast cancer categorization,” Computers in Biology and Medicine, vol. 64, pp. 334–346, 2015, Epub 2014, Oct 14. PMID: 25453323.

[16] Y. Todroroki, Y. Iwamoto, L. Lin, H. Hu, and Y.-W. Chen, “Automatic detection of focal liver lesions in multi-phase CT images using a multi-channel & multi-scale CNN,” in Proceedings of the 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 872–875, PMID: 31946033, IEEE, Berlin, Germany, July 2019.

[17] A. Ben-Cohen, R. Mechrez, N. Yedidia, and H. Greenspan, “Improving CNN training using disentanglement for liver lesion classification in CT,” in Proceedings of the 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 886–889, PMID: 31946036, Berlin, Germany, July 2019.

[18] K. Wang, A. Mamidipalli, T. Retson et al., “Automated CT and MRI liver segmentation and biometry using a generalized convolutional neural network,” Radiology: Artificial Intelligence, vol. 1, no. 2, Epub 2019, Mar 27. PMID: 32582883; PMCID: PMC7314107, Article ID 180022, 2019.

[19] S. Lee, E. K. Choe, S. Y. Kim, H. S. Kim, K. J. Park, and D. Kim, “Liver imaging features by convolutional neural network to predict the metachronous liver metastasis in stage I-III colorectal cancer patients based on preoperative abdominal CT scan,” BMC Bioinformatics, vol. 21, no. 13, p. 382, 2020, PMID: 32938394; PMCID: PMC7495853.

[20] S. Agrawal, R. K. Dhiman, and J. K. Limdi, “Evaluation of abnormal liver function tests,” Postgraduate Medical Journal, vol. 92, no. 1086, pp. 223–234, 2016, Epub 2016, Feb 3. PMID: 26842972.

[21] D.-H. Chang, S. Brinkmann, L. Smith et al., “Calcification score versus arterial stenosis grading: comparison of two CT-based methods for risk assessment of anastomotic leakage after esophagectomy and gastric pull-up,” Therapeutics and Clinical Risk Management, vol. 14, pp. 721–727, 2018, PMID: 29713180; PMCID: PMC5909785.

[22] M. Xu, S. Qi, Y. Yue et al., “Segmentation of lung parenchyma in CT images using CNN trained with the clustering algorithm generated dataset,” BioMedical Engineering Online, vol. 18, no. 1, p. 2, 2019, PMID: 30602393; PMCID: PMC6317251.

[23] J. M. Wolterink, R. W. van Hamersvelt, M. A. Viergever, T. Leiner, and I. Isgum, “Coronary artery centerline extraction in cardiac CT angiography using a CNN-based orientation classifier,” Medical Image Analysis, vol. 51, pp. 46–60, 2019, Epub 2018, Oct 22. PMID: 30388501.

[24] O. I. Alirr, “Deep learning and level set approach for liver and tumor segmentation from CT scans,” Journal of Applied Clinical Medical Physics, vol. 21, no. 10, pp. 200–209, 2020.

[25] A. D. Weston, P. Korfiatis, K. A. Philbrick et al., “Complete abdomen and pelvis segmentation using U-net variant architecture,” Medical Physics, vol. 47, no. 11, pp. 5609–5618, 2020.

[26] X. Chen, X. Wei, M. Tang et al., “Liver segmentation in CT imaging with enhanced mask region-based convolutional neural networks,” Annals of Translational Medicine, vol. 9, no. 24, p. 1768, 2021.

[27] D. I. Cha, K. D. Song, S. Y. Ha, J. Y. Hong, J. A. Hwang, and S. E. Ko, “Long-term follow-up of oxaliplatin-induced liver damage in patients with colorectal cancer,” British Journal of Radiology, vol. 94, no. 1123, Article ID 20210352, 2021.

[28] T. N. Bukong, Y. Cho, A. Iracheta-Vellve et al., “Abnormal neutrophil traps and impaired efferocytosis contribute to liver injury and sepsis severity after binge alcohol use,” Journal of Hepatology, vol. 69, no. 5, pp. 1145–1154, 2018, Epub 2018, Jul 18. PMID: 30030419; PMCID: PMC6310218.

[29] H. Y. Zhou, C. X. Long, L. Luo, Y. Y. Chen, P. P. Liu, and Z. H. Xiao, “[Effect of mogroside VI on acute liver injury induced by sepsis in mice and related mechanisms],” Zhong Guo Dang Dai Er Ke Za Zhi, vol. 22, no. 11, pp. 1233–1239, 2020, Chinese.

[30] G. Chen, H. Deng, X. Song et al., “Reactive oxygen species-responsive polymeric nanoparticles for alleviating sepsis-induced acute liver injury in mice,” Biomaterials, vol. 144, pp. 30–41, 2017, Epub 2017, Aug 11. PMID: 28820966.

[31] Z. Xu, S. Mu, X. Liao et al., “Estrogen protects against liver damage in sepsis through inhibiting oxidative stress mediated activation of pyroptosis signaling pathway,” PLoS One, vol. 15, no. 10, Published 2020 Oct 1, Article ID e0239659, 2020.