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Detection and Classification of Kidney Disorders using Deep Learning Method

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Abstract

The main objective of this work is to detect and classify the chronic kidney diseases (CKDs) particularly kidney stone, cystic kidney and suspected renal carcinoma. CKDs make a ground for developing several numbers of diseases other than urinal system. It will cause the pervasiveness of Coronary heart diseases, stroke, cardiomyopathy, pulmonary hypertension, and heart valves diseases, Early prediction of chronic kidney disease will save life from worse diseases, Ultrasound imaging is widely used diagnostic method for abdominal studies. In this proposed system chronic kidney diseases have detected using a framework containing Histogram of oriented gradient feature and Adaboost Algorithm. Convolution Neural Network (CNN) multi layered architecture has trained for kidney diseases classification, Batch prediction method is evaluated for prediction of chronic kidney diseases. The performance accuracy for detection of kidney disease is given as 96.67% The accuracy for the classification of CKD ultrasound using CNN is given by 85.2 %..

Keywords : Adaboost, Chronic Kidney Diseases, HOG, Convolutional Neural Network, Ultrasound image

I. Introduction

Among the several number of emerging medical diagnostic modalities, Ultrasound is most widely used. Need of ultrasound images will be increasing due to its radio free, noninvasive and portability properties. The non-intravenous findings of diseases which makes physician complacent for surgery, Ultrasound images uses high frequency sound waves to acquire the internal elements of the body. Attenuation due to the sound waves producing an artifact which results in poor diagnosing performance. [III] Chronic Kidney diseases (CKD) are most prevalent diseases that can affect entire systems of the human body. In this paper, three main CKDs namely kidney stones, cystic kidney, and renal cell carcinoma are analyzed for automatic detection and classification. Kidney stones are mainly composed of calcium oxalate, uric acid, struvite and cystic oxide, typically the kidney stones are identified as echogenic material with posterior acoustic shadow floating between calyces infundibulam and pole region of the kidney. kidney stones have no definite anatomical structure, shape and size. The vertical shadow followed by stone region would be the sign for presence of stone. For cystic kidney, a lesion with fluidic structure having small hyperechoic shadow describes presence of kidney cysts. Cysts is covered by a thick-walled septal pattern which having the posterior acoustic shadow. Complex multiple cysts may have irregular septal with each other. Another important CKD is Renal Cell Carcinoma RCC or it is termed as Kidney Cancer. Usually kidney cancer is growing as small tumor and spreading up even to the lungs. More number of researches have worked for noise reduction, segmentation, classification on ultrasound images of kidney diseases for developing radiation free diagnosis. Medical field requires highly meticulous outcomes on diagnosing diseases. Deep learning is a recent concept framed with grade of concepts placed in an order, that has relationship with each other

Related works

High frequency sound waves are quickly responses with tissue region. The echoes are produced from relatively small area of tissue region with different intensity and angle. The bumpy region would cause frequency deviation that makes amplitude waves are dropped at different decibels. This deviation makes speckle noise in ultrasound scanning. Anisotropic diffusion filter is a gradient based image denoising method, Diffusion has to be taken place within the homogenous area of an image. Adaptive boosting uses set of features to form a group of classifiers and classifying them into strong and weak classifier. It eliminates weak classifier by updating weights with training classifier. Algorithm in [I] computes different feature set with Adaboost classifier which results better performance in their work. Adaboost classifier with HOG features [IV]have significant outcomes on detection of different kidney diseases. A deep convolution neural network is recently used method that produces better results for image classification. Anisotropic diffusion filters [X] are effectively worked for speckle noise reduction without destruct edge information, Combination of Back Propagation and DWT features [V] have computed for medical image compression produced noteworthy results. [CNN] showed the comparative results for hyperspectral image cell classification using CNN with discriminative semantic features.

Contribution to the work

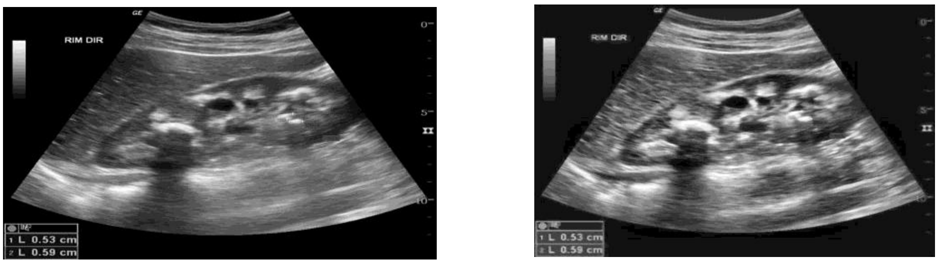
In this work Automatic detection and classification of major chronic kidney diseases, First the input ultrasound images were pre-processed with Anisotropic diffusion filter. Second, integration of Adaboost classifier with hog feature is used for detection of CKD. Third, CNN architecture is used to classifying the detected kidney diseases; Finally, the prediction for the classification is evaluated using batch prediction validation method.

II. Pre-processing.

Speckle artifacts conceals edges and other spatial information of an image, speckle noises spread all over the image surface which is independent to image. it suppresses the detection and classification performance of given images. Typically, this type of artifacts is present in ultrasound images due to backscattering of sound waves from inhomogeneous location of the body, Anisotropic diffusion filter gives the better performance on reducing the speckle noises in ultrasound images Diffusion filters have designed by convolving gaussian kernel on input image to obtain noise reduced image [XIV] proposed the idea of speckle reduction diffusion technique using the following equation.

$$I_t = div(c(x,y,t)\ \nabla I) = c(x,y,t) \vartriangle I + \nabla_c . \nabla I \tag{1}$$

Where div denotes divergence operator, ∇ denotes Gradient operator, $\vartriangle$ denotes Laplacian operator concerning with space variables and $c(x,y,t)$denotes the diffusion coefficient and I denotes Input Image



(a) (b)

Fig. 1. Pre-processing. a) Input ultrasound image b) Diffused output ultrasound image

Above figure Fig. 1 a) shows the input ultrasound image to the Anisotropic diffusion filter and Fig. 1 b) shows Diffused output ultrasound image

III. Detection of chronic kidney disease

In this work three major kidney diseases namely kidney stone, Cystic kidney, carcinomic cell suspected kidney are to be taken for detection. Adaboost framework is utilized to distinguish the above outlined illnesses. In this calculation recognized ailments are appeared by draw a jumping box over the disease found location.

Histogram of Oriented Gradient features

HoG [XV] is a visual-based feature mainly used for object identification. The descriptors for HoG feature are sketched based on local stuff such as magnitude and orientation. After pre-processing input images, gradient of the images has computed by applying single dimension centered mask on both vertical and horizontal direction of given images. The discrete single dimension mask is given by

$$[-1, 0, 1] \ and \ [-1, 0, 1]^T \tag{2}$$

Next to the gradient calculation, histogram bin has created along with different orientation of the images. In this work unsigned angles from 0 to 160 degree totally 9 bins ($0^{\circ}, 20^{\circ}, 40^{\circ} 60^{\circ}, 80^{\circ}, 100^{\circ}, 120^{\circ} 140^{\circ}, 160^{\circ}$) have taken for storing histogram values from calculated gradient and magnitude. The gradient and orientations for the images are calculated using the equations (3) and (4).

$$g = \sqrt{g_x^2 + g_y^2} \tag{3}$$

$$\theta = \tan^{-1}\left(\frac{g_y}{g_x}\right) \tag{4}$$

Histogram of bins are filled with vote-based method. Voting refers to weighting gradient depending on its orientation of the images. Finally, 4X4 subset orientation with 9 bins of histogram produces 144 descriptors as the feature vector

Adaboost Algorithm

From given input data (x_(1,) y_(1,)),…..,(x_(n,) y_(n,)) number of complex classifiers [VIII] constructed with cascade structures and trained for finding a strong classifier. Samples with strong classifier is considered as diseases affected area. Both positive and negative samples have categorized with uniform weights by normalized us-ing probability distribution function. Find weighted error for each feature from equation (5).

$$\epsilon_t = \sum_{i=0}^{n} w_{t,i} \| h_t(x_i) - y_i \|^2 \tag{5}$$

Where ϵ_t represents error rate with weak learner h_t.

Select the classifier having lowest error rate and keep move on the iteration until achieving minimized error rate with updated weights. The final strong classifier has taken based on weighted error of each classifier. The learning parameter is given in the equation (6)

$$\alpha_t = \frac{1}{2} \ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right) \tag{6}$$

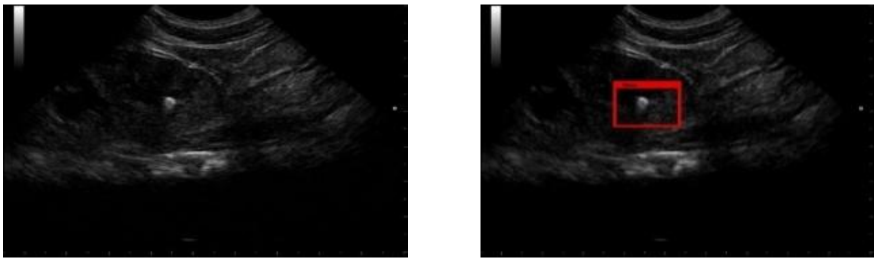
Weight update is given in the equation (7)

$$w_{t,i} = w_{t,i} \times \begin{cases} e^{-\alpha_t} & if h_t(x) = y_i \\ e^{\alpha_t} & if\ h_t(x) \neq y_i \end{cases} \tag{7}$$

Where $w_{t,i}$ represents weight updates of weak learner for next iteration.0

The final classifier is given by equation (8)

$$H(x) = \begin{cases} 1,\ if\ \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ -1, \quad otherwise \end{cases} \tag{8}$$



(a) (b)

Fig. 2 Adaboost classifier. (a) Input ultrasound image, (b) Disease detected using Adaboost classifier

Fig. 2 a) denotes input ultrasound image to Adaboost classifier and Fig. 2 b) denotes diseases detected image from the Adaboost classifier

IV. Classification of kidney diseases

Deep learning technology [II] is incepted from machine learning which plays an important role on medical imaging diagnosis. It processes large number of hidden layers, when compared to conventional layered architecture. Without any extraction method, it learns features by consume large set of labeled data. CNN is one of the intrinsic deep learning methods produces most desirable outcome on several databases namely Cifar-10, MS-coco Mnist and so on. Mnist databases contains multiple images each of having different types of local and global structures ConvNets [VII] is used for classification of cervical cell with outperforming results. In this work, CNN model is used for classifying and recognizing different types of detected Kidney diseases

Convolutional neural network (CNN)

CNN [XI] is worked based on feed forward neural network mainly used to analyse computer vision-oriented problems, Architecture is modelled with multi-layered perceptron that has shift invariant property. Interconnection of multiple layers structured based on human visual cortex. Three main layers namely input layer, hidden layer and output layer are used for constructing CNN architecture. Input layer illustrates nature of image to be inputted, it pre-processes input image into uniform height, width and number of channels present in it. Second major layer illustrates convolution operation [XIII]. In this layer an array of uniform filter is convoluted to the input image with striding and padding. For this work convolution layeris defined by the equation (9)

$$D_{i,i,j} = \sum_{k=0}^{k-1} \sum_{p=0}^{H-1} \sum_{q=0}^{H-1} I_{i+p,j+q,k}^{l-1} \; h_{pqkm} + b_{ijm} \tag{9}$$

Where $D_{i,i,j}$ is the output of the convolution, Irepresents input image $i = 1 \dots mandj = 1 \dots n$ represents row and column indexes of input image, F_{pqkm} represents weight applied to the convolution and b_{ijm} represents bias applied to the convolutionStriding and padding are derived by (10)

$$([W-F+2P]/S) +1 \tag{10}$$

where the W is the number of input volume size, F is the size of filters to be convoluted with input, p is the padding and S is the stride

(a)

69	67	65	65	64
64	56	48	45	44
48	43	40	40	42
41	43	46	49	51
49	51	55	59	60

(b)

278	263	256
242	233	229
235	239	246

(c)

1	0	1
0	1	0
1	0	1

(d)

Fig. 3. Convolution(a) input image, (b) input intensities for R component (c) Filter, Fig. 3. (d) Convolution output

Stride is defined by the moving of filter or weight matrix per pixel over the input image, if the weight matrix moves with single pixel on image it is referred as stride 1 otherwise if the weight matrix moves with double pixel over the image, it is referred as stride 2

0	0	0	0	0
0	69	67	65	65
0	64	56	48	45
0	48	43	40	40
0	41	43	46	49

(a)

1	0	1
0	1	0
1	0	1

(b)

125	179	166
174	278	263
147	242	233

(c)

Fig. 4 Striding and Padding. (a) Input of R Component (b) Filter, (c) Convolution

The above Fig. 4 a), 4 b), 4 c) represent single stride with zero padding for convolution operation, Rectified linear unit (ReLU) [XII] is widely used activation function in deep learning techniques. ReLU activation function is used for identification of multiple sclerosis in CT brain images produces significant results It is complex to enhance weight through the gradient descent if the input has narrow derivative, ReLU allows to reduce the vanishing gradient problem. ReLU activation function is derived by the following equation (11).

$$f_{ReLU}\left(d_{i,k}\right) = \max\left(0, D_{i,k}\right) \tag{11}$$

$$f(x) = \begin{cases} \alpha x \; for \; x < 0 \\ x \;\; for \; x \geq 0 \end{cases}$$

Where $f(x)$ denotes ReLU parametric function and $D_{i,k}$ denotes convolutional output from the filter and diseased image. Pooling layer serves to reduce the spatial resolution of convolutional outcome on each dimension. Pooling has designed using maximum, minimum or mean values of the kernel in an image. Max pooling [IX] is widely used for convolutional neural network. Let K x K block is taken from the NXN image. Maximum value is selected from KXK block and placed it in a pool. Commonly 2X2 window is preferred for pooling layer.

125	179	166	176
174	278	263	225
147	242	233	240
129	187	175	209

(a)

278	263
242	240

(b)

(b) Fig. 4. Pooling layer (a) 4X4 convoluted output, (b) 2X2 Max pooled output

The above fig. 4 (a) represents values from the convolution layer, and fig. 4 (b) represents max pooled values from given convolution layer

After extracting features from convolutional layer, the outcomes are processed through pooling layer and it is converted as single dimension vector using flattened layer. Flatten filter maps 2X2X64 convoluted 2D vector to 256 flat vector Dense layer is the final layer which connects output from the flattened layer with activation function. Each output node is connected by each input node Let w_k is weight function present in the kth node of flattened layer, ReLU activation function is used to normalize the data in dense layer. In this work multicategory diseases has classified using CNN. The trained model for the classification of CKD has done using prediction class of keras model, it takes trained data as input as Numpy Arrays. In this work, multiple classes are used, so multiple inputs have mapped to Numpy arrays as dictionary. The class weights are assigned to indices of each sample during training processes. Probability distribution for each label is categorized using SoftMax activation function [VI]. Classification results returns prediction of NumPy arrays that indicating dependence class of samples

Softmax activation function is given by (12)

$$f_i(D) = \frac{\exp(d_i)}{\sum_j^n \exp(d_j)} \tag{12}$$

Where, x denotes input vector to the output layer

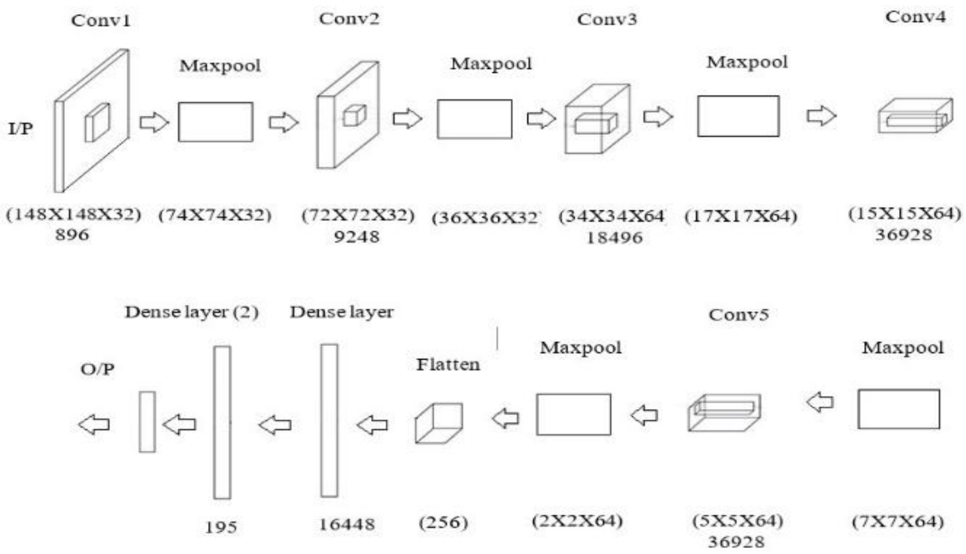


Fig. 5. Flowchart for CNN Implementation.

V. Results and Discussions

The main objective of this work is automatic detection and classification of CKD using ultrasound B-mode images. 90 positive ultrasound images with different types CKD have used for detection and classification of kidney diseases, ultrasound images were acquired from Philips Mindray -DC 70 ultrasound machine Each image have converted to grayscale and resized with 640 X 480 dimension for processing

Detection of CKD using Adaboost classifier

Training and Testing phase

For training phases, ultrasound images have taken with 640 X 480 dimension for detection, 60 images with different category of CKD are inputted to the framework. At first 144-dimensional HOG features were extracted from the inputted samples. The extracted HOG features have given as input to the Adaboost classifier for learning. For testing 30 images with 640 X 480 dimension of hog features is given to the classifier. Based on the strong classifier predicted by Adaboost classifier, disease portion is drawn using bounding box

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Classification of CKD using CNN

Training and Testing phase

For training, detected portion of ultrasound is converted into grayscale and resized to 150 x 150 height and width respectively for classification. First convolution for input image has 32 number of filters with the size of 3X3, it produces 896 param for

Activation function for this convolution is ReLU. Resultant 2-dimensional vector from the convolution layer is max pooled with 2X2 array matrix. Second convolution from the resultant data takes 32 number of filters with kernel size of 3X3 array, it uses ReLU activation and produces 9248 params. Max pooling filter size for this convolution is 2X2. Third convolution onwards from the resultant data takes 64 number of filters with size of 3x3 array, it also uses ReLU activation and produces 18496 2D vector. The output from the third convolution 18496 parameters are again convoluted and resultant parameter is produced as 36928 parameters. These 36928 values are converted as single dimension vector using flattened layer. The final dense layer is the output layer for the network architecture. First dense layer processes nonlinear operation on flattened input vector and produces 16448 parameters as the output. In this work SoftMax activation is used due to multilevel diseases classification, it processes single dimension data as input from flattened layer. This architecture produces 119, 139 features from the input images Compiling model with metrics, loss, and learning rate methods. Train the model using fit complied data from architecture. On training 91% of accuracy is yielded,

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 148, 148, 32)	896
activation_1 (Activation)	(None, 148, 148, 32)	0
max_pooling2d_1 (MaxPooling2	(None, 74, 74, 32)	0
conv2d_2 (Conv2D)	(None, 72, 72, 32)	9248
activation_2 (Activation)	(None, 72, 72, 32)	0
max_pooling2d_2 (MaxPooling2	(None, 36, 36, 32)	0
conv2d_3 (Conv2D)	(None, 34, 34, 64)	18496
activation_3 (Activation)	(None, 34, 34, 64)	0
max_pooling2d_3 (MaxPooling2	(None, 17, 17, 64)	0
conv2d_4 (Conv2D)	(None, 15, 15, 64)	36928
activation_4 (Activation)	(None, 15, 15, 64)	0
max_pooling2d_4 (MaxPooling2	(None, 7, 7, 64)	0
conv2d_5 (Conv2D)	(None, 5, 5, 64)	36928
activation_5 (Activation)	(None, 5, 5, 64)	0
max_pooling2d_5 (MaxPooling2	(None, 2, 2, 64)	0
flatten_1 (Flatten)	(None, 256)	0
dense_1 (Dense)	(None, 64)	16448
activation_6 (Activation)	(None, 64)	0
dropout_1 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 3)	195
activation_7 (Activation)	(None, 3)	0

Total params: 119,139
Trainable params: 119,139
Non-trainable params: 0

Table 1. CNN Training implementation with output parameters using Python

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For testing, three category of CKD images with the sizes of 150X150 have stacked to the batch. The prediction matrix with corresponding classes are identified through the prediction matrix prediction matrix is given by

Prediction Matrix = $\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

⇨ For kidney stones

⇨ For Cystic Kidney

⇨ For kidney Cancer

Performance Analysis

The performance analysis for the predicted matrix have calculated based on confusion matrix. For confusion matrix, true positive, true negative, false positive and false negative, values are calculated from the prediction matrix on the validation of CKD. The performance measures have calculated

Accuracy = TP+TN / (TP+TN+FP+FN)

Precision = TP/(TP+FP)

Recall = TP/(TP+FN)

F score = 2*Precision*Recall / (Precision + Recall)

	Training samples (%)		
Testing Samples (%)	85	3	2
	2	86	2
	4	3	83

Table 2. Confusion matrix

Classification Methods	Accuracy (%)	Precision (%)	Recall (%)	F-measure(%)
SIFT with SVM	82.60	73.80	73.80	73.80
SURF with SVM	84.30	83.25	83.25	79.63
CNN	85.21	93.70	93.70	93.70

Table 3: Performance Analysis for Classification of Chronic Kidney Diseases (CKDs)

The above table 2 and 3 depicts confusion matrix and performance metrics comparison between conventional and deep learning techniques for classification of CKDs

VI. Conclusion and Future Enhancement

In this work automatic detection and classification of CKDs have done using both conventional and deep learning methods, For Detection of kidney diseases, Adaboost classifier is used and the portion of diseases is located by drawn a bounding box over it. The performance accuracy for detection of kidney diseases has predicted as 97.67%. For classification Convolutional neural network is used. Convolution layer directly observers the features form input images and also it has shift invariant output. Three convolutions with multiple number of filters have processed to the input images. The training stages are fine-tuned with different epochs. The final results for the classification of CKD are achieved and showed through the decision matrix. The performance accuracy for predicted diseases has given as 85.21% In future conventional detection scheme may replaces current featuring techniques in order to yield better detection rates for CNN, improved network architecture with different hyperparameters will be worked out for better classification results. The below fig. 6. Shows the comparative results between the conventional method and deep learning method.

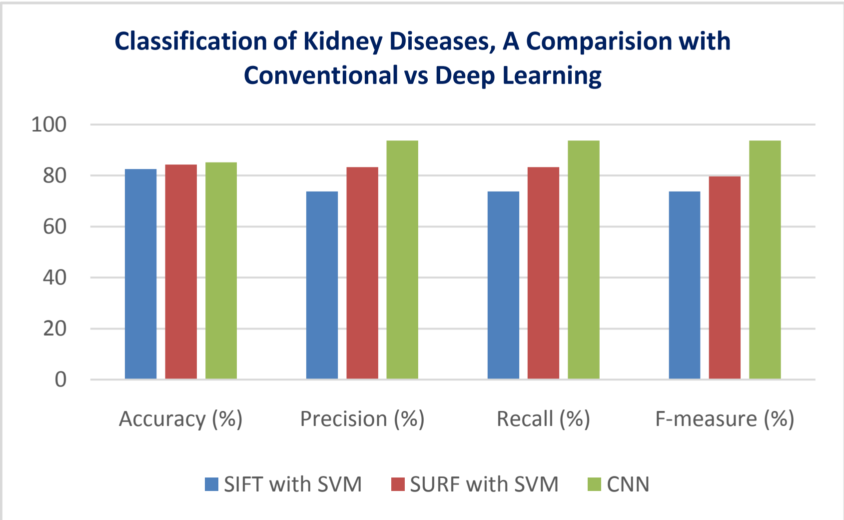

Fig. 6. Performance chart for classification of kidney diseases

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