Segmentation of Acute Pulmonary Embolism in Computed Tomography Pulmonary Angiography Using the Deep Learning Method

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Research Article

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Abstract

Background

Pulmonary embolism is a type of thromboembolism seen in the main pulmonary artery and its branches. This study aimed to diagnose acute pulmonary embolism using the deep learning method in computed tomographic pulmonary angiography (CTPA) and perform the segmentation of pulmonary embolism data.

Methods

The CTPA images of patients diagnosed with pulmonary embolism who underwent scheduled imaging were retrospectively evaluated. After data collection, the areas that were diagnosed as embolism in the axial section images were segmented. The dataset was divided into three parts as training, validation, and testing. The results were calculated by selecting 50% as the cut-off value for the intersection over union.

Results

Images were obtained from 1,550 patients. The mean age of the patients was 64.23 ± 15.45 years. A total of 2,339 axial computed tomography images obtained from the 1,550 patients were used. There were a total of 5,992 labels, with 1,879 images. PyTorch U-Net was used to train 400 epochs, and the best model, epoch 178, was recorded. In the testing group, the number of true positives was determined as 471 and false positives as 35, while 27 were not detected. The sensitivity of CTPA segmentation was 0.95, the precision value was 0.93, the F1 score value was 0.94, and the learning rate was 0.0001. The area under the curve value obtained in the receiver operating characteristic analysis was calculated as 0.88.

Conclusions

In this study, the segmentation of acute pulmonary embolism in CTPA performed using the deep learning method provided successful results.

Background

Pulmonary embolism is a type of thromboembolism seen in the main pulmonary artery and its branches. It is important to make a rapid diagnosis of pulmonary embolism in order to reduce associated mortality and morbidity [1]. Tests and methods such as D-dimer assay, ventilation perfusion scintigraphy, lower extremity ultrasonography, and computed tomography pulmonary angiography (CTPA) are used in the diagnosis of pulmonary embolism [2–5]. CTPA is the gold standard for the detection of pulmonary
embolism [6]. due to its higher sensitivity and specificity compared to other examinations [7, 8]. However, the radiological interpretation of CTPA examination is also important. In CTPA, the diagnosis of pulmonary embolism is made by detecting the appearance of filling defects in the arterial lumen and related increase in diameter, partial filling defects causing the appearance of the polo mint sign and railway track appearance, and peripheral intraluminal filling defects causing acute angulation in the arterial wall [9, 10]. For the diagnosis of pulmonary embolism, the main branches, lobar, segmental and subsegmental branches in the whole lung are examined on CTPA images, which is a process that takes a long time [11]. Therefore, new and up-to-date approaches are needed. Recently, deep learning in artificial intelligence technology has come to the fore in many fields of medicine. Deep learning has components such as lesion detection, classification, segmentation, and quantification, among which segmentation is an important framework used in medical image analysis in structures such as organs and lesions [12, 13]. However, only a limited number of studies have reported successful results in the diagnosis of acute pulmonary embolism using deep learning [14]. Considering the need for up-to-date approaches and supportive data, the current study aimed to diagnose acute pulmonary embolism using the deep learning method and perform the segmentation of pulmonary embolism data.

Materials And Methods

Patient Population

After obtaining approval from the ethics committee, patients presenting to the radiology department between January 1, 2016, and January 1, 2021, were retrospectively screened. Patients aged over 18 years, who underwent scheduled CTPA and were diagnosed with pulmonary embolism, were included in the study.

Imaging Procedure

CT scans were performed using 128-section (GE, Revolution EVO) and 64-section (Toshiba, Aquilion) devices with the bolus tracking method and a threshold of 100 Hounsfield Unit (HU). Contrast volume 60 mL non-ionic contrast with a 100 mL saline chaser at 4.5/5 mL/s were used for each patient. The section thickness of the scans varied between 0.5 mm and 0.625 mm. The images were obtained in the mediastinum window with a width of 300 HU and a height of 50 HU, and the scans were performed at a kV value of 100 and mA value of 244. The remaining parameters were as follows: detector coverage, 40 mm; rotation time, 0.4 s; pitch, 1.375:1; and speed, 55.00 mm/rot. The sections taken in the mediastinum window were converted to the png format.

Imaging Analysis

The images were evaluated by a radiologist with seven years’ experience (N.A.) and a radiology assistant (C.C.) with three years’ experience based on consensus. After pulmonary embolism was detected in the CTPA images of the patients, axial cross-sectional images were obtained in the mediastinal window.
Images with motion artifacts and poor contrast were excluded from the study. Following data collection, the areas that were diagnosed as embolism in the axial section images were segmented.

The mask images of the labeled regions were created in the computer department of our faculty and saved with the same names, and then the dataset was divided into three groups as training, validation, and testing at the ratio of 80, 10, and 10%. The mixed-size images were resized to 512x512. By applying 50% zoom to the images, the regions to be segmented were enlarged as much as possible to fit the image. The clarity of the regions to be segmented was increased by applying contrast-limited adaptive histogram equalization. Augmentation was performed on the training and validation groups (both horizontal and vertical), and the number of data was quadrupled. Epoch training was undertaken using the traditional PyTorch U-Net architecture, which was extended to handle volumetric input. The jump links used between the corresponding encoder and decoder layers allowed for the deep parts of the network to be trained efficiently and facilitated the comparison of the same receiver features with different receiver domains [15].

The results were calculated by selecting 50% as the cut-off value of the intersection over union statistic (Jaccard index), which measures the similarity between finite sample sets and is defined as the size of the intersection divided by the size of the union of the sample sets [16].

**Statistical Analysis**

Continuous data were presented as mean ± standard deviation values, and categorical data as percentages (%). IBM SPSS Statistics v. 21.0 (IBM Corp. Released 2012. IBM SPSS Statistics for Windows, Version 21.0. Armonk, NY: IBM Corp.) was used for the statistical analysis of the data.

The sensitivity, precision, F1 score, area under curve (AUC) values and learning rate were calculated. The F1 score was calculated according to the following formula with true positive, false negative, false positive values [17]:

\[
F1 = \frac{2 \times \text{True Positive}}{2 \times \text{True Positive} + \text{False Positive} + \text{False Negative}}
\]

**Results**

Images obtained from 1,550 patients were included in the study. The mean age of the patients was 64.23 ± 15.45 years. A total of 2,339 axial CTPA images obtained from 1,550 patients were used. A total of 5,992 labels were obtained, with 1,879 images and 4,929 labels being used in the training stage, 230 images and 530 labels in the validation stage, and 230 images and 533 labels in the testing stage. By applying augmentation (both horizontal and vertical) on the training and validation sets, the number of data was quadrupled (training set: 7,516 images and 19,716 labels; validation set: 920 images and 2,120 labels) (Table 1 and Table 2). Using PyTorch U-net, 400 epochs were trained, and the best model, epoch
178, was recorded. In the testing group, the number of true positives was determined as 471 and false positives as 35, while 27 could not be detected. The sensitivity of CTPA segmentation was 0.95, the precision value was 0.93, the F1 score value was 0.94, and the learning rate was 0.0001. In the receiver operating characteristic (ROC) analysis, the area under the curve (AUC) value was calculated as 0.88 (Table 3). The graph of the ROC analysis showing the AUC value is given in Fig. 1. The image of the patient whose segmentation was successfully performed is given in Fig. 2. The image of the U-net architecture is given in Fig. 3.

<table>
<thead>
<tr>
<th>Number of patients</th>
<th>Number of images</th>
<th>Number of labels</th>
<th>Number of images after data augmentation</th>
<th>Number of labels after data augmentation</th>
</tr>
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<tbody>
<tr>
<td>1,550</td>
<td>1,879</td>
<td>4,929</td>
<td>7,516</td>
<td>19,716</td>
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</table>

Table 1
Number of images and labels in the training set

<table>
<thead>
<tr>
<th>Number of patients</th>
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<th>Number of labels after data augmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1,550</td>
<td>230</td>
<td>530</td>
<td>920</td>
<td>2,120</td>
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</table>

Table 2
Number of images and labels in the validation set

<table>
<thead>
<tr>
<th>Number of patients</th>
<th>Number of images</th>
<th>Number of labels</th>
<th>Number of images after data augmentation</th>
<th>Number of labels after data augmentation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1,550</td>
<td>230</td>
<td>533</td>
<td>0.95</td>
<td>0.93</td>
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Table 3
Number of images and labels, and sensitivity, precision, F1 score and AUC values in the testing set

AUC, area under the curve

Discussion

Artificial intelligence studies are increasing day by day in all fields of science, especially medicine. As a current issue, in our study, we segmented pulmonary embolism using the deep learning method on axial section images of patients with pulmonary artery embolism who underwent CTPA. In the testing group of our study, the sensitivity, precision, F1 score and AUC values obtained with our artificial intelligence model were measured as 0.95, 0.93, 0.94, and 0.88, respectively, indicating successful results in the diagnosis and segmentation of pulmonary embolism.

Weikert et al. evaluated the performance of an artificial intelligence algorithm called AI-powered algorithm and detected pulmonary embolism on CTPA images. The authors used approximately 28,000 CTPA images for validation, and utilized the ResNet architecture in the convolutional neural network application. The sensitivity value of the AI-powered algorithm in the detection of pulmonary embolism
was found to be 92.7% [18]. In contrast, in our study, segmentation was performed instead of detection. Our sensitivity value was 95%, which is slightly better compared to the value reported by Weikert et al. In addition, we did not include the images of patients without pulmonary embolism, unlike the previous study [18].

In another study using the computer-aided detection algorithm, the sensitivity was calculated separately for the detection of emboli in the main pulmonary artery, lobar, segmental and subsegmental arteries, and as expected, the sensitivity in the detection of embolism in the main pulmonary artery (87%) was found to be higher compared to the subsegmental artery (61%) [19]. Different from this study, we did not perform separate calculations for embolisms detected in the main pulmonary, lobar, segmental and subsegmental arteries.

Rucco et al. used the neural hypernetwork for the diagnosis of pulmonary embolism and obtained from the images of 1,427 patients. This method successfully diagnosed pulmonary embolism at a rate of 94% [20], which is quite similar to our study. In another study conducted using the deep learning method, multimodal fusion was used, and both clinical and laboratory data and images of the patients were evaluated [21]. The AUC value of that study was higher than we obtained. This may be due to the previous authors’ inclusion of clinical and laboratory data in their evaluation.

Huang et al. used the PENet system and attempted to diagnose pulmonary embolism on volumetric CT images with 3D CNN in the infrastructure [22]. The authors found the AUC value to be approximately 0.85, indicating that our method was more successful. In addition, different from our study, Huang et al. performed detection rather than segmentation.

In another study that aimed to detect pulmonary embolism with deep learning, clot burden assessment was also performed, and segmentation was applied [23]. Unlike our study, the authors also calculated the volume of embolism and measured cardiovascular parameters on CT for pulmonary embolism.

We consider that our study is clinically important because the method presented shortens the patient service and evaluation time. In addition, the workload of radiology departments can be reduced using the deep learning-based segmentation model we created, and this will contribute to this field.

One of the limitations of our study is that the segmental branches of the pulmonary artery and the main pulmonary arteries were not considered separately. In addition, the success of the model presented in our study can be increased by including the clinical and laboratory findings of the patients and evaluating cardiovascular parameters that contribute to the course of pulmonary embolism using CT. This will help obtain more successful model alternatives.

**Conclusions**

In conclusion, in this study, the segmentation of acute pulmonary embolism in CTPA was performed using the deep learning method, and successful results were achieved. We consider that in future,
artificial intelligence-based algorithms will find more place in clinical operation and facilitate the work of clinicians and radiologists.

Declarations

Ethics approval and consent to participate

Ethical approval for this study was obtained from the ethics committee of the Medical University of Eskisehir Osmangazi (Ethics committee decision number: 14, Date: 15 February 2022). All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants in the study.

Consent for publication

Not applicable.

Availability of data and materials

All data generated or analysed during this study are included in this published article.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Not applicable

Authors' contributions

NA and FA conceived the idea for the study. NA and CC performed literature search. CC collected data. NA, OC, AFA and AO performed data analysis. NA and HY wrote the article. All authors critically revised the manuscript, commented on drafts of the manuscript, and approved the final version.

Acknowledgements

Not applicable

Abbreviations

CTPA
Computed tomography pulmonary angiography
ROC
Receiver operating characteristic
AUC
Area under the curve
HU
Hounsfield Unit

References


Figures
Figure 1

Graph of the ROC analysis (ROC, receiver operating characteristic; AUC, area under the curve).
Figure 2

Computed tomographic pulmonary angiography examination revealed filling defects consistent with acute pulmonary embolism in the pulmonary arteries and segment branches of the lower lobes of both lungs in a 63 years old male patient. Segmentation of the areas consistent with the detected acute pulmonary embolism was performed.

Figure 3

The image of the U-net architecture