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Original Article

Automatic Segmentation, Detection, and Diagnosis of Abdominal Aortic Aneurysm (AAA) Using Convolutional Neural Networks and Hough Circles Algorithm

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Abstract
Purpose—An abdominal aortic aneurysm (AAA) is known as a cardiovascular disease involving localized deformation (swelling or enlargement) of aorta occurring between the renal and iliac arteries. AAA would jeopardize patients' lives due to its rupturing risk, so prompt recognition and diagnosis of this disorder is vital. Although computed tomography angiography (CTA) is the preferred imaging modality used by radiologist for diagnosing AAA, computed tomography (CT) images can be used too. In the recent decade, there has been several methods suggested by experts in order to find a precise automated way to diagnose AAA without human intervention base on CT and CTA images. Despite great approaches in some methods, most of them need human intervention and they are not fully automated. Also, the error rate needs to decrease in other methods. Therefore, finding a novel fully automated with lower error rate algorithm using CTA and CT images for Abdominal region segmentation, AAA detection, and disease severity classification is the main goal of this paper.
Methods—The proposed method in this article will be performed in three steps: (1) designing a classifier based on Convolutional Neural Network (CNN) for classifying different parts of abdominal into four different classes such as: abdominal inside region, aorta, body border, and bone. (2) After correct aorta detection, defining its edge and measuring its diameter with the use of Hough Circle Algorithm (which is an algorithm for finding an arbitrary shape in images and measuring its diameter in pixel) is the second step. (3) Ultimately, the detected aorta, depending on its diameter, will be categorized in one of these groups: (a) there is no risk of AAA, (b) there is a medium risk of AAA, and (c) there is a high risk of AAA.
Results—The designed CNN classifier classifies different parts of abdominal into four different classes such as: abdominal inside region, aorta, body border, and bone with the accuracy, precision, and sensitivity of 97.93, 97.94, and 97.93% respectively. The accuracy of the proposed classifier for aorta region detection is 98.62% and Hough Circles algorithm can classify 120 aorta patches according to their diameter with accuracy of 98.33%.
Conclusions—As a whole, a classifier using Convolutional Neural Network is designed and applied in order to detect AAA region among other abdominal regions. Then Hough Circles algorithm is applied to aorta patches for finding aorta border and measuring its diameter. Ultimately, the detected aortas will be categorized according to their diameters. All steps meet the expected results.

Keywords—Abdominal aortic aneurysm (AAA), Convolutional neural networks (CNN), Hough circles algorithm, CTA images, CT images, The state of the art result.

INTRODUCTION

One of the most common diseases among elderly people, especially men, is Abdominal Aortic Aneurysm (AAA). About 1.3% of death in men aging over 65 years is caused by rupturing aorta in abdominal region.[15]

An AAA is known as a cardiovascular disease involving localized deformation (swelling or enlargement) of an aorta that occurs between the renal and

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iliac arteries.[10] The normal diameter of an aorta is around 20 mm, and it will be considered as an aneurysm commonly when the diameter of the infra-renal aorta increased 50% compared to the normal diameter.[10] An AAA is a kind of asymptomatic disorder until the event of rupture occurs. Although repair of large AAA is highly recommended, surgery for small ones is not useful.[15]

The AAA is made of two sections. The inner section is called Lumen and the outer part, the fatty part, is Thrombus.[14] As a result of aortic wall weakness and its deformation, the thrombus will be generated by coagulation during blood flow between the aorta layers.[3,6,10]

Endovascular Aneurysm Repair (EVAR) can be considered as an alternative way for AAA treatment, that avoids the expanded tissue dissection compared to open repair. Placing a stent within the lumen of the aorta covers the entire lumen and can decrease the blood pressure impact on the aortic wall. Also attention is paid to newer devices, such as fenestrated and branched stent grafts, which will further expand the number of patients eligible for EVAR treatment.[17]

Computerized Tomography Angiography (CTA) is used to provide accurate information about the pre- and post-operative treatment, and evaluating the patient health status during the period of disease as well.[6,18] However, the overall diagnosis rate of AAA is low, and it is equal to 6.3% in a 10 years' time span.[2]

Radiologists use CTA images to segment AAA in order to diagnose the severity of disease and measure the accurate aorta diameter. However, the process of AAA 3D visualization is an exhausting and time-consuming job as it is done in the slice to slice process. On the other hand, the human error in AAA diagnosis may involve in this procedure. Therefore, presenting a fully automatic procedure for AAA segmentation and measuring its diameter will be very beneficial. In recent years several methods have been proposed by researchers in order to segment and diagnose AAA which can be classified in two categories: semi-automatic, which human interventions take part in AAA diagnosis, and fully automatic procedures that are done completely by computers.

Related Work and Motivations

Generally, there are a few categories of AAA segmentation techniques such as machine learning techniques, deformable models, probabilistic graphical models, and knowledge-based methods. Olabarriaga *et al*. suggested a 3D discrete deformable model-based approach, which accepts a nonparametric statistical grey level model provided from training data with a supervised learning classification technique. This method was able to initialize the model with minimal user intervention and also to generate acceptable results in interactive response time.[13] In Subasic *et al.* work, level-set algorithm which is able to model the complex shapes that can frequently happen in aortic aneurysm area was used. Although the proposed method is semi-automatic, and also required user intervention is minimal, it still encounters difficulties due to the lack of domain knowledge about the object of interest with respect to the segmented results.[16] In the research work by Majd,[11] the proposed method utilized a region-based level set method which is devised in terms of energy minimization. The Bayesian risk which was incorporated into the level set is able to cope with classification error which occurs during segmentation. This method is semi-automatic where user's interaction is needed for initial contour drawing by selecting or drawing a polygon around the AAA region. In the study by Maiora and Grana, a novel active learning hybrid approach for semi-automatic detection and segmentation of the lumen and thrombus of the AAA is introduced, where image intensity features and discriminative Random Forest (RF) classifiers are used for the segmentation of AAA regions.[10] In this method, the parameters of the process for a large number of dataset need to be fine-tuned and the model needs to be pre-trained. A DBN (Deep Belief Network) classifier has been designed in Ho Aik Hong and his colleagues research in order to segment abdominal regions and detect AAA in CTA images.[5] This classifier consists two hidden layers, 40 neurons each layer, 25 iterations, and batch size of 100 and 160. However, the classifier has 10% error rate in AAA segmentation when the AAA size is large in batch size of 160, and 20% error rate in classifying other classes of the test set in a batch size of 100.[5]

As it can be seen, several works have done on detecting and diagnosis AAA, but most of them suffer from lack of fully automated method for purposes like Computer Aid Diagnosis for clinical approaches, and human intervention is unavoidable in them. On the other hand, some methods like the work done by Ho Aik Hong *et al.,*[5] despite its fully automated method for detecting and segmenting AAA, suffers from the lack of precision, and the error rate is between 10 and 20%. Therefore, finding a more precise fully automated method will be useful. So, in this paper we attempt to suggest a novel method to cover our purposes.

CNNS and Hough Circle Algorithm

Convolutional Neural Network (CNN) is a well-known deep learning architecture inspired by the natural visual perception mechanism of the living creatures.[4] A basic CNN consists of three types of layers, namely convolutional, pooling, and fully connected layers.[4] CNNs are one of the most important deep learning algorithms that their several layers can be trained with a powerful method.[9] Due to the CNNs great capability of feature extractions, they are mostly used in image processing projects. CNNs need two steps procedure for training: (1) Feed Forward step, and (2) Backpropagation step. In the first step, the network learns features due to the convolutional processes and the network error is calculated using loss functions, and in the second step, the obtained error is minimized with the help of chain rule in backpropagation algorithm. These two steps are repeated frequently till the network error becomes the least.

The Hough transform is a method for detecting curves by exploiting the duality between points on a curve and parameters on that curve.[7] Hough circle algorithm and Generalized Hough Transform have been proposed for detecting arbitrary shapes in images.

In this paper, a novel automated algorithm with the state of the art result for AAA detection and segmentation using a Convolutional Neural Network (CNN) classifier combined with Hough Circle algorithm[7] is proposed.

The rest of this paper is organized as follow: In "Methods", we describe the proposed method in detail. "Results" section illustrates the results and "Discussion" section provides a comparative discussion of the proposed algorithm with existing methods. We conclude the paper in the last section ("Conclusion").

METHODS

Proposed algorithm has the following steps respectively:

(1) Getting CT or CTA image as input and resizing it to an image with the size of 384 × 384 pixels.
(2) Scanning through CT or CTA images with a 64 × 64 pixel's window, cropping patches from the images with an adjustable step rate.
(3) Classify the extracted patches, using designed CNN classifier, in four different categories and defining the aorta region.
(4) Segmenting aorta, using aorta region in the previous step, by Hough circle algorithm and measuring its diameter.
(5) Defining disease severity according to the aorta diameter.

Based on the proposed algorithm, this section is divided into three main steps such as (1) data preparation and data preprocessing, (2) designing an appropriate convolutional neural network for classifying different parts of the abdomen in order to segment AAA region, and the last step is (3) AAA measurement and diagnosis of disease severity.

Dataset Preparation

Collecting Data

The required data is extracted from ten patients CT and CTA datasets from Shariatee Hospital (Tehran, Iran) that two of them have obvious AAA. Every patient dataset contains 160 CT or CTA slices from the abdominal region (Fig. 1).

Patches' Extraction

The extracted slices from Marco Imaging diVision Lite software have.jpg format with the size 512 × 512 pixels and they have been captured by FOV of 480. As we considered the size of 64 × 64 pixels for network input, so the extracted images first resized to 384 × 384 pixels in order to patches consist a larger field of view, and then patches were extracted by scanning through the CT image with a 64 × 64 pixels' window, cropping from the original images using MATLAB codes. After extracting the patches, they are divided into four different classes including abdominal inside region, aorta, body borders, and backbone.

A total number of extracted patches are 5800 with an equal number of 1450 samples for each class (Fig. 2).

Dataset Preprocessing

In order to enhance the quality of the dataset, all patches were denoised using *Median* filter codes in MATLAB. Having considered training method as supervised training, all patches were labeled according to their related class. Labels 0, 1, 2, 3 stand for abdominal inside region, aorta, body borders and bones respectively. Finally, 60% of images were separated for train dataset (3480 images), 25% for test dataset (1448 images), and 15% for validation dataset (870 images). To avoid over learning on a specific class, a number of patches in all classes are equal. Before creating the essential LMDB files (required dataset format for Caffe framework) all patches from all classes were shuffled.

Data Augmentation

As having more datasets leads to having a better trained network,[12] during the training phase, the Mirror Transformation was used and the number of train dataset was doubled. The separated train dataset consists of 3480 images which was increased to 6960 images after using data augmentation.

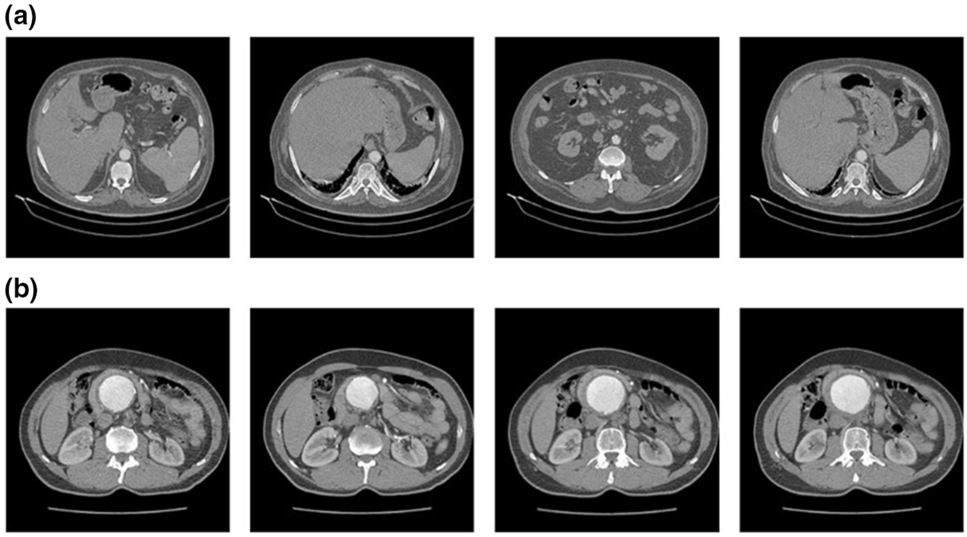

FIGURE 1. Samples of collected datasets, the first row (a) indicates images with the normal abdominal aorta, and the second row (b) shows images with obvious AAA in.

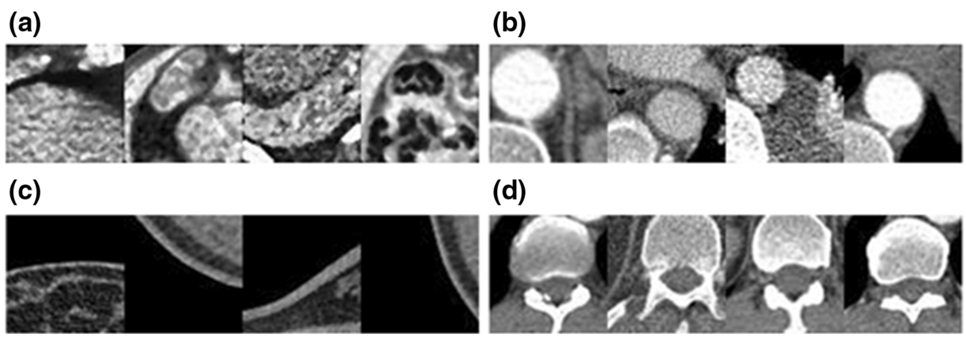

FIGURE 2. Samples of extracted patches in four classes: (a) abdominal inside region, (b) aorta, (c) body borders, (d) backbones.

Designing a CNN

In order to build the classifier for the detection of AAA patch and classification of abdominal regions, we relied on the use of Convolutional Neural Network designing and training on a Nvidia Geoforce 1060 graphic card with 6 Gb RAM. CNN is chosen to be applied in this AAA image segmentation problem as it is believed that the advantages and strength of using this deep architecture can be leveraged to solve the problem effectively. Although CNNs require a huge dataset, they are very powerful and also they give the state of the art results.

Every Convolutional Neural Network consists several layers such as data layer, convolutional layer, RELU, pooling layer, fully connected layer, drop out layer and so on.

Proposed CNN Classifier

CNN layers were arranged in various ways and layers' parameters were changed frequently. Every time the designed network was trained by train dataset and validated using validation dataset. Finally, the best design was obtained as shown in Fig. 3.

Table 1 illustrates the designed CNN in details. As shown, the proposed architecture consists a data layer as input, three convolutional layers for feature extraction, five RELU layers as activation function layers, one pooling layer for downsampling network parameter, two fully connected layers, one drop out layer with ratio of 0.1, one accuracy layer for calculating the accuracy of the training and validation datasets, and a loss layer for computing data loss during training phase.

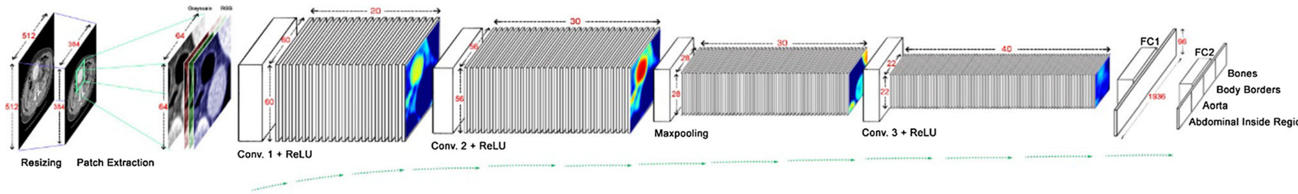

FIGURE 3. Designed CNN for different abdominal regions classification.

TABLE 1. Designed convolutional neural network layers and parameters.

Layers	Training parameters
Data	Dim: 64 × 64 × 3 Batch size: 100 Data augmentation: mirror true
Conv 1	Output Num: 20 Kernel size: 5 Stride: 1 Pad:0
ReLU 1	Type: ReLU
Conv 2	Output Num: 30 Kernel size: 5 Stride: 1 Pad:0
ReLU 2	Type: ReLU
Pooling 1	Type: Max Pooling Kernel size: 2 Stride: 2
Conv 3	Output Num: 40 Kernel size: 7 Stride: 1 Pad:0
ReLU 3	Type: ReLU
FC 1	Output Num: 96 Type: InnerProducts
ReLU 4	Type: ReLU
FC 2	Output Num: 4 Type: InnerProducts
ReLU 5	Type: ReLU
Drop out 1	Drop out Ratio: 0.2
Accuracy	–
Loss	Type: SoftMax with loss

(1) *Convolutional layers (Conv1, Conv2, Conv3)* Convolutional layers, using different kernel sizes, perform feature extraction with the output of the previous layer.
(2) *ReLU layers (ReLU1, ReLU2, ReLU3, ReLU4)* The rectifier function $f(x) = \text{Max}(0, x)$ is an activation function which is used to add nonlinearity to the networks would only ever be able to compute a linear function.
(3) *Pooling layer (pooling 1)* Pooling layer performs network parameters downsampling to reduce the parameters in order to facilitate network calculations.
(4) *Fully Connected layers (FC1, FC2)* The output of a Convolutional Neural Networks most of the time is fully connected layers. These layers are connected to all neurons in the previous layer and usually flat high-level extracted features in data and produce outputs.
(5) *Drop out layer (Drop out 1)* This layer reduces network parameters randomly and protects the network from being overfitted.
(6) *Accuracy layer* This layer calculates the percentage of correct predictions in datasets.
(7) *Loss layer* This layer usually is used as the last layer in CNNs in order to define the losses in networks during training and testing phases. In this proposed network we use SoftMax (Eq. 1) With Loss (known as a normalized exponential function or Softmax regression) which returns the probability of each target class given the model predictions and also computes multinomial logistic loss, returned as output.

$$Softmax(yi) = \frac{\exp(yi)}{\sum_{i=1}^{k} \exp(yi)} \quad i = 1, 2, \ldots, k \qquad (1)$$

where yi are network outputs, and k is the number of outputs.

Solver Parameters

Training a designed CNN requires some hyper-parameters to be modified. In Caffe framework these parameters are modified as a solver.prtotxt file which defines the learning algorithm. Adam is an algorithm for gradient-based optimization of stochastic objective functions.[8] As Adam algorithm converges very fast and easily, so we used Adam solver as our solver type. While most of designed CNNs have a lot of layers, in this classifier we reduced the number of layers. In order to compensate the effect of layer number reduction, we decreased the learning rate to 0.0001 with a fixed learning policy (without any further decrease), and it worked great. The solver file parameters were modified as follow:

Type: Adam
Test Iteration: 15
Test interval: 200
Lr- base: 0.0001
Max iteration: 4000
Learning policy: fixed

Training

Training phase using Nvidia GeForce 1060 graphics card took two minutes and five seconds, and the proposed network was fed with 6960 image patches as training dataset (3240 extracted patches and 3480 augmented data), and 870 image patches as validation dataset. according to Fig. 2, which indicates the pro-

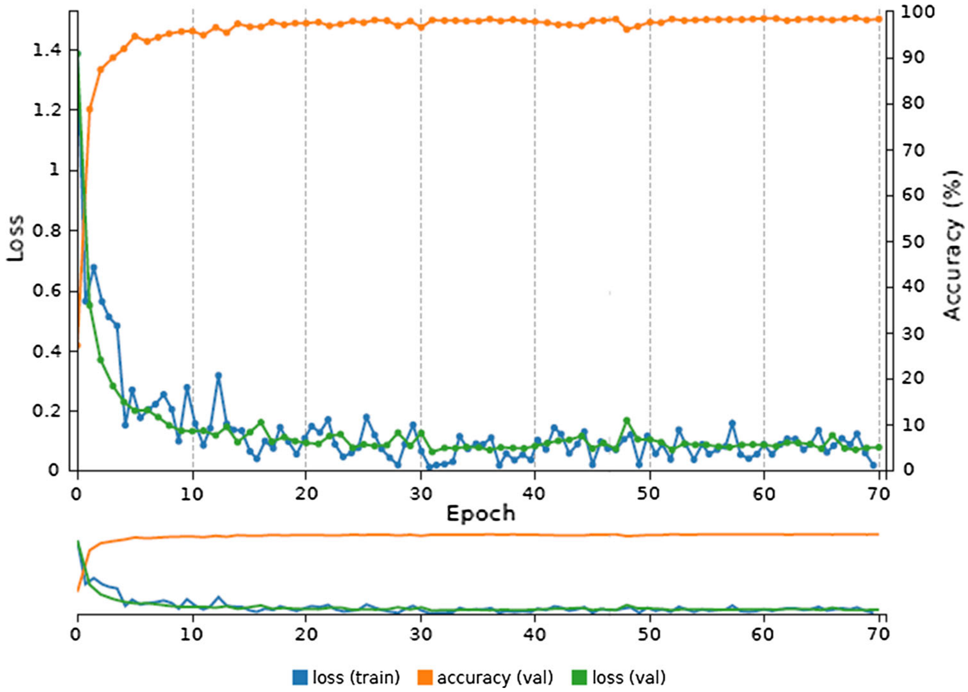

FIGURE 4. Proposed CNN architecture learning curve.

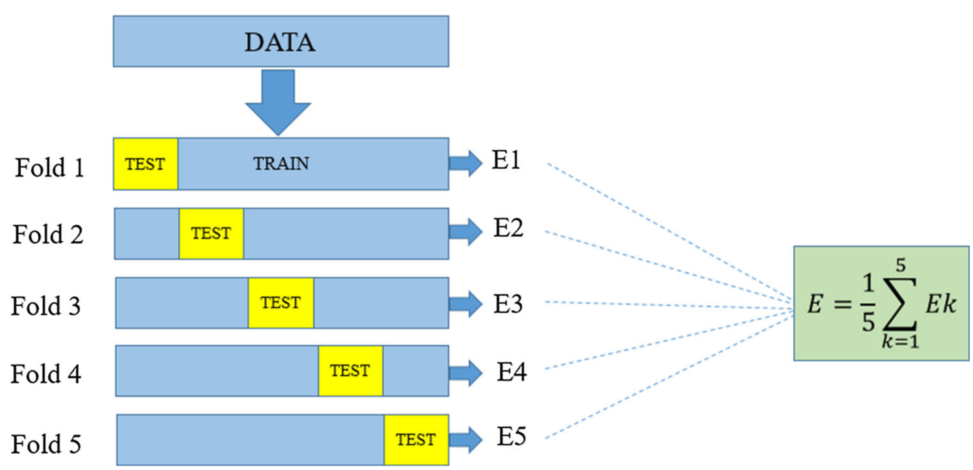

FIGURE 5. Fivefold cross-validation performed on the proposed CNN classifier.

posed CNN learning curve, the accuracy raised fast to 90% after two epochs while training and validation loss curve declined to less than five and network reached the accuracy of $98.5 \pm 0.3\%$ on validation dataset. This high accuracy can be counted as the state of the art result (Fig. 4).

Fivefold Cross-Validation

After the first round of training, in order to estimate the stability of the proposed classifier, a fivefold cross-validation performed. The prepared dataset (3240 patches for train dataset and 810 patches for validation dataset) consists of 4050 extracted patches as a whole and was divided to fivefolds. Every time, one of the folds left out (as validation dataset) and training performed with the rest of data while the Mirror Transformation was True during the training phase (Fig. 5). Table 2 Shows the acquired result.

Aorta Diameter Measurement

As seen in the previous sections, the target of this paper is to detect aorta using CT and CTA images and

TABLE 2. Fivefold cross-validation performed on the proposed classifier.

Fold #	Total number of train data + augmented data	Total number of validation data	Training time	Error (%)
Fold 1	6960	870	2 min 4 s	1.53
Fold 2	6960	870	2 min 5 s	1.42
Fold 3	6960	870	2 min 5 s	1.66
Fold 4	6960	870	2 min 6 s	1.62
Fold 5	6960	870	2 min 4 s	1.51
Average	–	–	2 min 6 s	1.54

measure its diameter to define the severity of AAA disease. Till now, we designed a CNN which can classify different part of abdomen successfully. After aorta detection, we should measure the diameter in order to determine the presence of disease and its severity.

The Hough transform is a method which can extract and detect curves in images.[7] The Generalized Hough Transform (GHT), introduced by Dana H. Ballard in 1981, is an algorithm using not just for line and curve detection, but for detecting arbitrary shapes such as circle and elliptic in images.[1]

In this section, we used Hough Circles algorithm using OpenCV library (Open Source Computer Vision Library), which is developed under a BSD license, in order to define exact aorta borders and measure its diameter with some modifications in the algorithm parameters. The output of Hough Circles algorithm is the diameter of the aorta in pixels, so it should be converted into millimeter in order to be understandable by users and to prepare a report in a correct way. The capturing FOV assumed to be 480, and the size of the captured image after resizing is 384×384 pixels. On the other hand, the scanning window for patch extraction is 64×64 pixels. Therefore, every time the scanning window will cover 80×80 mm of the whole image. Converting the diameter of the aorta in this way is very easy too. Thus the output of the Hough Circles algorithm, which is in a number of pixels, will be multiplied in 1.25. After measuring the diameter of the aorta, it will be categorized in one of these groups:

(a) If the measured diameter is less than 24 pixels, the output will show the exact diameter in mm and will print out "There is NO risk of AAA".
(b) If the measured diameter is more than 24 pixels and less than 40 pixels, the output will show the exact diameter in mm and will print out "There is a medium risk of AAA".
(c) If the measured diameter is more than 40 pixels, the output will show the exact diameter in mm and will print out "There is a High risk of AAA".

RESULTS

The CT and CTA images from abdominal region of ten human subjects, both patient, and healthy ones, were collected, and every set of data consisted 160 slices. Patches were extracted in four different classes, and the number of patches was totally 5800. The extracted patches were separated into 3480 (6960 patches after data augmentation) image patches as the train dataset, 870 image patches as the validation dataset, and 1448 image patches as the test dataset. After designing and training the proposed CNN, testing the network was done and total accuracy of 97.93% obtained. The results are illustrated in Table 2 as a confusion matrix:

As shown in Table 3, the proposed classifier achieved total sensitivity, precision, and accuracy of 97.93, 97.94, and 97.93% respectively. The obtained aorta region detection accuracy is 98.62% and it is not depended on the size of the aorta. According to the Table 3, there are five images in aorta category which were classified wrongly. Therefore, those aortas, which were classified mistakenly (Fig. 6), were identified and it was found that two of them were really noisy and one of them consisted mostly other parts of the abdominal region. The two remained patches were almost fine and they can be counted as real classifier error.

As the final step in AAA detection, we used Hough Circles algorithm in order to segment aorta and measure its diameter. Thus, we applied the Hough Circles algorithm to the majority of patches in aorta class and it could successfully define the aorta and measure its diameter. Some samples of segmented aortas are shown in Fig. 7.

As the last step, we chose a dataset containing 120 aorta patches with various aorta sizes. The Hough algorithm was tested using this dataset and the result was as follow:

According to Table 4 and the experimental results, the Hough Circle algorithm has a high sensitivity, precision, and accuracy in detecting aorta border and measuring its diameter (98.41, 98.33, and 98.41% respectively).

DISCUSSION

One of the former proposed algorithm in AAA detection and classification was the work by Ho Aik Hong,[5] and the suggested method is very close to ours.

TABLE 3. The designed CNN classifier confusion matrix.

	Abdominal inside regions	Aorta	Body borders	Bones	Sensitivity (%)	Precision (%)	Accuracy per class (%)
Abdominal inside regions	353	7	2	0	97.53	96.18	97.53
Aorta	4	357	0	1	98.62	97.01	98.62
Body borders	5	2	354	1	97.79	99.15	97.79
Bones	5	2	1	354	97.79	99.43	97.79
Total	367	368	357	356	97.93	97.94	97.93

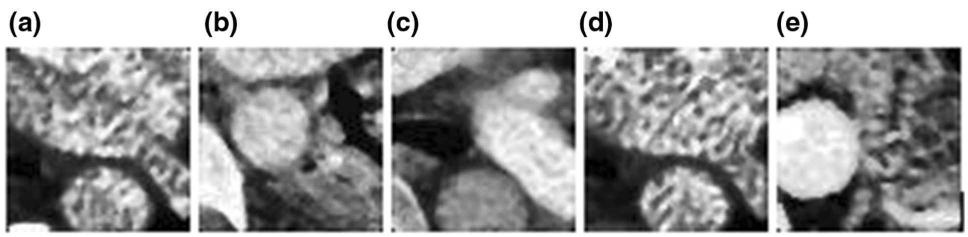

FIGURE 6. Aorta patches classifying wrongly. Two patches are really noisy (a and d), and one of them consists mostly other parts of the abdominal region (c). The two remained patches were almost fine and they can be counted as real classifier error (b and e).

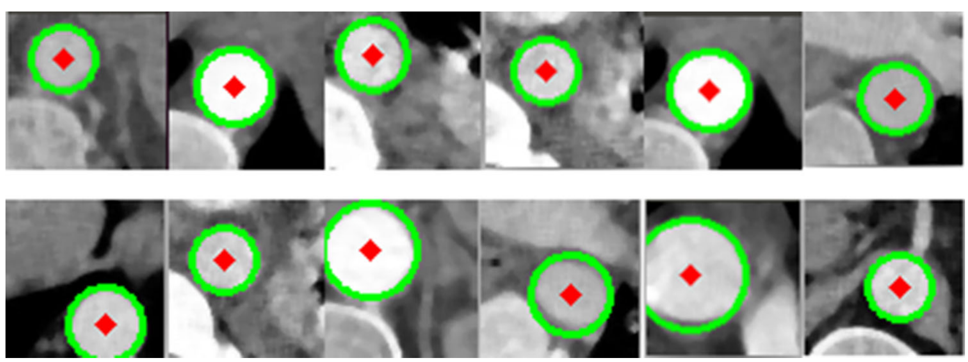

FIGURE 7. Samples of detected aortas using Hough Circles algorithm.

TABLE 4. Test result of Hough algorithm for 120 aorta patches (*D = aorta diameter).

	$D < 30$ mm	30 mm $< D < 50$ mm	$D > 50$ mm	Sensitivity (%)	Precision (%)	Accuracy per class (%)
$D < 30$ mm	39	1	0	100	97.5	100
30 mm $< D < 50$ mm	0	40	0	95.23	100	95.23
$D > 50$ mm	0	1	39	100	97.5	100
Total	39	42	39	98.41	98.33	98.41

In Ho Aik Hong and his colleague work, a Deep Belief Network (DBN) for different abdominal regions classification was designed and trained. According to their paper, the proposed algorithm was depended to the size of the aorta, and it missed patches containing large AAA in a trained network with a batch size of 160, and it missed other abdominal regions' patches when the network is trained with a batch size of 100. Thus, in our work, a CNN based classifier proposed, and its result shows much better accuracy (98.62%) in aorta detection. On the other hand, this classifier is in depended to aorta size and the extracted patch rotations.

In the research work by Majd,[11] the proposed method is semi-automatic where user's interaction is needed for initial contour drawing by selecting or drawing a polygon around the AAA region while in our paper finding aorta border will be done by Hough Circles Algorithm making human intervention minimal.

In the study by Maiora and Grana,[10] despite semi-automatic detection and segmentation of the AAA, the parameters of the process for a large number of dataset need to be fine-tuned and the model needs to be pre-trained. In contrast, in our work there is no need for fine tuning and pre-training the classifier as it was done before with an almost large dataset.

CONCLUSION

In this paper, we suggest an automated algorithm for detecting aorta region among other regions of the abdomen in order to diagnose AAA and its severity. A Convolutional Neural Network (CNN) was applied as a classifier in the first step for detecting aorta region and its diameter would be measured in the next step using Hough Circles algorithm. Decreasing both numbers of layers and learning rate at the same time with a fixed learning policy, in this work, did a great job, and gave us the state of the art result in this classification case. The proposed algorithm detects and classifies AAA successfully with the state of the art result, and it can be used for clinical purposes in order to diagnose AAA without human intervention.

Suggestion for Future Works

Despite the good results in this paper, the aorta in AAA is not always in circle or ellipse shape, sometimes it will be deformed in a way which is not in arbitrary shape. So as a suggestion for future works, collecting more patients with obvious AAA data in different shapes for training another CNN as a second classifier for AAA categorizing in three mentioned classes is recommended.

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CONFLICT OF INTEREST

Saba Mohammadi has received research grant number 96210 from the Research Council of Kermanshah University of Medical Sciences. Vahab Dehlaghi has received research grant number 96210 from the Research Council of Kermanshah University of Medical Sciences. Mahdi Mohammadi and Arash Ahmadi declare that they have no conflict of interest.

ETHICAL APPROVAL

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

Informed consent was obtained from all individual participants included in the study.

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