Hookworm Detection in Wireless Capsule Endoscopy Images Using Deep Learning with Tubular Region Detection

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***Abstract*— As one of the foremost common human helminths, hookworm could be a leading reason behind maternal and kid morbidity, that seriously threatens human health. Wireless Capsule endoscopy (WCE) could be a relative novel technology, which might read entire gastrointestinal (GI) tract. Recently, wireless capsule endoscopy images has been applied to automatic hookworm detection.Unfortunately, it remains a difficult task. In recent years, deep convolutional neural network (CNN) has demonstrated performance in varied image and video analysis tasks. During this paper, a unique deep hookworm detection framework (DHDF) is projected for WCE images, that at the same time models visual appearances and hollow patterns of hookworm.Two CNN networks, namely edge extraction network and hookworm classification network, are seamlessly integrated in Deep learning method.In this paper hookworm can be detected by using colormap extraction, tubular region detection and pixel value of the image. The high sensitivity and accuracy of the projected methodology in detective work hookworms shows its potential for clinical application.**

***Keywords*—Convolution neural network, Automatic hookworm detection,deep learning,wireless capsule endoscopy.**

I.INTRODUCTION

Human hookworm infection is known as helminthes infection.Hookworms live in small intestine and result in blood loss to cause anemia and malnutrition. The infections also retard growth and mental development of children. However, eggs are difficult to find in mild infections. Most GI track diseases such as hookworm can be easily detected by Wireless Capsule Endoscopy.It is a noninvasive technology which can inspect the entire GI track without anesthesia and air insufflation. As a miniature medical device for gastrointestinal (GI) diagnosis, Wireless Capsule Endoscopy travels through the digestive system to collect images or physiological data after swallowed by the patient. It will take two or more color images of GI tract per second, which will la st for a few hours to capture the whole GI tract, totally around 50, 000 images. It is a laborious and tedious process for trained endoscopists to identify suspicious areas and analyze the potential diseases, which usually take a couple of hours to manually examine these images.Unfortunately, automatic hookworm detection [1], [2] in WCE images has not been fully explored. Automatic hookworm detection in WCE images remains a challenging task. The quality of WCE images is usually poor due to the hardware limitation and the light condition. Its resolution is only 256x256 pixels. Abdominal CT images have been widely used in medical applications. Some of the current interests are the automatic diagnosis of Hook Worm pathologies and three dimension rendering. The first and fundamental step in all these studies is the automatic Hook Worm segmentation, which is still a complex problem. There are several reasons make the accurate segmentation in Hook Worm difficult. Firstly, the image is always very noisy and the partial volume effect causes the Hook Worm boundary ambiguous. Secondly, the overlaps result in gaps and cavities. Thirdly, there are large variations in human Hook Worm geometric properties like Hook Worm size and shape between patients, this can be worse if the patient has Hook Worm operations before due to alcoholic cirrhosis or Hook Worm tumor. Finally, the nearby organs such as right kidney, stomach, spleen and abdominal wall, have similar intensity values with Hook Worm, which makes it harder to extract Hook Worm only. They can be categorized into four groups:

Intensity based approaches: The most common procedure is to apply threshold operators to discard regions with intensity outside the Hook Worm range. Prior knowledge based approaches: The topological, distance and orientation relations are the foremost common used previous data.They always combine with other approaches.

Statistical based approaches:A statistical model discrimination of the Hook Worm is established from quantities of data sets, and then the model is used to pre-process the images and obtained Hook Worm likelihood images for further process.

Active contour models: It is the most popular used method in Hook Worm segmentation, including fast marching level set method snake model. Most of the models compound the computing time and get unsatisfied results for the slices with fuzzy Hook Worm boundary.

In the region growing method is introduced, the principle methods and theories in our Hook Worm segmentation process are described. The experimental results are presented.

Accurate Hook Worm segmentation on computed tomography (CT) images is a challenging task because of inter and intra-patient variations in Hook Worm shapes, similar intensity with its nearby organs. We proposed a Hook Worm segmentation method based on region growing approach. First of all, basic theory of region growing approach is introduced in this project.Pre-processing method using anisotropic filter and Gaussian function is employed to form Hook Worm likelihood images for the following segmentation.An improved slice-to-slice region growing methodology combined with centre of mass detection and intensity distribution analysis is projected.

Finally, the superior Hook Worm region is extracted by applying the morphologic operation. Experiments on a variety of CT pictures show the effectiveness and efficiency of the proposed technique.There are several reasons make the accurate segmentation in Hook Worm detection. Firstly, the image is converted from RGB to Gray scale image,then the image is pre-processed to detect the hookworm by using region growing approach finally the image is segmented.This paper is used to identify the hookworm easily by using Tubular region detection method.

- In the proposed system, hookworm detection and visual appearances of tubular patterns of hookworm
- More specifically, hookworm region can be detected by using tubular region detection technique and also find the pixel value of each region..
- Experiments have been conducted on one of the largest WCE datasets with 440*K* images.The 90% accuracy with comparable sensitivity and specificity makes the proposed method clinically practical.

II. RELATED WORK

In this section, we will first review the works on pathological abnormality detection for WCE images, and then introduce the deep learning techniques used for medical image processing.

A.Pathological Abnormality Detection

Recently, computer aided detection systems for WCE have been extensively conducted, which bring endoscopists great convenience and efficiency. Comprehensive surveys [10] and[11] systematically summarize the latest development on WCE research from different aspects.The majority of the WCE research is related to bleeding detection since it is the main clinical pathology in GI tract. Bleeding region detection and frame localization is solved with support vector machine (SVM) and KNN classifier [4]. A rapid bleeding detection method for WCE video is proposed in [3], in which red ratio of RGB color space is extracted from each super pixel and then classified with SVM. For the polyp and the perforated ulcer detection, a synergistic framework based on the range ratio color is proposed in [5]. Based on this feature, the images are segmented to candidate regions, and geometric characteristics like curvature and eccentricity are applied to produce the final polyp candidates. Polyps are detected based on the geometrical analysis and the texture content of WCE frames [6]. An improved bag of features (BoF) method is proposed in [7] to assist classification of polyps in WCE images. Color texture feature is integrated with uniform local binary pattern (LBP) and wavelet for polyp and tumor detection [8]. Feature selection is further employed to improve the detection accuracy. Discrete lesions created by mucosal inflammation in Crohn's disease are first classified, and the lesion severity is also assessed [9]. A coding method called saliency and adaptive LLC (SALLC) is proposed in [12] to detect multiple abnormal images, including bleeding, polyp, and ulcer from WCE images.

Although extensive works have been conducted on pathological abnormality detection for WCE images/videos, there are limited works on automatic hookworm detection. In [1], hybrid color gradient and contourlet transform are utilized to detect hookworms. However, this work is evaluated in a relative small and balanced dataset with 1,500 images. Recently, we explore the automatic hookworm detection on a very large and imbalanced dataset [2], in which the piecewise parallel regions are first detected and then represented in the consistent format, i.e., uncurled tubular regions (UTR). To discriminate the unique features for different components of GI, the histogram of average intensity (HAI) is proposed to represent their properties. The experiments demonstrate promising performance. In this paper, instead of using the hand-drafted features, we further boost the performance by tailoring deep learning methods for this task.

B.Deep Learning for Medical Image Processing

Inspired by biological processes and designed to recognize patterns directly from image pixels, deep convolutional neural network (CNN) [13], [14]–[16] has achieved great success in various tasks, such as image classification, object detection, image segmentation, and so on. Recently, deep learning has been imported into medical image processing and presented impressive performance on different applications in image segmentation and lesion detection [17]–[24]. In this subsection, we will first introduce the lesion detection works based on deep learning, followed by other aspects affecting deep learning performance, such as network architecture, training strategy, and so on.The majority research based on CNN focuses on magnetic response (MR) and CT images.

Cerebral microbleeds from MR images, which takes full advantages of spatial contextual information in MR volumes to extract more representative high-level features, achieving better detection accuracy.The convolutional classification restricted Boltzmann machine is proposed in [27] for lung texture classification and airway detection in CT images, which combines a generative and a discriminative learning objective. A deep neural network based segmentation method is proposed in [28] to detect retinal blood vessels, in which several network architectures and image preprocessing methods are explored. A CNN is proposed for interstitial lung disease classification [29].

In addition to lesion detection, deep learning techniques have been investigated in other aspects of medical image processing. Three important factors, i.e., network architectures, dataset characteristics and transfer learning, are discussed for thoraco-abdominal lymph node detection and interstitial lung disease classification [30]. A fast method is proposed in [31] to speed up the CNN training for medical image analysis tasks, by dynamically selecting misclassified negative samples during training. One relevant CNN-based work for WCE images is digestive organ classification [32], in which a deep CNN framework is employed to learn layer-wise hierarchy models to classify the digestive organs in WCE images. Four distinct medical imaging applications based on deep learning are explored in three specialties (radiology, cardiology, and gastroenterology) [33], including polyp detection, pulmonary embolism detection, colonoscopy frame classification and intima-media boundary segmentation from different imaging modalities.Although various works based on deep CNN have been applied to medical image processing, existing deep learning based approaches for other medical applications are not directly applicable for hookworm detection.

III. PROPOSED ALGORITHM

In this section, we will introduce the region growing technique in Fig. 1. To capture the tubular patterns of hookworms, region growing method is used to identify the region of the hookworm is first adopted to produce the edge maps and then they are fed into colormap extraction is used for tubular region detection.A novel automatic hookworm detection process is proposed for WCE images, which analyzes the characteristic of hookworms. The contributions of this work are as follow:The piecewise parallel region detection (PPRD) and the uncurled tubular region (UTR) are novelly proposed to detect the parallel regions and represent the extracted regions.To discriminate the distinctive options for various part of GI, like hookworms, bubbles and folds, the histogram of average intensity (HAI) is projected to represent their properties.The experiments are performed on the datasets for WCE detection, WCE images of the patients.

A.Region Growing Technique

Region growing methodology has been widely been widely utilize in image process that segments pictu-res into many homogeneous regions based on a seed point set. As the name implies, region growing method begins with the seed point set and grows by adding neighbor pixels that satisfy the similarity constraint. This method is continual till all pixels belong to some region. Region growing could be a easy region-based image segmentation methodology. It's additionally classified as a pixel based image segmentation technique since it involves the choice of initial seed points. This approach to segmentation examines neighboring elements of initial “seed points” and determines whether or not or not the pixel neighbors need to be extra to the region.The method is iterated in the same manner as general information cluster algorithms.The first step in region growing is to select a seed points. Seed point selection is based on some user criterion. The initial region begins because the exact location of those seeds. The regions are then full-grown from these seed points to adjacent points depending on a locality membership criterion. The criterion may be, for instance, constituent intensity, gray level texture, or color.Since the regions are full-grown on the idea of the criterion, the image data itself is very important. for instance, if the criterion were a constituent intensity threshold price, information of the histogram of the image would be of use, as one could use it to see a suitable threshold price for the region membership criterion.There's a very easy example followed below and therefore the criteria we build here is that the same pixel value. That is, we tend to keep examining the adjacent pixels of seed points. It's an iterated method till there are not any modification in 2 successive iterative stages. Of course, we are able to build alternative criteria, however the most goal is to classify the similarity of the image into regions.A general discussion of the region growing algorithmic program is represented below.

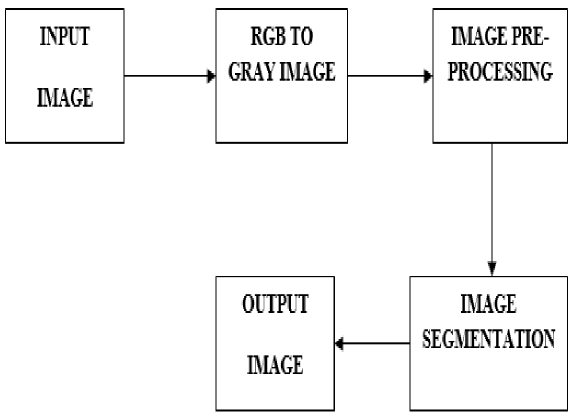

Fig.1 Block Diagram of Region Growing

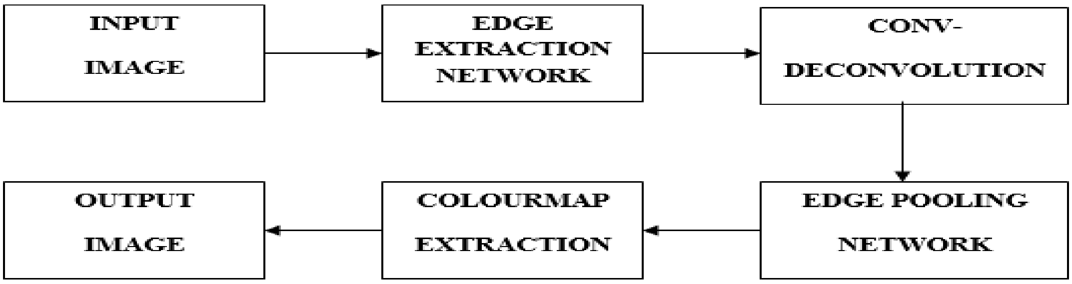

Fig.2 The Deep hookworm detection framework of colormap extraction

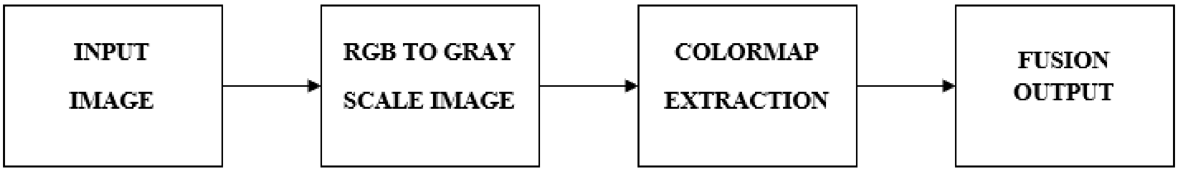

Fig.3 Block diagram of fusion output

B.Image Pre-Processing

Anisotropic filter could be a diffusion process, which may be used as a preprocessing step to morphological definition of the input image by sharpening discontinuities, and take away noise in homogenized regions while preserving object boundaries and fine details.

C.Region Based Segmentation

Region based mostly segmentation could be a technique to spot the region of the image.Segmentation refers to the strategy of partitioning a digital image into multiple.The goal of segmentation is to change and/or change the representation of a picture into one thing that's a lot of substantive and easier to investigate. Image segmentation is often used to find objects and boundaries (lines, curves, etc.) in pictures. a lot of exactly, image segmentation is that the method of assignment a label to each picture element in a picture such pixels with an equivalent label share certain visual characteristics.The results of image segmentation could be a set of segments that collectively cover the complete image, or a collection of contours extracted from the image. The main goal of segmentation is to partition an picture into regions.Some segmentation ways in which like "Thresholding" reach this goal by finding out the boundaries between regions supported discontinuities in gray levels or color properties.

D.Colormap Extraction

The side-outputs at different scales are illustrated in Fig. 5. From this figure, we can see that there exists a curled tubular-like hookworm in the top-right region of this WCE image. The detailed edges in side-outputs become vague and are not easy to be discerned as the level of side-outputs increases. For the side-outputs in higher levels (e.g., the 4th and 5th layers), the edge predictions are coarse. The edges of hookworms are merged with the borders of folders. Only the outline of the whole WCE image is remained and many critical edges are absent. On the contrary, the side-outputs in lower levels (e.g., the second and third layers) include more details, in which the edges of hookworms can be well detected, especially the third layer side-output. It is critical to ensure that the edges of hookworms are preserved in the side-outputs, so that tubular regions of hookworms can be captured. Therefore, in this paper, the second and the third side-outputs are selected as the inputs of tubular region detection.

E.Tubular Region Detection

Multi-scale dual matched filter (MDMF) proposed in [11] is used to detect the tubular regions in WCE images. It is a Gaussian-shaped template based on prior information that the cross-section of a hookworm is Gaussian-shaped. The tubular region will produce a higher response when the matched filter convolves with the image. The side-outputs produced by HED contain a large number of edges, among which only a small portion of edges belongs to the hookworms. The side- outputs are then passed to MDMF to emphasize the edges of the hookworms and suppress the noisy ones.In order to adapt to different orientations of hookworm bodies, the kernel is rotated to all possible orientations, and a set of filter banks is obtained. The filter bank is normalized to zero mean after rotation. The final response is the one with the maximum convolution in the filter bank.Since the match filter is rotated to eight different orientations and resized into two scales there are totally sixteen tubular region maps containing the part of the hookworm.

F.Spatial And Temporal Filtering

Spatial and temporal filtering are used to modifying or enhance image to boost the performance and examine the spatial variations of an image.Temporal filtering occurs when you have series of images taken at different time.This method is used to find the hookworm in wireless capsule endoscopy images.Filtering is used to remove noise and enhance the images,but this Laplacian filtering is mainly for reconstruct the filtering image of Laplacian and get the final hookworm detected image.In this paper,spatial and temporal filtering of hookworm images is used to detect the hookworm in this filtering.Correlation are used in spatial and temporal between the image to identify the changes in the image.

IV .RESULTS AND DISCUSSION

Region Growing Technique has been widely utilize in image process that segments pictures into many regions based on a seed point set.

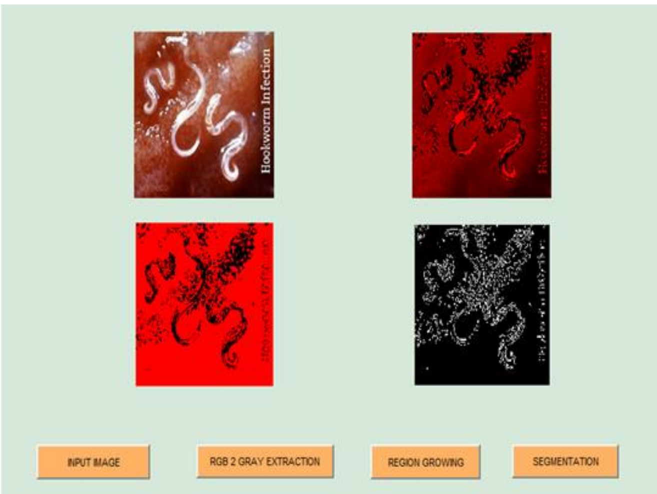

Fig.4 Region growing

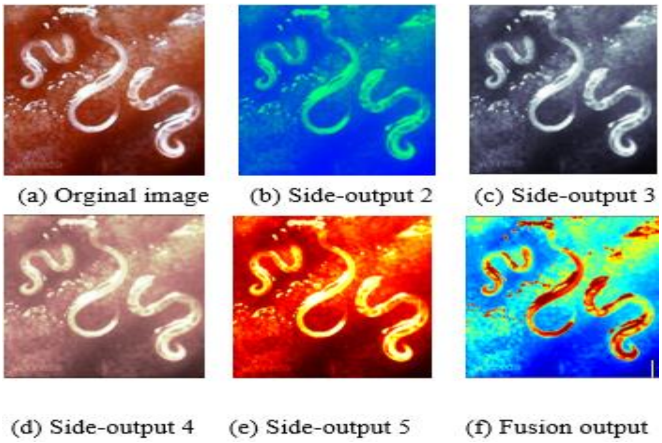

Fig.5 Five side-outputs and a fused output

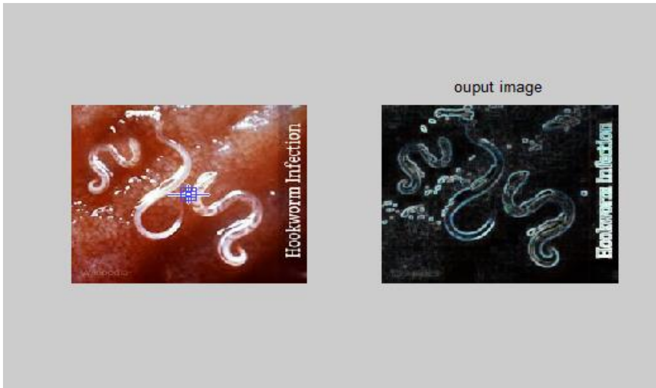

Fig.6 Tubular Region Detection

Pixel value can be detected to identify the pixel value of each region in the input image.The pixel value of the image represents the brightness of the pixel.

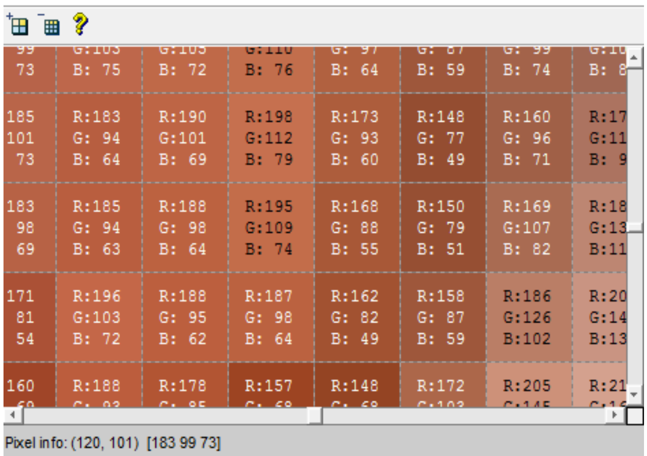

Fig.7 Pixel value of an image

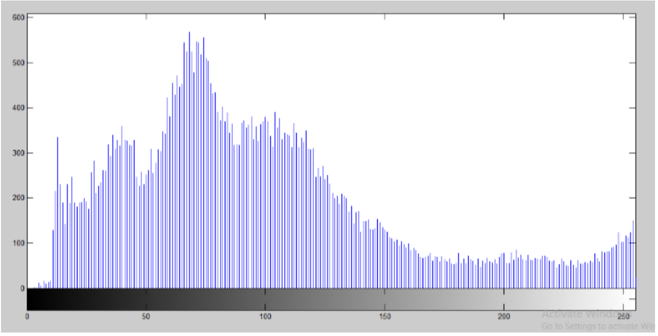

Fig.8 Histogram of average intensity

Spatial filtering method is an image processing technique is used for changing the intensities of a pixel of the image according to the intensities of the neighboring pixels of the image.

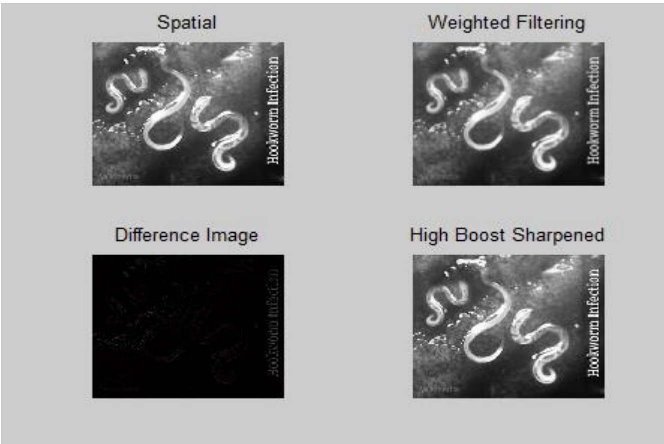

Fig.9 Spatial filtering

Temporal filtering is used to remove unwanted frequencies within the raw signal.This should be substantially improve the signal to noise ratio.

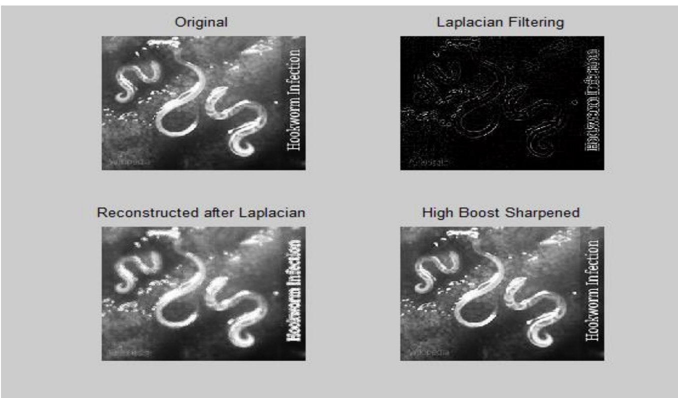

Fig.10 Temporal filtering

V. CONCLUSION

In this paper,hookworm can be detected by using region based segmentation of tubular region detection method, pixel value of the image can be identified in WCE image also visual appearance and tubular regions of hookworms can be detected. The influence of background can be completely avoided by using tubular region detection.The noisy edge maps have been filtered by MDMF and regularized edge pooling in the existing systems,but in this project the noise can be removed by using spatial and temporal filtering.The spatial and temporal filtering can be used to sharpened the edges and reconstruct the images by using Laplacian filtering in the hookworm.Histogram of average intensity is used to represent the properties of the hookworm.

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